SENS-IT: Semantic Notification of Sensory IoT Data Framework for Smart Environments

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ABSTRACT

Internet of Things (IoT) is becoming commonplace in people's daily life. Even, many governments' authorities have already deployed a very large number of IoT sensors toward their smart city initiative and development road-map. However, lack of semantics in the presentation of IoT-based sensory data represents the perception complexity by general people. Adding semantics to the IoT sensory data remains a challenge for smart cities and environments. In this thesis proposal, we present an implementation that provides a meaningful IoT sensory data notifications approach about indoor and outdoor environment status for people and authorities. The approach is based on analyzing spatio-temporal thresholds that compose of multiple IoT sensors readings. Our developed IoT sensory data analytics adds real-time semantics to the received sensory raw data stream by converting the IoT sensory data into meaningful and descriptive notifications about the environment status such as green locations, emergency zone, crowded places, green paths, polluted locations, etc. Our adopted IoT messaging protocol can handle a very large number of dynamically added static and dynamic IoT sensors publication and subscription processes. People can customize the notifications based on their preference or can subscribe to existing semantic notifications in order to be acknowledged of any concerned environmental condition. The thesis is supposed to come up with three contributions. The first, an IoT approach of a three-layer architecture that extracts raw sensory data measurements and converts it to a contextual-aware format that can be perceived by people. The second, an ontology that infers a semantic notification of multiple sensory data according to the appropriate spatio-temporal reasoning and description mechanism. We used a tool called Protégé to model our ontology as a common IDE to build semantic knowledge. We built our ontology through extending a well-

known web ontology called Semantic Sensor Network (SSN). We built the extension from which six classes were adopted to derive our SENS-IT ontology and fulfill our objectives. The third, a fuzzy system approach is proposed to make our system much generic of providing broader semantic notifications, so it can be agile enough to accept more measurements of multiple sensory sources.

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LIST OF ABBREVIATIONS

Acronym	**Description**
ATV	Actual Timeframe Value
CEV	Correlation Efficiency Value
CPS	Cyber Physical System
ECG	Electrocardiography
FIS	Fuzzy Inference System
ICT	Information and Communication Technologies
FML	Fuzzy Markup Language
GUI	Graphical User Interface
IoT	Internet of Things
MCB	Micro-Controller Board
MQTT	Messaging Query Telemetry Transport
PTV	Predicted Timeframe Value
SoC	Software on Chip
SSN	Semantic Sensor Network
QoL	Quality of Location

Chapter 1 INTRODUCTION

1.1 Internet of Things (IoT)

The vision of a digital twin, as introduced by Prof. El Saddik (El Saddik, 2018), is a digital replication of a living or non-living physical entity. By bridging the physical and the virtual worlds, data are transmitted seamlessly, allowing the virtual entity to exist simultaneously with the physical entity. A digital twin facilitates the means to monitor, understand, and optimize the functions of the physical entity and provides continuous feedback to improve quality of life and wellbeing. A digital twin is hence the convergence of several technologies such as AI, AR/VR and Haptics, IoT, Cybersecurity and Communication networks. A component of the digital twin vision is to fill the gap in the Internet of Things (IoT) revolution, which has a key impact on people's environments. The IoT is needed to build assistant tools like ontologies and fuzzy systems, which help humans understand their environment and therefore facilitates their daily interactions with the environment. The IoT revolution is considered to be a structured cyber physical domain in all of people's day-to-day domains.

In order to provide their citizens with smart transportation, context-aware environments, healthcare, high level education, reduced pollution, efficient power consumption, instant event notifications based on predefined individual preferences, etc. and, in turn, an improved quality of life, many governments are tailoring their future development projects in ways that support smart environment deployments. A smart city is a commonplace term used as a smart environment application. The smart city is referred to in many definitions, according to its domain or perspective. The first known smart city definition appeared in the early nineties

(Harrison et al., 2010). Smart city, by definition, is an integration of all life aspects through the use of Information and Communication Technologies (ICT) and other facilities, all of which contribute to a person's necessities of daily living. Numerous smart world applications, including a smart environment (Stankovic, 2014), rely on the evolution of Internet of Things (IoT) as the main enabling factor in their progress. The IoT is expected to dominate the consumer and industrial sectors, since it is becoming commonplace in our daily life (Evans, 2011; Gartner, 2017). The usefulness of sensing and actuating things exists in broad and diverse environments such as indoors, transportation, health, energy, entertainment, education, and farming, just to name a few. What makes the IoT unique is that it can help collect data about anybody or any device and it can do so anywhere, through any service, and in any context that provides a bridge between people and their physical or virtual spaces (Perera, Zaslavsky, Christen, & Georgakopoulos, 2014). The evolution of the IoT over the years has involved the creation of many connections within people's environments. Thanks to the progress of a IoT microchip component and Nano technologies, it is expected that, by 2020, the number of items connected by the IoT, globally, will reach approximately 50 billion sensors and actuators, streaming real-time IoT data (Evans, 2011). Semantic feedback of IoT sensors/actuators provides agile data processing and administering of IoT outcomes (Palavalli, Karri, & Pasupuleti, 2016). Many smart environment applications tend to rely on semantic approaches placed at cloud or edge locations for rich analytics and visualization.

1.2 Motivation

The Internet of Things (IoT) is an evolving technology that takes place in a plethora of commonplace areas in our lives, such as health care, transportation, homes, education, industry, supply chains, Earth sustainability. Its evolution over the years makes the IoT a unique technology that is embedded in different applications. The importance of the IoT is expected to grow in the near future due to people's queries toward real-time events happening around them in their different environmental contexts. Also, the growth of the IoT is expected to be dominant in the consumer and industrial sectors (Ziegeldorf, Morchon, & Wehrle, 2014).

With the obvious increase in the volume and importance of the IoT in modern-day life, several challenges arise that can create obstacles during the IoT deployment process, mainly related to the perception complexity of different people's environmental contexts like environment quality, crowdedness, reading suitability, health and so on.

Synchronization of sensory data timestamp is considered a challenge in IoT space. Although Ottawa City uses a station of some environmental sensors to monitor air quality status that affects its residents and natural environment (Ontario, 2018), the city dataset shows that there is no a unified timestamp clocking for streaming the whole disseminated environmental sensory sources. Instead, the city uses a separate timestamp for each environmental sensory source (OttawaCity, 2018b, 2018a), which is considered a clock synchronization problem. There is a need to come up with a platform that synchronizes all sensors' streaming in a unified timestamp. So, all locations have to stream its sensory data in a synchronized clock way for data integrity optimization.

Since a vast number of IoT sensors are (or will be) deployed in smart environments, the quantity of sensory feedback that will be generated will add substantial traffic, which might adversely affect the overall scalability and the quality of the notification services of the IoT applications, consequently affecting the network's performance (Al Nuaimi, Al Neyadi, Mohamed, & Al-Jaroodi, 2015; Kitchin, 2014; Stankovic, 2014). Also, sensors normally provide raw values representing low-level feedback, which is considered a lack of information. We need to overcome this lack by providing approaches with more interpretable and understandable abstraction, above the raw sensory data. The proper interpretation of people's environment requires agents to play a further role such as translating what the sensors observe around us into easy to understand notifications or feedback. In order to present descriptive information resulting from the low-level feedback, data link integrity between sensory sources and their environment should be prepared as a source of semantic knowledge.

1.3 Research Statement

Considering the promising impact of IoT technologies and applications on communities and government developments (in the fields of health, transportation, city urbanization, etc.), very few research works have addressed the ways in which the IoT can improve people's perception of their indoor and outdoor environments. Semantic notifications of people's environments aim to translate a one-dimensional perception of an environment, received through a number of raw notifications streaming from various sensory sources, into a single descriptive notification that combines the information from multi-sensory sources, according to specific thresholds, in a spatio-temporal way.

Therefore, briefly put, how can we overcome the complexity perception of multiple raw sensory data feedbacks received from people's environments and instead offer a meaningful and easy to understand notification?

Two key points that fall under the research question are as follows:

- Propose a framework to identify SENS-IT layers according to a hypothetical analysis. Streaming the sensory data in a unified clocking of all deployment nodes is proposed for sensory data integrity.

- Propose an ontology-based approach to identify the reasoning knowledge and generalize the ontology using a fuzzy logic approach.

Although environmental sensors measure people's ambiance and provide single dimensional feedback, there is no approach or model that describes people's environments using a combination of multiple sensory sources to provide a descriptive and semantic notification.

1.4 Thesis Contributions

The main thesis contributions are listed as follows:

1. An analysis of existing systems for geo-temporal multi-sensory systems based on some criteria.

2. A design and development of an IoT framework called the Semantic Notification of Sensory IoT data (SENS-IT) that satisfies the analysis criteria by using Edge and Cloud technologies. For proof of concept, we conducted an empirical study in the city of Ottawa to analyze the degree of correlation between noise and air quality in different outdoor locations.

We intentionally chose to calculate the correlation efficiency to determine whether or not the two sensory sources are linearly related.

3. An ontology that can interpret raw multi-sensory data to make sense of data in textual and easy to understand format. The ontology is an extension of the Semantic Sensor Network (SSN) to identify IoT sensors and their observations. To our knowledge, this is the first work that combines the data from several raw sensors into an ontological mechanism in order to perceive people's environments.

4. The design and development of a fuzzy logic system to make the system more agile, allowing uncertainty or the ambiguity caused by missing values, to be overcome.

1.5 Scholarly Achievements

1. **Majed Alowaidi**, Ali Karime, Mohammed Aljaafrah, and Abdulmotaleb El Saddik, Empirical Study of Noise and Air Quality Correlation Based on IoT Sensory Platform Approach, IEEE I2MTC 2018, Houston, USA. (Published)
2. Mohammed Al Jaafreh, **Majed Alowaidi**, Hussein Al Osman, and Abdulmotaleb El Saddik, "Multimodal Systems, Experiences, and Communications: A Review Towards The Tactile Internet Vision", Springer 2018, (in press).
3. **M. Alowaidi**, M. A. Rahman, E. Hassanain, and A. El Saddik, A Semantic Notification Approach for IoT-Based Sensory Data, Proceedings of the Second International Conference on Internet-of-Things Design and Implementation - IoTDI 17, no. 1, pp. 289290, ACM 2017. (Published)
4. **Majed Alowaidi**, Best Demo Award at The Sensor Application Development Workshop 2017, IEEE SAS.

5. **M. Alowaidi**, Mohammad Aljaafreh, Ali Karime and Abdulmotaleb El Saddik, A Fuzzy Markup Language-Based Approach for a Quality of Location Inference as An Environmental Health Awareness", International Journal of Extreme Automation and Connectivity in Healthcare (IJEACH), 2018, (Accepted)

1.6 Thesis Organization

The thesis is organized according to the following chapters:

Chapter 1: We present the revolution of IoT and motivations of this work, as well as the main contributions and scholarly achievements.

Chapter 2: We present an abstract view of Internet of Things, concepts, and frameworks, an overview of context-aware and semantic views, edge computing overview and its related work.

Chapter 3: We present an overview proposed SENS-IT system design and the detail of its tiers.

Chapter 4: We present the implementation of SENS-IT by describing its components and functionality.

Chapter 5: We present an ontological approach aiming to build a reasoning and knowledge base of the sensory data of people's environment.

Chapter 6: We present a design and development of a fuzzy logic system aiming to make the ontology generic, so it can cover wide range of semantic notification. Also, this chapter includes a mathematical model needed to our SENS-IT that presents a fuzzy system inference conceptually.

Chapter 7: We present an evaluation of the SENS-IT system. Also, the chapter provides an analysis and discussion of the achieved results.

Finally, in **Chapter 8,** we will summarize and conclude the thesis and state our forecast about the future work view.

Chapter 2 BACKGROUND AND RELATED WORK

2.1 Introduction

In this chapter, we introduce the concept of the IoT, its definitions and hardware, and we also consider some of its several applications. We present a summary of current IoT frameworks, provide a literature review of the most relevant works, and present some concepts used in smart environment space. Additionally, we show the Edge Computing concept and its impact on IoT as shown in a hierarchal depiction. Finally, based on our analysis outcome of related work, we show some key criteria needed for the design and development of our framework.

2.2 IoT Abstract View

The Internet of Things (IoT) is considered the most recent evolution enabler and a commonplace influencer that aims to connect a variety of entities with the ability to sense, communicate, gather, analyze and publish data. The IoT allows us to increase our knowledge of indoor and outdoor environments, enabling us to react according to these environments. The interaction between various IoT components is based on a thing-to-thing or thing-to-person relationship. Several IoT definitions in the research community chronicle the significance of the IoT on people's daily lives. The term IoT initially appeared in the supply chain business in 1999, when RFID was a new technology for object sensing (Evans, 2011; Gubbi, Buyya, Marusic, & Palaniswami, 2013). Based on multiple research studies, the IoT is a promising and key actor in commonplace areas of our lives, therefore the number of connected things is expected to reach several billions by 2020 (ABI Research, 2013; Evans, 2011; Gartner, 2017).

The IoT has been described extensively in academia and industry. One definition states that it is, "*the general idea of things, especially everyday objects, that are readable, recognizable, locatable, addressable and/or controllable via the Internet, including RFID, wireless LAN, wide-area networks or other means*" (National Intelligence Council, 2008). Atzori et al. defined it as "*an object that can be tracked through space and time throughout its lifetime and that will be sustainable, enhanceable, and uniquely identifiable*" (Atzori, Iera, & Morabito, 2010). We consider the IoT as a collection of distributed things/beings, with intelligence and context-awareness via sensors/actuators and seamless Internet connectivity.

The IoT is known as an enabling technology and it is considered an important factor in many people's daily lives, as it is present in the fields of health, education, transportation and sports, in both government and industry. Many smart application domains were deployed before the IoT emerged and evolved (Bainbridge & Steinberg, 2010; Gubbi et al., 2013; Kidd, Orr, Abowd, Atkeson, & Essa, 1999; Murty et al., 2008). From a semantic perspective, the IoT is composed of two words and concepts as defined by (Alessandro Bassi and Geir Horn, 2008) : Internet can be defined as the world-wide network of interconnected computer networks, based on a standard communication protocol, the Internet suite (TCP/IP), while Thing is an object not precisely identifiable. Therefore, semantically, the Internet of Things means a world-wide network of interconnected objects uniquely addressable, based on standard communication protocols. Today, most deployments are designed to be IoT-ready, which means the infrastructures are compatible with IoT sensors and actuators. We discuss some recent IoT applications in the following examples.

Health care and critical mission monitoring and controlling are significant factors in people's lives, and both can benefit from the development of the IoT. In health, IoT technologies such as RFID, WSN and smartphones offer complete cooperative biomedical services in hospitals and homes to monitor and track patients' activity. Amendola et al. (Amendola, Lodato, Manzari, Occhiuzzi, & Marrocco, 2014) studied IoT applications for people's health and wellness. For example, RFID tags used to sense volatile compound materials are positioned in walls, food and drug locations, fire detection devices, and high heat indoor appliances. Similarly, an RFID labeling chip implanted in a human body can monitor real-time or on-demand patient status. Rohokale et al. (Rohokale, Prasad, & Prasad, 2011) proposed a cooperative IoT approach to monitor and control health in rural locations. Their model can monitor heartbeats as well as blood pressure and blood sugar levels, which can be used for energy efficient motherhood health-care programs. In critical or emergency cases, such as heart attacks, installed IoT nodes with ECG and gyroscope sensors can monitor irregular heartbeats or sense if a patient has fallen in their indoor environment, and subsequently send a real-time notification to the person in charge, for example a family physician or a relative. This notification is based on a cooperation threshold between all sensors for specific monitoring and tracking requirements.

For athletes or fitness types, geared devices such as wearables and smart watches have been developed to a high degree and have had a huge impact on the technology industry. The IoT evolution has also made training and regular exercise more efficient and trackable with device connectivity and online cloud processing (Wei, 2014). Santamaria et al. (Santamaria, Raimondo, De Rango, & Serianni, 2016) proposed an IoT wearable-based solution for human activity recognition based on fuzzy logic, which recognizes users' habits and initiates alerts when signals become irregular. This method gathers human activity signals from sensors in a person's body and builds a reference to allow for real-time monitoring and analysis of their activity.

The home is considered one of the hot areas of the IoT and smart environment evolution. Applications for home monitoring and control systems became possible when IoT-based solutions transformed homes into smart environments, thus enabling end users to easily manage their ambient objects. Hafidh et al. (Hafidh, Osman, & Arteaga-Falconi, 2017) proposed a smart IoT enabler framework (SITE) for end users, using simple language that allows them to build their own rules to control and administer smart objects in their homes. This IoT approach is designed to support IT and non-IT end users and meets most people's everyday requirements regarding their ability to control and monitor their indoor environment.

The IoT revolution has promising transportation-enhancing potential, including traffic management, and road and vehicle safety. Academia has enriched transportation development progress by proposing various approaches and models. He et al. (He, Yan, & Xu, 2014) proposed an IoT platform for vehicular and transportation data in a cloud-based environment that could enhance traffic control in urban regions. Their architecture is a SaaS cloud service that performs tasks such as street crossing control, smart parking discovery, vehicle sensing and other services. It provides IoT-based capabilities for vehicle and device integration that enhances overall transportation environments.

Governments want to provide sustainable environments that are clean and climate friendly, as well as maintain a quality of life for current and future generations. Many studies have been conducted to address environmental problems using computer science and other engineering disciplines, and IoT-based approaches have been considered to help overcome certain environmental impacts. Fang et al. (Fang et al., 2014) developed an integrated four-tier IoT system to monitor and manage regional environments. Their approach is based on environmental informatics that aggregate domains such as computer science, environment, information and industrial engineering. The system combines several sources of perception, transformation, cloud processing and sharing, for environmental control and monitoring in the Xinjiang region of China.

The IoT evolution now plays a key role in a wide variety of applications, and it will be applied extensively in the near future. There is no doubt that the success of IoT will impact enablers that are considered fundamental for present and future IoT infrastructure projects (Alessandro Bassi and Geir Horn, 2008). These include smart objects and smart environment implementations that benefit from the IoT's rapid improvement, as we will discuss in the next section.

The IoT platforms use technologies that help fulfill the requirements needed for optimizing its performance. One of these platforms is application protocols, which are needed for IoT things to communicate. Several application protocols are used for the IoT, according to their suitability for the final applications. The two most commonly used IoT application protocols are Messaging Query Telemetry Transport (MQTT) and Constrained Application Protocol (CoAP) (Al-Fuqaha, Guizani, Mohammadi, Aledhari, & Ayyash, 2015; Karagiannis, Chatzimisios, Vazquez-Gallego, & Alonso-Zarate, 2015).

2.3 Smart Environment Concept

Smart environments have the potential to improve all aspects of people's lives, as well as their surrounding areas, and the concept has been utilized based on the task context of the intended areas. Smart cities are important and highly trending applications of smart environments. Before the smart city term emerged, it was called by many names, including virtual city, ubiquitous city, intelligent city, digital city, knowledge city, smart community (Cocchia, 2015). Today, digital city and smart city are the most interchangeable identifiers of smart environments.

A smart environment agent is able to understand people's context or state and physical ambiance using sensors and controllers, and can trigger actions that optimize planned performance outcomes (Cook & Das, 2004). A specific smart environment application is a smart city. The British Standards Institution defined smart city (Bloomberg, 2014) as, " *an effective integration of physical, digital and human systems in the built environment to deliver a sustainable, prosperous and inclusive future for its citizens*". Smart environments are envisioned as urban solutions to promote, improve and simplify life, fully utilize and deliver services to residents, and reduce power consumption (Khan, Anjum, Soomro, & Tahir, 2015; Schleicher, Vögler, Inzinger, & Dustdar, 2015). It is worth mentioning that ICT is a key player in the smart environment transformation and the integration of information and communication technologies (Anthopoulos & Fitsilis, 2015). Thus, an environment with potential intelligence, efficiency and on-demand services to end users is a prospective smart environment.

Several smart environment definitions have been used in the literature to describe environmental knowledge and context-aware features. We cover the most cited and relevant definitions as follows: The authors in (Washburn & Sindhu, 2009) define it as: "*New generation of integrated hardware, software, and network technologies that provide IT systems with real-time awareness of the real world and advanced analytics to help people make more intelligent decisions about alternatives and actions that will optimize business processes and business balance sheet results*".

Chourable et al. (Zanella, Bui, Castellani, Vangelista, & Zorzi, 2014) define a smart city as a well-known smart environment application: "*The new intelligence of cities, then, resides in the increasingly effective combination of digital telecommunication networks (the nerves), ubiquitously embedded intelligence (the brains), sensors and tags (the sensory organs), and software (the knowledge and cognitive competence*)".

Many governments are keen to adopt smart environmental solutions in infrastructure development plans, in order to enrich their citizen's lives. Some challenge their communities to help with smart city transformations by offering prizes or incentives for the best and most innovative ideas. For example, in the Fall 2017 Smart Cities Canada Challenge (Canada Government, n.d.), Canadians were invited to participate by suggesting ideas to improve their environment—whether a city, town or community—and recommend what smart evolution would have the highest impact in their communities.

Many approaches and models have been proposed to assess smart environmental solutions, from many domains and different locations. Dameri et al. (Dameri & Rosenthal-sabroux, 2016) recognized smart environment domains as a smart introduction of mobility, economy, people, governance, healthcare, transportation, society and living. They considered the domains to be essential components in projects targeting ease of life planning. Schleicher et al. (Schleicher et al., 2015) viewed smart environment domains as holistic heterogeneous views meant for industrial and government stakeholders. Their proposal assumes an ideal loop of smart environments that will collaboratively support undeveloped territory, while still performing their fundamental role of enabling cities to become smart ready.

Smart environment frameworks or platforms designed for end users' demands and contexts are often discussed in the literature. Transportation, healthcare, community development, security, public involvement (crowdsourcing), optimal energy usage, and city management are the most frequent uses of smart environment initiatives. Table 2-1 highlights some smart environment frameworks and contexts used, according to people's requirements. In transportation, for example, traffic can be enhanced to decrease congestion and reduce the number of accidents. In various contexts, the ability to take smart decisions can help encourage energy efficient solutions. In the field of healthcare, wearables play an important role in smart environment platforms, since they deliver real-time sensory readings. The readings can be obtained via wireless body area network (WBAN) devices for leisure or health-monitoring instruments, such as fitness watches and ECG sensors. The elderly and those with special needs are often the focus of many smart healthcare projects.

Smart cities initiatives play an important role in the growth of other smart environment sectors in communities' development or urbanization. This will not happen without offering the required ICT infrastructure to increase education and awareness and boost sustainable environment initiatives. In other words, the urbanization of communities can effectively bridge or integrate other smart environment frameworks. In crowdsourcing, governments ask their citizens to share their hard or soft sensor data for smart environment projects, such as the public's ability to upload wrong behavior witnessed to the authorities' applications.

Smart Environment Framework(platform)	**Framework Contexts**						
	Health Care	Transportation	Energy	Earth	Urbanization	Crowd-sourcing	Security
A Traffic-Aware Street Lighting Scheme for Smart Cities using Autonomous Networked Sensors (E. M. Daly, Lecue, & Bicer, 2013)			✓	✓			
CitR: A Scalable System for Quick Spatial Retrieval of Resident Involvement Information for Smarter Cities (Gubbi et al., 2013) (Jin, Gubbi, Marusic, & Palaniswami, 2014)		✓				✓	
Using mobile crowd sensing for noise monitoring in smart cities (Aleyadeh, Oteafy, & Hassanein, 2015)				✓		✓	
A cloud-assisted internet of things framework for pervasive healthcare in smart city environment (Mrazovic et al., 2016)	✓					✓	✓
Social Smart City: A Platform to Analyze Social Streams in Smart City Initiatives (Souza et al., 2016)						✓	✓
Crowd Sourcing, with a Few Answers: Recommending Commuters for Traffic Updates (E. Daly, Berlingerio, & Schnitzler, 2015)		✓				✓	
An information framework for creating a smart city through Internet of things (Jin et al., 2014)	✓	✓		✓	✓	✓	
Scalable Transportation Monitoring using the Smartphone Road Monitoring (SRoM) System (Aleyadeh et al., 2015)		✓				✓	
CIGO! Mobility Management Platform for Growing Efficient and Balanced Smart City Ecosystem (Mrazovic et al., 2016)		✓			✓	✓	✓
Fix My Street or Else: Using the Internet to Voice Local Public Service Concerns (King & Brown, 2007)		✓				✓	
SAIS: Smartphone Augmented Infrastructure Sensing for Public Safety and Sustainability in Smart Cities (Liao et al., 2014)						✓	✓
Human sensing for smart cities (Mukherjee et al., 2014)		✓		✓		✓	✓
Architecting Smart Home Environments for Healthcare: A Database-Centric Approach (Morais, 2015)	✓						
BlueParking: An IoT based Parking Reservation Service for Smart Cities (Taherkhani, Kawaguchi, Shirmohammad, & Sato, 2016)		✓	✓				
Smart City: An Event Driven Architecture for Monitoring Public Spaces with Heterogeneous Sensors (Filipponi et al., 2010)		✓					✓

Table 2-1 Smart Environment Frameworks and Usage Contexts

Residents can also share their claims of unmaintained streets or neighborhoods. Crowdsourcing is considered a fundamental aspect of most smart environment frameworks, as it is clearly shown in the aforementioned table. However, public participation in smart environment transitions is a challenging issue, as it relies on mutual loyalty and transparency between cities and residents. Therefore, governments motivate residents to participate by granting them incentives for their involvement (Mukherjee et al., 2014).

The requirements for an optimal smart environment transition are the indicators or measurements that enable an environment to be smart. Every project heading toward smart capability has its own transition indicators or measurements that define its goal; that is, a set of methodologies or metrics prepared in advance to evaluate the smartness potential of an environment (Lazaroiu & Roscia, 2012; Lombardi, Giordano, Farouh, & Yousef, 2012). The metrics can be related to human, institutional or technological dimensions (Nambi, Sarkar, Prasad, & Rahim, 2014). In

Table 2-2, we highlight some key indicators or enablers of a smart environment roadmap according to its context and dimension.

Smart environment implementations, such as smart cities, have been used for different purposes worldwide ("Intelligent Communities List," 2015). Every smart environment initiative is calculated purposely in order to meet community interests, and is based on the size of the city, the available ICT services, or a predefined future vision of the smart environment application. Governments are concerned about releasing proactive legislation that addresses potential challenges, so they support transitions to smart environment applications. Thus, every citizen's life can be improved with much fewer side-effects on their environment. One of the most important procedures in disseminating smart environment projects is to motivate citizens in their city-related applications. For example, city authorities can offer their residents incentives for reporting events using their unique IDs, such as participating in city projects, sending notifications of waste collection delays or abandoned items in the community (King & Brown, 2007; Mukherjee et al., 2014).

Smart Environment Context	**Indicators (requirements)**	**Dimension**		
		I	**H**	**T**
Health (Hassan, Albakr, & Al-Dossari, 2014)	- Integration between smart objects. - Communication protocols reliability especially nomadic services. - Security and privacy. - Sophisticated data retrieval per patients' needs.	✓	✓	✓
Earth (Giffinger, 2007)	- Sustainable resource management - Pollution monitoring. - Appealing natural conditions.	✓	✓	✓
Smart Living (Lazaroiu & Roscia, 2012)	- Frequent usage of recreational sports and leisure. - Health conditions. - Community center services. - Theater and cinema. - Safe neighborhood.	✓	✓	✓
Transportation (Giffinger, 2007)	- ICT infrastructure availability - Communication protocols reliability especially nomadic services. - Security and privacy. - Sustainable, innovative and safe transport.	✓	✓	✓
Smart people (community) (Giffinger, 2007; Lombardi et al., 2012)	- Level of education or qualification. - Computer and Internet skills percentage. - Creativity. - Loyalty. - Involvement in community life. - Spoken international language.	–	✓	✓
I: Institutional, **H**: Humanitarian, **T**: Technological				

Table 2-2: Main Smart Environment Indicators (Metrics)

A variety of smart environment initiatives exist in cities around the world (Caragliu, del Bo, & Nijkamp, 2011) and each has its own vision and roadmap to achieve their smartness-aware target. In the following, we briefly highlight three cases of smart environment initiatives.

Barcelona became a smart city (Alawadhi et al., 2012; Bakıcı, Almirall, & Wareham, 2013) by transforming traditional city roles of transportation, management and other assets, with the objective of providing an integrated model of versatile urban development. The city developed features that influence community urbanization, proving that the system can be effectively managed. The Smart City of Barcelona is built on the elements of three main components: infrastructure, human capital, and information. This can be observed in an example project such as 22@Barcelona, which is a complete transformation of a territory with advanced needs. The project involves huge infrastructure changes targeting city services development, including WiFi coverage and an optical fiber network that covers 325 kilometers.

Guadalajara City is another smart city initiative, proposed by the University of Guadalajara (Larios, Gomez, Mora, Maciel, & Villanueva-Rosales, 2016). The aim was to provide Living Lab solutions as a testbed for verification and validation of what is required to assess the city's smart performance according to certain environments contexts. The main technologies used in their Living Lab are IoT, SDN Networks and Private Cloud. The Guadalajara project has a three-phase development plan. The first phase started in 2015 with catalysts, validation and design fundamentals. The second phase was implemented in 2016 to conduct deep testing and collect feedback, and the third phase, planned for 2018, will include the integration and stakeholder update. The project also provides an educational dimension by establishing partnerships with other schools in Mexico and the US, allowing students from multiple disciplines to find solutions to challenges faced by the Guadalajara initiative.

The SmartSantander initiative is an empirical research testbed to support applications and services related to smart city projects (Sánchez et al., 2013). It was initiated as a two-purpose project. The first is as a global experiment for IoT parts, including protocols and applications, and the second is to provide the city of SmartSantander with quality of life development services. The project includes four cities in Europe and comprises more than 20,000 smart objects deployed over different technologies. SmartSantander targets academic fields, the public, and service providers, although it can also be applied to other usage profiles in the smart city context. The project covers a wide range of preferences that its infrastructure was designed for and has already applied four service dimensions: environmental monitoring, traffic management, augmented reality and crowdsensing.

2.3.1 Context-Aware Overview

Environments that involve people are equipped with a host of physical and embedded objects, whether they are in homes, workplaces, campuses or other spaces. The applications used in these spaces need to be context-aware, so they can adapt to instantaneous variations and be understood by people involved in the applications. Smart environments increasingly require context-aware features that rely on different technologies, such as semantic perception, context querying and context reasoning (Wang, Dong, Chin, Hettiarachchi, & Zhang, 2004). Context-aware innovations were initially proposed in 1994 (Schilit, Adams, & Want, 1994).

The literature contains several definitions for the term context-aware. Dey et al. (Dey, Abowd, & Salber, 2001) proposed a context-aware conceptual framework and defined it from two perspectives. The first is a high-level definition of context as information that benefits the distinguishing status or activity of an object or area in which it functions or has influence; this definition is categorized as subject control access. The second definition is context centric, which is a direct characteristic of a policy and its execution process; once used in an explicit specification, it will make the policy of the context valid. Abowd et al. (Dey & Abowd, 1999) defined context as any information used to qualify an entity. Moreover, the authors defined the term context-aware as the exploitation of perspective to provide users with needed information and services according to their ambiance. A broader context definition by the authors is: "*Context is any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves*".

Context-aware sources adapt to their context, based on the perspective of their soft and hard sensors. Hard-based sensors such as Bluetooth, WiFi and GPS are used for proximity, spatial and temporal applications, and are the most commonly employed context-aware sources in workplaces, smart-environments, healthcare, athletic facilities and other areas. Soft-based sensors play a crucial role in social media applications by extracting users' feedback about their environment or specific events.

Table 2-3 shows some context-aware approaches, the context types in which they were proposed, and the sensor types used for the context, whether soft or hard.

Approach	**Context Types**	**Sensors Used** Soft/Hard
A Modular Approach to Context-Aware IoT Applications. (Venkatesh, Chan, Akyurek, & Rosing, 2016)	Spatial and temporal user activity Indoor & outdoor	GPS
AWARE: A mobile context instrumentation middleware to collaboratively understand human behavior. (Ferreira, 2013)	Spatial, behavioral	GPS
CASP: Context-Aware Stress Prediction System. (Alharthi, Alharthi, Guthier, & El Saddik, 2017)	Spatial-temporal, ambiance, behavioral	GPS, ECG, Bluetooth
EmotionSense: A Mobile Phones Based Adaptive Platform for Experimental, Social Psychology Research. (Rachuri et al., n.d.)	Emotional behavioral, spatial	GPS, Accelerometer, Bluetooth, Positioning
The Affect-Aware City. (Guthier, Abaalkhail, Alharthi, & Saddik, 2015)	Emotional, behavioral, spatial, temporal	Social networks (e.g. Twitter)

Table 2-3: Context-Aware Approaches

2.3.2 Semantics View

Since we discussed the meaning of context in the previous section, it is important to understand the semantics of the term from a linguistic perspective. According to Huang et al. (Huang & Snedeker, 2009) the meaning of semantics is: "*the aspects of the interpretation that can be directly calculated from the meanings of words and the structural relationships between them*".

As semantics can help in the modeling and the management of entities (Huang & Snedeker, 2009), this definition implies that a close relationship between semantics and context is required to achieve a better perception of IoT sensory data. Several approaches and studies have addressed various aspects of IoT sensory development, including semantic annotation and reasoning services. In this section, we review the literature of semantic and context platforms according to the IoT.

Venkatesh et al. (Venkatesh et al., 2016) proposed a modular context engine that exploits specific context-aware applications of user activity and location, in order to minimize processing complexity and increase computation efficiency. Using wearable sensors for different indoor and outdoor activities, they found optimal results of up to a 65% reduction in application delay, and up to 50% less enforcement load. However, the accuracy reduction was small compared to the competitive results.

Toninelli et al. (Toninelli, Montanari, Kagal, & Lassila, 2006) researched a policy of access control for pervasive computing by adopting a semantic and context-aware approach to securely control the access policies of resources. Their approach applied description logics (DL) and Web Ontology Language (OWL) to model the protection of source, actor and environment, as a set of context elements. The main reason for using a combination of DL and OWL is to overcome any insufficient reasoning in a context, which also makes the access control context far more expressive. This mechanism is intended to create workable correlations of contexts between relationships of unknown individuals, such as resource requested and resource owner.

Bonte et al. (Bonte et al., 2017) presented a platform called MASSIF for semantic perception and reasoning of IoT data. MASSIF can render a high-level perception of IoT data by presenting context information and several IoT reasoning types of raw sources data, thereby providing end users with perceived knowledge and enabling them to take the most effective decisions. MASSIF is an extension of the SSN ontology (Compton, Barnaghi, & Bermudez, 2011) and has concepts and relations to model sensory readings from multiple sources.

Wu et al. (Wu et al., 2017) proposed a framework called the semantic Web of Things (SWoT) for cyber physical systems (CPS). SWoT is an integrated SSN extension solution and machine learning mechanism, based on a model called entity linking (EL). It is intended to overcome the constrained manual construction of device knowledge by providing semantic logical reasoning. This can be achieved by calculating the probability of common contexts within SWoT metadata.

Ali et al. (Ali, 2015a) designed a linked data infrastructure approach to overcome information integrity issues from heterogeneous enterprise sensory sources. The approach is a semantic information model that can extend current semantic models, including SSN, FOAF and PIMO, which are needed to integrate diverse collaborative sensory sources such as personal and professional online communication. With this approach, the exchange of flexible and dynamic information from different IoT sources is feasible.

2.4 Edge Computing

Edge computing is the method used to place computing and storage at the Internet’s edge so that devices that need to store or process their data can be in close proximity to a device (Shi & Dustdar, 2016). In the next subsections, we will present an overview of the emergence and development of edge computing, as well as the benefits it provides for the IoT revolution. A block diagram of edge computing is shown in Figure 2-1.

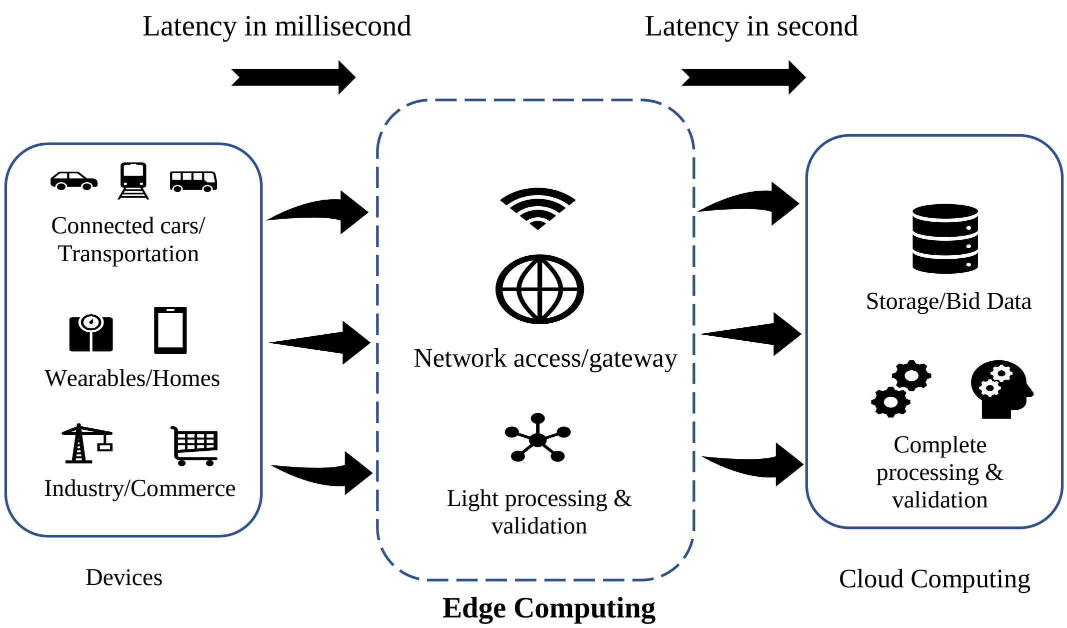


Figure 2-1: Block Diagram of Edge Computing

2.4.1 The Emergence of Edge Computing

Edge computing originally appeared in the late ninety's, when content delivery networks were introduced to optimize web acceleration (Satyanarayanan, 2017; Shi & Dustdar, 2016). The need for edge computing appeared in order to help optimize the performance of devices and applications. Edge computing has many benefits for the IT industry and the economy in general.

Unlike cloud computing, it distributes its services to be as close as possible to devices or nodes, so it can enhance the relevant applications and services to their optimal production and performance levels. It is at times also referred to by other terms such as fog computing and cloudlet (Shi, Cao, Zhang, Li, & Xu, 2016). Edge computing is characterized by many aspects, some of which are listed below (Satyanarayanan, 2017):

- **Proximity feature**: This feature implies reduced latency by some specific services or applications, in order to satisfy customer demands. The shorter distance from the service requester helps optimizing its performance.
- **Streaming distribution architecture**: Unlike cloud computing, where the processing is centralized, the streaming of process demands is disseminated at many locations, so it can support a large volume of end user devices. This feature helps eliminate the response time required for on-demand or interaction sensitive applications.
- **Scalability**: With the huge amount of streaming that currently takes place, the ability to scale to a large number of distinct locations is a key factor in sites that have different sizes. Edge computing can provide scalability to a high number of devices/nodes more efficiently than cloud computing.
- **Closer privacy validation**: Customer data validation is placed at their location, allowing for a faster validation process compared to when it is conducted on the cloud side.
- **Reduced network operational cost:** Caching the most frequent data on edge plays a significant role in reducing network operational costs. This feature impacts the final income of businesses.

- **Critical applications optimization:** Applications with reduced tolerance latency can more easily optimize their performance in edge computing sites than when they are placed in cloud.

2.4.2 The Edge Computing Impact on IoT

The revolution of the IoT involves finding solutions like edge computing as key components of its success. The IoT plays a role in every aspect of people's lives. However, to do that, a great deal of information needs to be traced and because of the things scattered around people's locations, this task requires a tremendous volume of bandwidth. Edge computing can benefit the IoT in several ways, as follows (Bonomi, Milito, Zhu, & Addepalli, 2012) :

- Low latency traffic between the service requester and the on-edge device or service.
- Location awareness according to the position of the sensors or actuators.
- A diverse dissemination of heterogeneous things with respect to the edge services/devices.
- For nomadic smartphones or devices like wearables, edge services provide freedom instead of relying on remote services placed in cloud computing locations.
- Due to the vast number of nodes expected, the processing needs to be partially completed in proximity to the sensor/things' proximity.
- Real-time sensors/things and actuators that stream sensitive and interactive applications/services tend to reduce the delay to a minimum. The most important traffic can therefore be processed close to a thing's location.

- Nearby edge devices can support a diversity of things/sensors, whether indoors or outdoors, to stream its data much more efficiently.

2.5 Related Work

The IoT revolution exists in people’s daily lives and applies in a diversity of indoor and outdoor environments. Huge sensors around people stream one dimensional feedback per sensory data. However, to the best of our knowledge, taking into consideration the data from several sensory sources in people's environments, via a spatio-temporal context, and reasoning the sensory data to a semantic and much insights feedback to leverage the level of the smart environment status notification, has not yet been widely addressed in the literature. In this section, we provide a comparison criteria analysis, in which we compare our work in terms to some existing semantic-based IoT platforms, as briefly shown in Table 2-4.

In the following, we list the criteria used in our analysis along with justifications as to why we chose that specific criteria. Based on the outcome of the analysis, we were able to develop our framework design.

1. **Reasoning Inference**:

This attribute is chosen in the comparison as an ontological description logic method because of the need to describe the property restrictions and class relationships of environmental-based events. This feature is important to provide data link integrity between several sensors/things and their environment usage. As shown in the table, most analyzed works also used OWL DL for the reasoning inference.

2. **Spatio-Temporal Context**:

This feature is needed in the comparison to show the time and space factors of each notification, according to spatio-temporal influences. In diverse and distant places, where environmental sensory data is streaming, it is necessary to provide a geotag and timestamp for all of the sensory data for further analysis and processing. Out of the 10 frameworks surveyed in this work, only two combined spatio-temporal information with sensory feedback.

3. **Sensory Sources**:

This feature shows whether the generation of sensory events is based on a single source sensor or multi-sensory sources. It is worth noting that latter has a greater impact on current IoT applications than the former. Only half of the reviewed works in the analysis had a single source and the rest had multiple sensory sources in their frameworks.

4. **Notification Location**:

This attribute infers the notification place, whether indoor (closed areas e.g. campus) or outdoor (open areas e.g. residence). We notice from the table that only one of the analyzed works (Ali, 2015b) considered indoor and outdoor contexts as components of the sensory sources feedback. We intentionally include this criterion to better identify the location of the sensory sources, based on people's position.

5. **Fuzzy Inference**:

This feature is needed for design optimization. Since we chose to include a reasoning inference that is built based on fixed knowledge, we needed to include a fuzzy inference system as part of the analysis to make the system more agile an enable it to support sensory feedback that does not fall in the reasoning inference. There is no single work in the analysis that contained this feature.

6. **Geotagged Event**:

This criterion is needed to obtain a geographical coordinate as a reference for several sensory sources. It is considered in the analysis to help visualize real-time or historical sensory streaming from different locations. We noticed from the analysis that there is only one work (Ryu, Kim, & Yun, 2015) that selected this feature in their research.

7. **Partial Processing on Edge (PPoE):**

This feature is needed to avoid publishing all of the sensory data that are streamed from the various sensors/things to cloud computing. Instead, this feature aims to publish the matched sensory data according to predefined rules. Furthermore, the partial processing of sensory data will be in the proximity of sensors/things, which means less latency in the analysis of the environmental status changes. PPoE brings crucial benefits for performance and scalability, which will be reflected positively on cloud computing. None of the surveyed works considered partial processing on edge in their frameworks.

We can deduce from the related work analysis that sensory feedback coming from sensory sources data lack proper representation of people's environments. Changes in people's indoor and outdoor locations need to be described much more clearly and efficiently, and this can be achieved by combining several sensory sources for the feedback.

2.6 Summary

This chapter covered the literature review of some concepts that are needed to Internet of Things (IoT). Additionally, several applications of IoT have been explored. As an emergence technology, Edge Computing and its impact on IoT has been covered exploring some characteristics that aim to benefit IoT. Based on a conducted analysis of key criteria needed for our framework, we shown a comparison criteria analysis that shows others' semantic-based IoT platforms according to our proposed framework that will be covered in the next chapter.

Research Contribution	Year	Reasoning Inference	Spatio-temporal Context	Sensory sources(s)	Notification Location	Fuzzy Inference	Geotagged Event	Partial Processing on Edge (PPoE)
Massif (Bonte et al., 2017)	2017	OWL DL	T	Single	N/A	×	×	×
Ali et al. (Ali, 2015b)	2015	AnsProlog	S	Single	I & O	×	×	×
SWoT4CPS (Wu et al., 2017)	2017	Logical & hybrid	S	Multiple	I	×	×	×
Poslad et al. (Poslad et al., 2015)	2015	OWL DL	S & T	Single	O	×	×	×
Nambi et al. (Nambi et al., 2014)	2014	OWL-S	S	Multiple	I	×	×	×
Maarala et al. (Maarala, Su, & Riekki, 2017)	2015	Jena reasoning	S	Multiple	O	×	×	×
D. Ali (Ali, 2015a)	2017	OWL	S & T	Multiple	N/A	×	×	×
ISSP (Ryu et al., 2015)	2015	SWRL-based rule	S	Single	N/A	×	✓	×
Dub-STAR (E. M. Daly et al., 2013)	2013	RDF encoding	S & T	Single	N/A	×	×	×
SeCoMan (Celdrán, Clemente, Pérez, & Pérez, 2016)	2016	SWRL-based rule	S	Multiple	I	×	×	×
SENS-IT	**2018**	**OWL DL**	**S & T**	**Multiple**	**I & O**	✓	✓	✓

I: Indoor, **O**: Outdoor, **S**: Spatial, **T**: Temporal

Table 2-4: Analysis Criteria of Existing IoT Frameworks

Chapter 3 THE PROPOSED SENS-IT SYSTEM

3.1 Introduction

In this chapter, we provide a description of the SENS-IT approach, which can translate the environmental perception of multiple raw sensory data feedback into a semantic, spatio-temporal and descriptive notification. The approach aims to extract the raw sensory measurements from surroundings and convert the sensory data into a simple and usable contextually aware format. We will introduce the high-level architecture of the SENS-IT design, describing each layer separately and, in the third section, we will provide the SENS-IT design from a methodological perspective. As any novelty appears, potential limitations will be briefed before the summary.

3.2 A Three-Layered SENS-IT Architecture

According to the IoT revolution and based on the analysis detailed in Chapter 2, we classify the SENS-IT system into a three-layered architecture:

- **Things/Physical Layer**
- **Communication Layer**
- **Application Layer**

A conceptual architecture of the proposed system is depicted in Figure 3-1: Conceptual Architecture of SENS-IT Framework and detailed in the following sections.

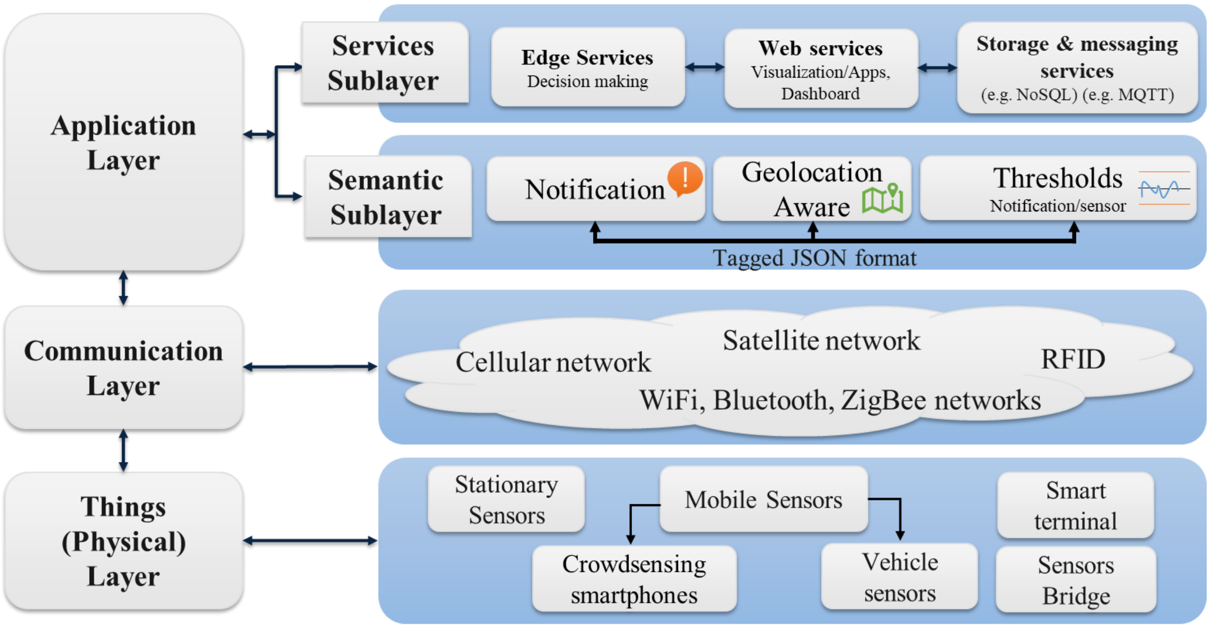


Figure 3-1: Conceptual Architecture of SENS-IT Framework

1. **Things/Physical Layer**

The Things layer is also considered to be the perception layer, located at the lowest level of the architecture. However, it is the most important layer of the system's architecture because it is the source of the IoT data generation. This layer represents the direct interface to the real world of sensors (things), where embedded sensor devices measure their ambient world status. Different types of sensors (like WSN, various environmental sensors, sensors in industries) collect useful information from their environment, which is processed by microcontrollers and converted to a digital format to be used in a future phase.

This layer also includes the parts used to integrate sensors with devices. For example, bridge shields for microcontroller integrity with an operating system like Linux, gateways used as central or access points for ubiquitous sensors, etc. Sensors can be classified into mobile sensors, such as the embedded ones in smartphones, wearables, VANET, etc., or stationary sensors like environmental sensors. IoT sensors need a gateway, which is one of IoT constraints, in order to seamlessly publish its sensory data to the Internet.

2. Communication Layer

This layer is the path the raw sensory data follows to publish the sensory measurements to the Application Layer. In addition to the de-facto transport protocols (TCP-UDP), this layer's components are the network access types used to connect the gateway to the Internet, whether wired or wireless. The Communication Layer is the core of the system, where end devices, including sensor/thing or actuator nodes, normally get access to the Internet. These nodes might have direct access to the Internet though cellular technology like 2G/3G or LTE, or by using a gateway. The IoT revolution is benefiting from the growth of the most used radio technologies like WiFi, Zigbee, and Bluetooth Low Energy (BLE), according to 802.11a/b/g, 802.15.4, and 802.15.1(v.4) standards respectively.

We incorporated the Communication Layer into our system because all nodes of things/actuators must carry out addressing and routing before publishing the sensory data to the on-edge or on-cloud computing services.

This main responsibility of this layer is to function as an intermediary between the hardware and application components, in order to transfer the collected sensory data to the visualization and processing phase, as detailed in the next layer.

3. Application Layer

This layer is where the generated sensory data is rendered in a readable and augmented reality way, according to end users' contexts. The sensory data in its raw format doesn't provide useful information unless it is analyzed and visualized according to specific preferences.

In this layer, instead of only showing a numerical format of the sensory sources data, we provide a very descriptive representation of the environmental sensory data. For example, based on predefined decision rules, semantic notifications about people's environment and public notifications of interest can be provided in this layer. We realized that a representation of the low-level sensory data is considered an important player when providing descriptive information about people's environments.

The Application Layer is composed of the following sublayers:

I. **Services Sublayer**: This sublayer provides storage, messaging, web, and on-edge services for sensory data as follows:

- **Storage and Messaging services**:

  Where the published events or topics from the edge processing part are received and managed by an IoT platform and stored in a cloud database as a service DBaaS. Each node is configured with subscribe/publish messaging or request/response mechanisms to transfer the raw sensory data. At the edge or cloud services, the sensory data will be processed based on actions or decisions according to predefined rules. Two common lightweight messaging protocols are the most used in IoT sensory data deployments, Messaging Query Telemetry Transport (MQTT) and Constrained Application (CoAP).

- **Web services**:

  A real-time analysis and visualization service can be used to monitor the published data so it can be simultaneously analyzed and visualized. Application platform interfaces (APIs) can be used for application-based monitoring and analyzing services, whether in cloud or local interfaces.

- **Edge computing service:**

  This is the location where the raw sensory data is investigated against some fuzzy (decision) rules before the results are submitted to the cloud repository location. Using edge processing brings many advantages including but not limited to reduced overhead on traffic, less latency, smaller storage space requirements, real-time or semi-real-time data analysis, and reduced processing on the cloud.

II. **Semantic Sublayer:** Once a sensory observation has been transferred in a raw format, it needs a more meaningful representation. Therefore, a semantic notification will be used to describe the ambiance status, based on a predefined set of sensory data thresholds. The semantic layer will analyze combinations of several sensory data sources - rather than only raw sensor measurements - to provide clear and descriptive feedback of the location status. This layer is composed of the following:

- **Notification**:

  This part is responsible for creating a standard or customizable semantic description of the environmental status. Each notification is triggered based on sensory data thresholds.

- **Geolocation tag**:

  This part shows a set of latitude and longitude coordinates that contains the location of a generated notification. Therefore, this tag can be used for real-time or in-future processing and analysis.

- **Thresholds**:

  Each semantic notification is structured based on triggering a combination set of specific sensory data thresholds. The combined set of predefined sensors is configured according to the relevant notification.

Any semantic notification can be provided as a categorization of standard-based or predefined preference-based. In Figure 3-2 we show a two-category chart that includes a sequence of a generic semantic notification for both categories, as follows:

- **Standard semantic notification:**

  According to multiple sensory sources, standard semantic notifications can be generated and shown to the public as the available sensory sources per location. This category does not require users to choose from a notifications list. Instead, the semantic notification sublayer provides notifications according to the availability of real-time sensory sources data per location. In other words, the public does not have the option of choosing from a list of notification preferences in order to be notified based on their selection.

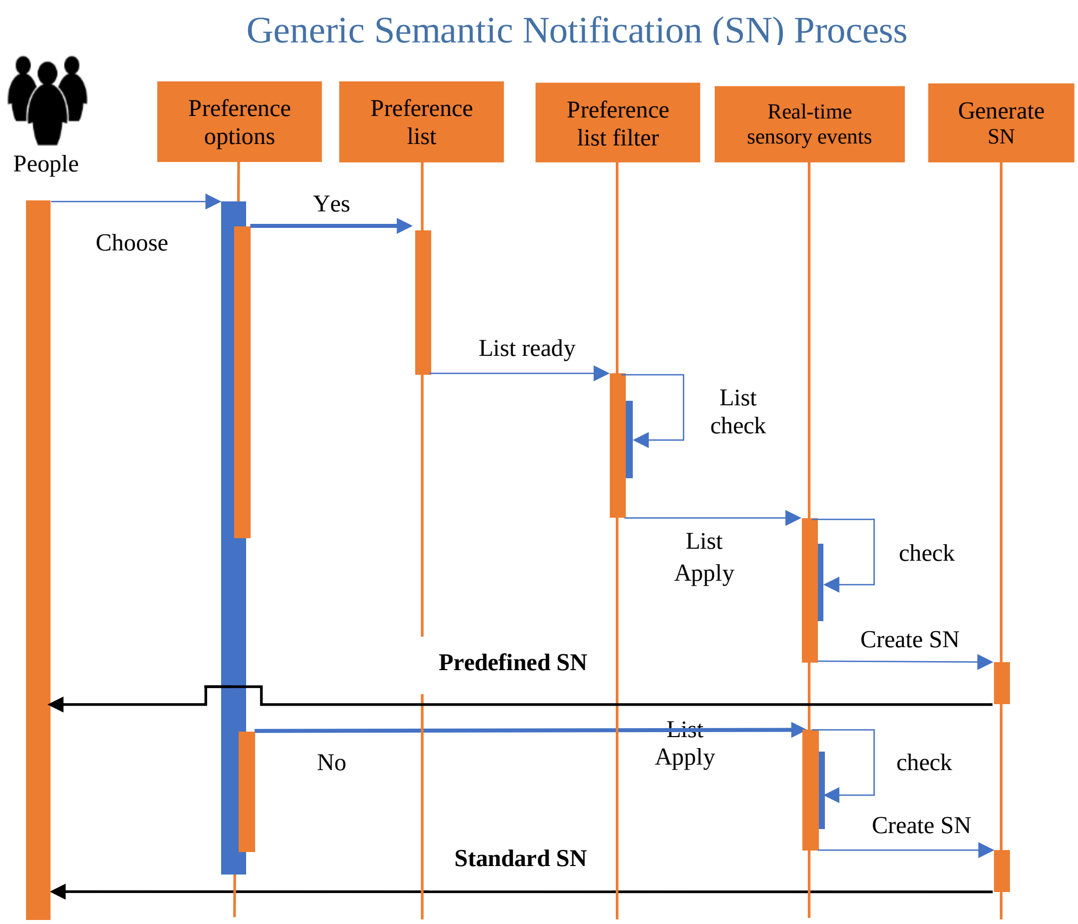


Figure 3-2: Generic Semantic Notification Sequence

- **Predefined preference semantic notification:**

This category assumes each location has different environmental sensory sources streaming real-time data. As there is a list of semantic notifications from which a user can select their favourites, the search for notifications is based on a match process between what a user chose from the list and what is available at each location. For example, semantic notifications like reading suitability, crowdedness, and quality of location, can all be part of a preferences list on which the sensory sources search is based. Historical data can also be part of the preferences list, where the user needs to consider the sensory sources according to specific times in the search process.

3.3 SENS-IT Design Tiers

We show in this section a high-level design of the proposed system, as depicted in Figure 3-3: The figure shows the design according to three tiers, which summarize the main system structure from a methodological perspective.

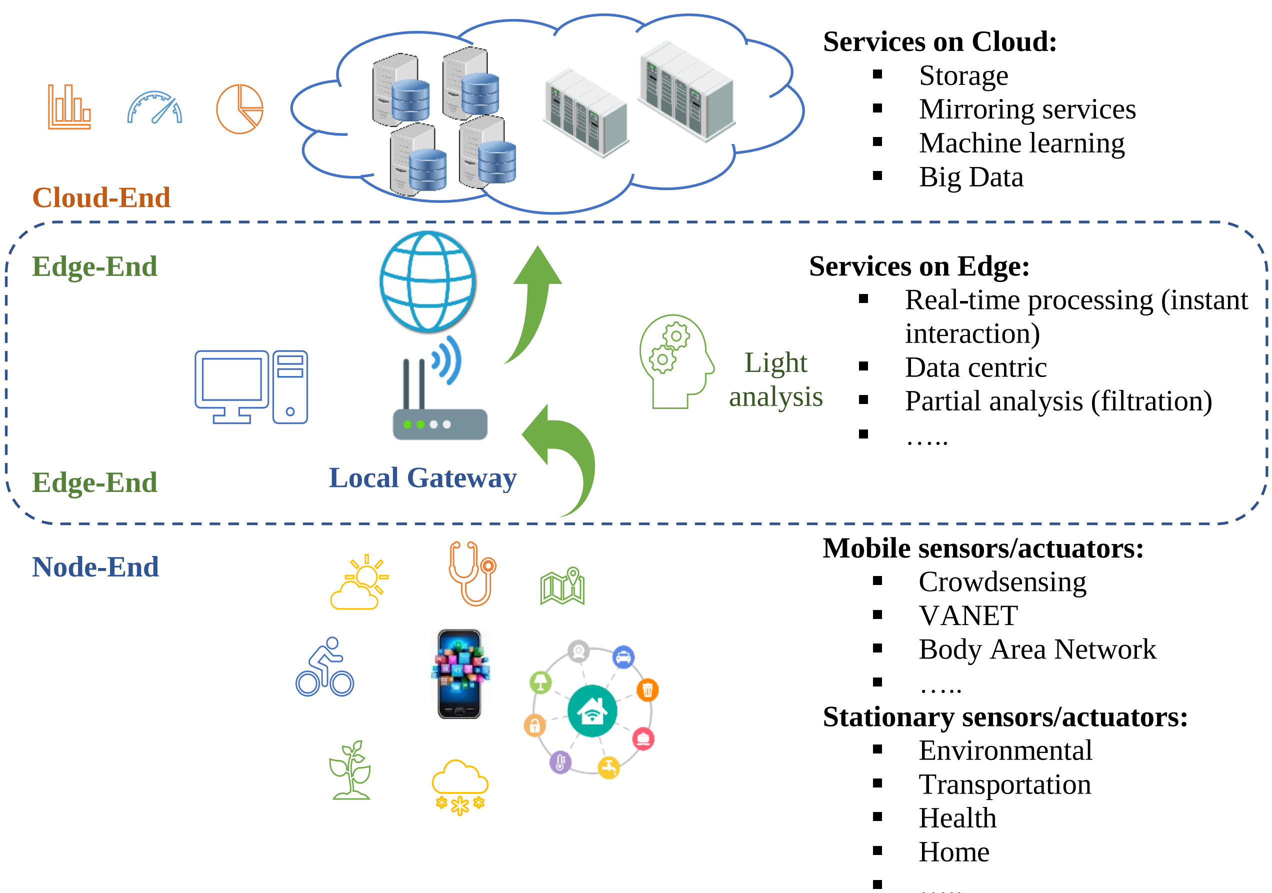


Figure 3-3: Main SENS-IT Tiers

The main architectural design of SENS-IT, as it will be detailed in the next chapter, is summarized in the following:

1. **Node End**:

   This is where micro-boards, sensors, and software tools are used to measure environmental events and transfer the measurements to edge processing and then to cloud services, via the Internet. This uses the backend code, where the microcontroller and its peripherals are programmed through an IDE tool. Also, this node end is supposed to first publish the sensory data to on-edge services/devices for validation and light processing.

2. **Edge End**:

   Prior to the process of publishing the raw sensory data to the cloud-end for repository and extra processing services, the sensory data will be partially analyzed to generate basic notifications based on predefined decision rules. This tier is necessary to position a service or device in the proximity of nodes, for applications that need a bounded delay due to sensitive interactions. This end brings many benefits for system performance optimization, as already discussed in Chapter 2.

3. **Cloud End**:

   Where the published events or topics from the nodes are received and managed by an IoT platform and stored in a cloud database as a service DBaas. Based on the desired service, an API configuration is conducted to provide analysis and visualization of the streamed sensory events.

3.4 The Limitations

- Edge computing might add overhead of complexity in the overall design in terms of computation, storage or network architecture.
- Distribution of devices as edge and gateway might have an increase in the cost of deployment, so from a cost perspective, this should be put into consideration in the design phase.
- As any hierarchy design, the SENS-IT Framework category might have some complication for large deployments. However, a hierarchy design is needed from scalability and organizational perspective.

3.5 Summary

Our SENS-IT approach has been covered extensively showing the three-layered conceptual architecture and the main design tiers containing node, edge and cloud ends in IoT space. The potential limitations of our proposal are briefed showing the expected overhead of our design that might appear in some parts as a tradeoff of any new proposal. After we covered the SENS-IT from a conceptual perspective, in the next chapter, we will present the SENS-IT framework implementation.

Chapter 4 SENS-IT IMPLEMENTATION

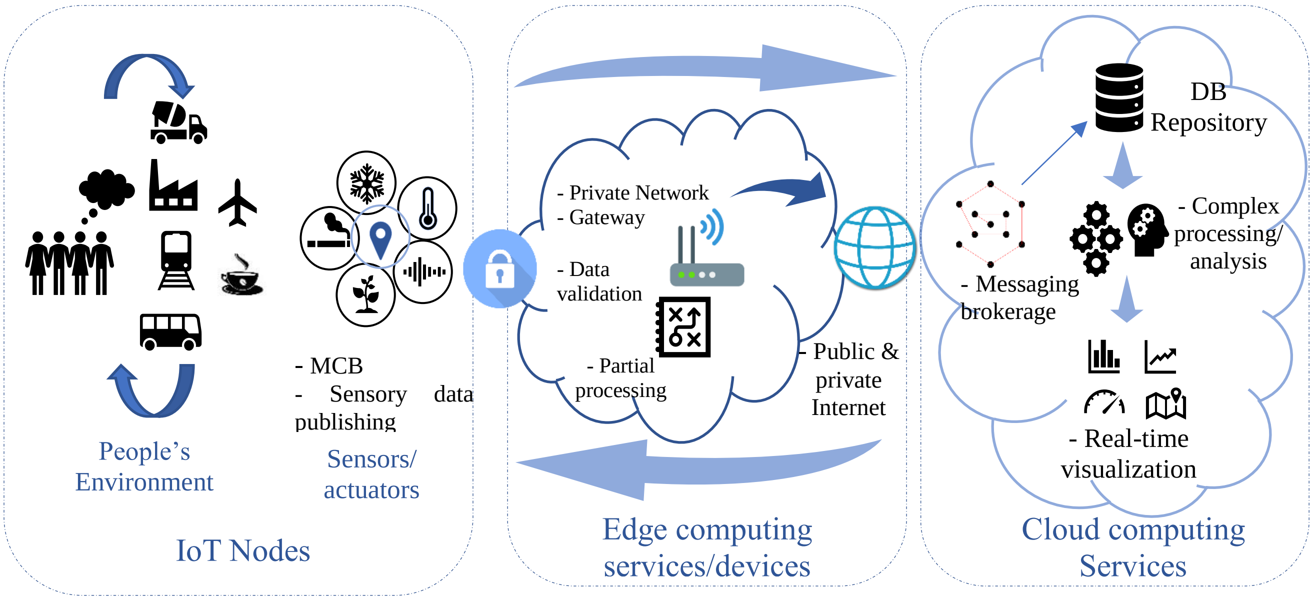


Figure 4-1: High Level of SENS-IT Implementation

4.1 Introduction

According to the layered architecture of the SENS-IT framework mentioned in Chapter 3, in this chapter we will present the deployment of the components used in our system's architecture, as depicted in Figure 4-1. The deployment includes three main parts: the IoT node component as it exists in layers 1 and 2, and components of edge computing services/devices and cloud computing services, as both exist in layer 3. In the next subsections, we will elaborate on each component separately. We briefly state them as follows:

1. **Node Components:** Where the board, sensors and tools are used to transfer people's environmental events to on-edge services/devices and then publish them to the cloud

via the Internet. This uses the backend code, where the microcontroller and its peripherals are programmed through an Arduino IDE.

2. **Edge Computing:** For frequent and interactive sensory data sources, it is ideal to provide partial processing services at the proximity of the data sources. Therefore, devices or services can be placed on the edge of a sensor's location.
3. **Cloud Services:** Where the published events or topics from the nodes are received and managed by an IoT platform and stored in a cloud database as a service DBaas. Cloud services can contain but are not limited to:
   a. **Real-time analysis and visualization:** Where the published data is simultaneously analyzed and visualized. Here we can configure APIs from the IoT platform.
   b. **Complex processing and analysis:** This is a cloud feature that cannot be achieved on edge computing locations, since deep learning or resource consuming processing need high performance equipment cannot offered on edge space.

4.2 IoT Multisensory Node Components

This section describes the hardware aspect of our system. We chose a set of off-the-shelf components, as they are always available when required. We deployed a set of nodes in the city of Ottawa, Ontario to measure the environmental status of the area. The node components are shown in Table 4-2 and Table 4-1 respectively.

The IoT node uses a backend code, where the microcontroller and its peripherals are programmed through an Arduino IDE. The backend code is used to publish each sensory event by following the procedures shown in **Algorithm 1**.

MCB	**Model**	**Image**	**Feature**
Arduino	Y`un		- Linux Microprocessor - Linino OS - Ethernet & WiFi support - 20 Digital I/O pins - 12 Analog channels
Seeed	Seeeduino Cloud		- Based on Dragino HE Module - Compatible with Arduino Y`un - Ethernet & - WiFi support - On-board two Grove connectors

Table 4-2: SENS-IT Microcontroller Board

Sensor	Model	Image	Function	Operating Temperature	Sensor Interface
Temperature & Humidity	DHT22		Measure surrounded temperature and humidity	-40 to +80 C	Digital port
PM 2.5-10	Amphenol SM-PMW-01C		Detect particulate matter suspended in surrounded air	-10 to +60 C	PMW digital port
Noise	LM386 amplifier &electric microphone		Detect the ambiance sound intensity between 16-20khz	-0 to +70 C	Analog port
Air quality	Seeed		Detect some gases like carbon monoxide, acetone, thinner, etc.	N/A	Analog port
Ultraviolet (UV)	SI1145		Measure UV index	-45 to +85 C	I^2C
Gas	Seeed(MQ2)		Detect some gases like CO2, Propane, Butane, H2, etc.	N/A	Analog port

Table 4-1: SENS-IT Sensors

Algorithm 1: A Pseudocode of preparing a json sensory event

```
procedure PUBLISHEVENT (sensorySet)
    bc ← Bridge communication
    wifi ← WiFI connection
    ff ← Create buffer x size
    while bc & wifi do (1)
        sens ← Collect sensory event set
        if sens <= ff then return true
            js ← json format
            wrap sens in js
            prepare js for publish (2)
        if js published then return true
            goto 1
        else
            goto 2
```

Each node has the following components:

- A micro-controller board (MCB) that is compatible with Arduino as an open-source testbed and has a WiFi adapter and a grove connector shield.
- A bridge communication feature to manage the communication between the MCB processor and the Linux processor.
- Typically, seven environmental sensors:
    - Temperature, humidity, UV, gas, noise, air quality and particulate matter.
- A library, known as the **PubSubClient** in the hardware prototype, used to manage the sensory event (topic) streaming of every node to the cloud. The library helps to prepare a sensory event in the JSON format as shown in **Algorithm 2**.

Algorithm 2: A Pseudocode of preparing a json sensory event

```
procedure WrapJsonEvent(sensorySet)
    Set a biffersize [size]                                      // Reserve a memory buffer
    Set a dynamicJsonBuffer [jsonBuffer]
    Set a jsonObject [payload] & assign it a dynamicJsonBuffer
    Set a jsonObject [data] & assign it a dynamicJsonBuffer
    Assign a name to data[nodeID]
    Set a jsonObject [coord] & assign it a nestedObject [Coordinate]
    Set a coord[Lat]
    Set a coord[Long]
    Read TempSensorValue & assign it to a data[Temperature]
    Read HumSensorValue & assign it to a data[Humidity]
    Read NoiseSensorValue & assign it to a data[Noise]
    Read AQSensorValue & assign it to a data[AirQ]
    Read GasSensorValue & assign it to a data[Gas]
    Read UVSensorValue & assign it to a data[UV]
    Set a jsonObject [pm] & assign it a nestedObject [PM2 5]
    Read ConcentrationValue & assign it to a pm[Concentration]
    Read PulsesValue & assign it to a pm[Pulses no]
end procedure
```

- An API can be used to provide the secure publishing of events to the IoT cloud platform.
- The Message Queue Telemetry Transport (MQTT) protocol is used to publish the sensory measurements to an MQTT broker, whether in a local edge place or a cloud platform.

- A geo-location coordinate tag, appended to each published transaction, for future processing and visualization demands.

4.3 On-Edge Devices and Services

At each node location, we deployed a gateway box as our IoT edge device that is to work as on-edge tool for the multisensory environmental data. As the high-level architecture of edge computing is depicted in Figure 2-1, the on-edge computing service's functions are listed as follows:

- Creating a direct gateway of each microcontroller, by location, before forwarding the data results to the other parts of the system.
- Partially conducting the required processing for each node.
- Data validating before publishing the data to the cloud.

4.3.1 On-Edge Space Components

Each on-edge location contains tools, services and devices, as shown in the following:

- Gateway device box running the Ubuntu Server 16.04 LTS operating system with WiFi capability. The device is used to run other on-edge tools.
- Local MQTT broker to publish the sensory data from the MIC node.
- Local NoSQL database to store locally the published sensory data. We used a Mongo[1] database for the local repository.

---

[1] https://www.mongodb.com

- Nodered[2] (footnote number) instance used as an IoT managing tool for the streamed sensory data.
- Fuzzy inference flow application inside Nodered, used to filter the sensory data based on some predefined rules.
- Credential information node instance used to validate the identity of each event before publishing to the cloud.

4.4 Cloud Services

Cloud services help extend and process applications that maintain and analyze the collected data from remote and disseminated sensors and devices. The communication between an end user and the cloud services is handled by an open source dashboard that shows the streamed sensory data separately in a real-time way as mentioned in Section 4.4.1. Also, the raw data can be accessed using a GUI interface for managing database as mentioned later. We utilized an IoT cloud-based platform to publish the sensory data readings generated by the nodes, and to store the sensory flow in a NoSQL cloud database. We intentionally chose to transfer the deployment data to a cloud service because we needed to maintain scalable and on-time IoT sensory reporting of the environment status, and it provides global access to the system in case of malfunctions. The IoT cloud platform is comprised of the following:

- An IoT platform that provides an MQTT broker to manage the publishing and subscribing of sensor events from the deployment locations. It also provides an open

[2] https://nodered.org

source tool called Nodered[3] to manage and control IoT flow devices, APIs and other related services.

- A Message Query Telemetry Transport (MQTT) broker to manage the publishing and subscribing of sensor events. MQTT resembles a client/server model in which a sensor is considered a client that connects to a server, called a broker over a TCP connection and via a gateway. Thus, every topic message, such as temperature and motion, is oriented.
- A NoSQL database[3]. The storage of all node readings will be done by day basis for all deployment locations. However, we deployed a local NoSQL database to replicate the cloud database, to ensure a high availability of the sensory events.
- A dashboard tool is used to maintain the monitoring of real-time observations from the deployment locations, as shown in our running IoT dashboard system [4]. Figure 4-7 illustrates a dashboard of our IoT sensory system.
- An API to securely connect our system devices according to usage applications. The APIs can also be used for simple and real-time analysis applications.

4.4.1 Real-Time Visualization

In this section, we show how the streamed raw sensory data from node fields is visualized in real-time. Node visualization is also supported in the cloud service, according to each event published to the IoT cloud platform.

---

[3] https://console.bluemix.net/services/cloudantnosqldb
[4] https://pollenmonitoring.mybluemix.net/ui/#/0

1- **Cloud-based visualization boards**: We used a visualization cloud service to indicate the streaming of the sensory data for each node.

- **Historical sensory data**: Based on the real-time streaming of the raw sensory data, we can visualize sensory data with a line chart card. The streaming visualization can be made per timeline within 24 hours or based on a range of multiple days. Figure 4-3 and Figure 4-2 show the two types of historical sensory data visualization.

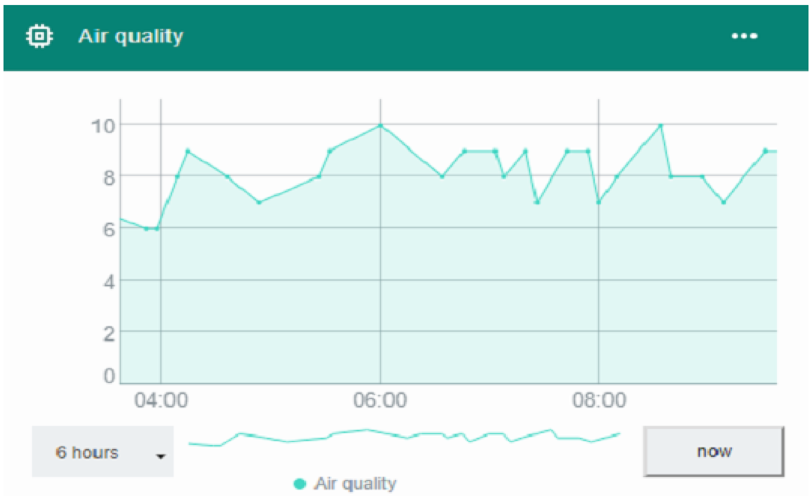


Figure 4-3: Time-line Visualization

Figure 4-2: Date-range Visualization

- **Rules-based analytic**: We can build a set of rules that show the results of conditions according to a set of sensory data thresholds, as depicted in Figure 4-4. Actions will be triggered according to set rules regarding the combination of conditions. Figure 4-5 shows the visualization of alerts of a rule known as *Crowded_places* that is predefined by two sensory data thresholds.

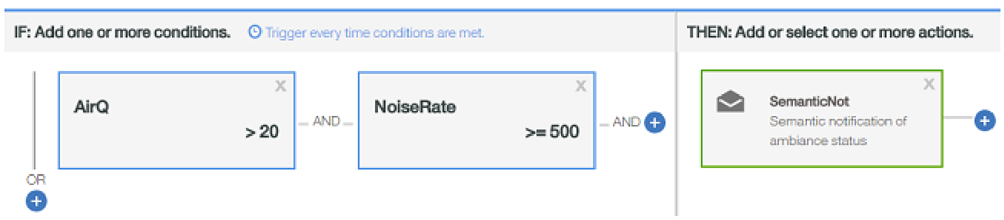


Figure 4-4: Rule-Based Setup

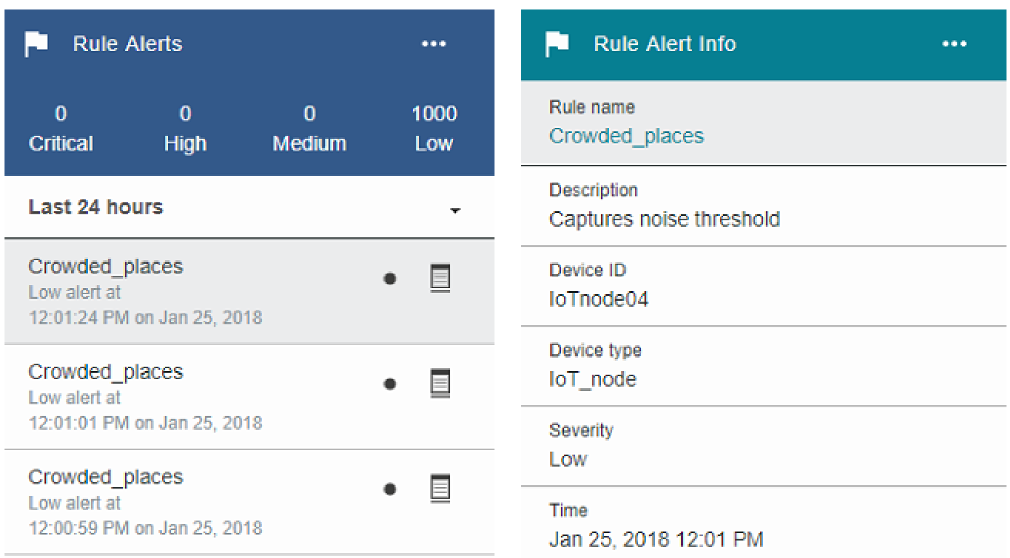


Figure 4-5: Rule-Based Visualization

2. **Open source visualization dashboard**:

As mentioned previously, since our IoT platform provides an open source tool called Nodered for further management tasks and other related services, we used a package known as *node-red-dashboard* 66 which is an extension of Nodered. The package helps build a set of customizable and comprehensive graphical dashboards, by specifying user interface nodes suitable for IoT applications, such as monitoring and controlling sensory data streaming. Figure 4-6 shows a simple flow setup for a dashboard in Nodered. The flow is made up of a real-time streamed event from the IoT, a function to prepare the sensory event, and the chart type.

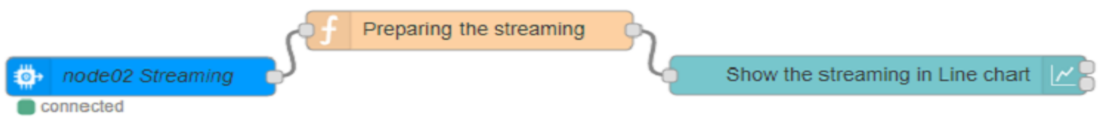


Figure 4-6: A Setup of a Simple Dashboard Flow

For the real-time monitoring of our SENS-IT sensor deployment, we plot the SENS-IT data from the IoT platform in a group of dashboard components, as depicted in Figure 4-7. The dashboard has multiple layouts of the streamed environmental events, and

Figure 4-7: A Dashboard of the Proposed System

each column represents a node's sensor feedback. Ultimately, we intend to develop a dashboard of semantic notifications according to the combination of sensors for each node.

4.5 Summary

In this chapter, we presented our SENS-IT components deployment. We elaborated separately in each section the three key parts: IoT node, Edge Computing services/devices, and Cloud Computing services. The chapter focused on the way the SENS-IT implementation was established and the sensory data was collected. The next two chapters will cover the design of our SENS-IT framework as two major aspects of the criteria analysis that was mentioned in Chapter 2.

Chapter 5 ONTOLOGICAL SENS-IT DESIGN

5.1 Introduction

This chapter presents details of our proposed semantic ontology (SENS-IT), which is an extension of the Semantic Sensor Network (SSN) OWL (Compton et al., 2011). The ontology detail is presented in the next subsection describing the structure and the main properties. In section 3.3.2, we present a scenario of semantic notification of the proposed ontology. From now onward, we denote the prefix SENS-IT as our SENS-IT ontology and ssn as the SSN ontology. Regular people can't understand this low-level feedback type of sensory data. Therefore, the motivation to build an ontology for our system was the need to convert the numerical format of sensory feedback to a textual and meaningful format. This can be achieved by building semantic reasoning and representation of people's ambiance that facilitates the perception of multiple sensory data sources as a meaningful and environment-aware notification. So, we need to build a knowledge base to formalize a linguistic feedback as semantic representation of environment status perception. We assume the ontology will cover most outdoor and indoor environment statuses perceived by the public. This will allow people to perceive location status variations according to their ambiance context, through a semantic feedback generated by multiple sensory readings. The development of the ontology will help in designing and developing fuzzy rules as explained in next chapter.

5.2 The SENS-IT Ontology Description

The purpose of building an ontology is to enhance our system performance by describing sensors' feedbacks more knowledgeably, and better represent user's ambiance context.

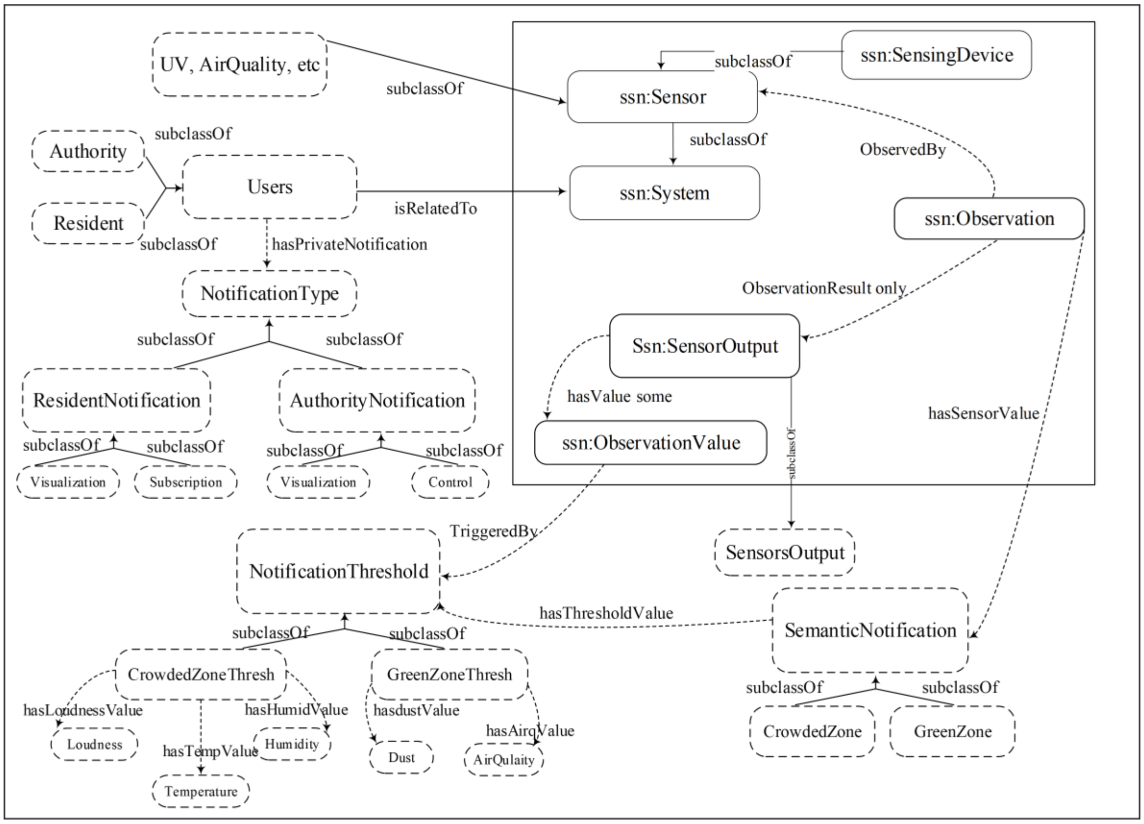


Figure 5-1: Overview of SENS-IT Extension Ontology

For example, sensors generate raw and standalone values of environment events such as motion, temperature, humidity, noise rate, air quality and particulate matter. However, a single sensor value gives only one context of sensory data, while establishing solid knowledge and representation of multiple relevant sensors sources allows us to perceive the environment with rich, contextual and more comprehensible ambiance status variations. Our SENS-IT ontology is depicted in Figure 5-1. In the figure, the section of the SSN OWL extension in which we used is inside a square box in the upper right corner, and our SENS-IT ontology components are in dashed curved boxes. The impact SSN classes we extended for our ontology are System, Sensor, *Observation*, *SensingDevice*, *SensorOutput*, and *ObservationValue*, because each SENS-IT major class is derived from the SSN ontology.

The main SENS-IT classes that structure our ontology are SemanticNotification as derived from *ssn:Observation*, Users as derived from *ssn:System*, and *NotificationThereshold* as derived from *ssn:ObservationValue*. We used two notifications thresholds, *CrowdedZone Thresh* and *GreenZoneThesh*, to model semantic notifications *CrowdedZone* and *GreenZone*. However, SENIST can model more notifications representation based on the desired contexts. The source of any semantic notification is a combination of two or more of the sensors involved in the ambiance perception. We used an open source ontology development and editor tool called Protégé OWL (Knublauch, Fergerson, Noy, & Musen, 2004) to build our ontology. As depicted in Figure 5-2, the main components of a single sensory data event are *Incident*, *Observation*, *Sensor*, *SensorOutput*, and *SensorVal*.

The conceptual representation of the involved elements in building a semantic notification, as shown in Figure 5-3, depicts how the linkage of multisensory data flow between semantic notification parts occurs. The properties *sensedBy* and *influencedBy* are the main components in any semantic notification function, since the former indicates the sensor ability to observe its ambiance, and the latter indicates the type of a semantic notification according to the surrounding influences. Each event or incident of an observation has a context that will be *sensedBy* the appropriate *sensor*. Each semantic notification has a special combination of

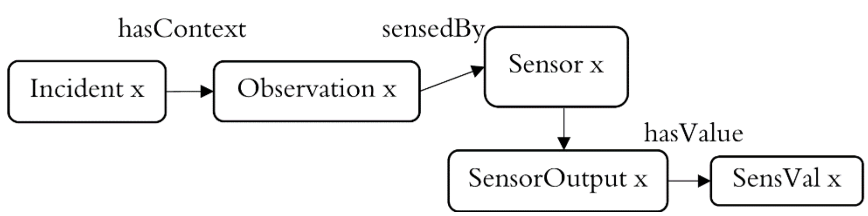


Figure 5-2: Basic Sensory Data Event

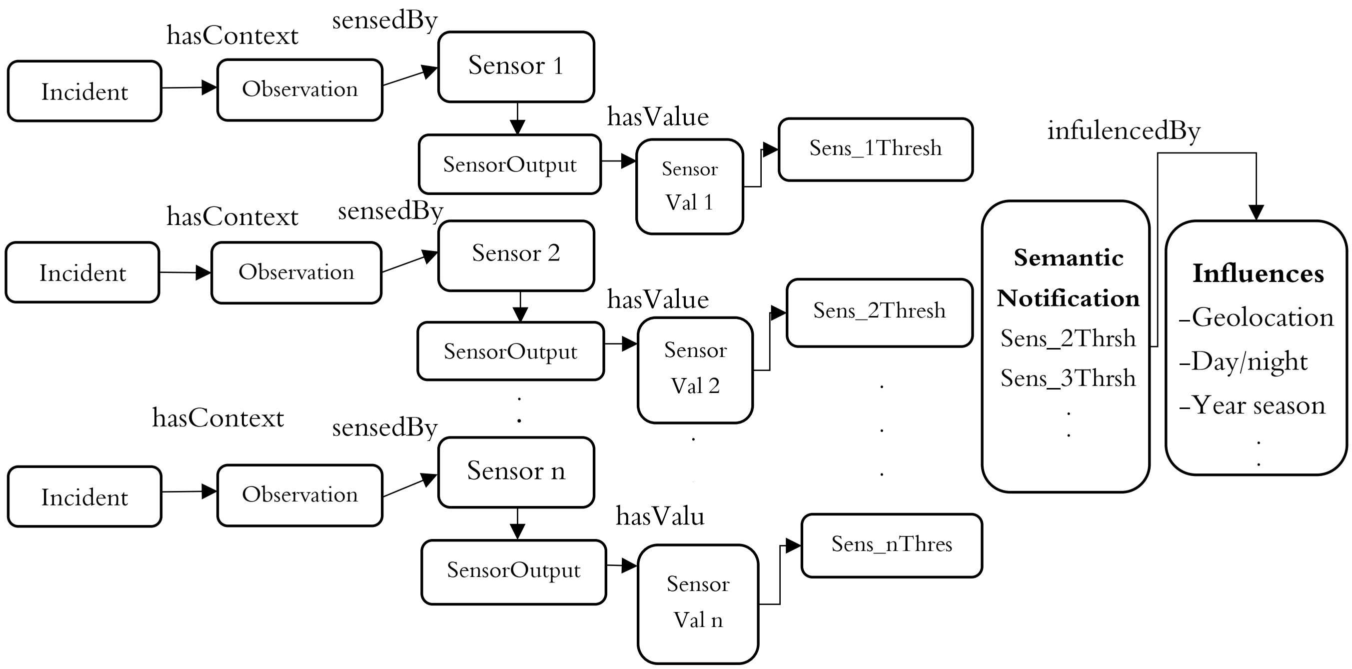


Figure 5-3: A Conceptual Representation of a Semantic Notification

sensors thresholds, or *Sens_Thresh*, that will trigger the notification once all thresholds are matched. The *influences* entity refers to the external factors that have direct impact on choosing a potential semantic notification, such as geo-location, the year or season and time of day, as spatio-temporal contexts.

Figure 5-4 depicts a visualization of the SENS-IT extension ontology. The external sources of SSN classes from which SENS-IT was derived are shown in dark blue. Each super class encompasses the subclasses around it. The visualization shows the data type that was used for each sensor subclass and each semantic value threshold in yellow. The semantic notification class, shown as rounded red entity, constitutes the most impactful component, since it has direct and indirect relations with other classes of the ontology.

Property	Property type	Relationship (Domain-Range)	Relationship to *SemanticNotification*
hasContext	**Object**	*Incident - Observation*	**I**
SensedBy		*Observation - Sensor*	**I**
hasPrivateNotification		*Users - Notification*	**I**
InfulencedBy		*SemanticNotification - Influences*	**D**
hasThresholdValue	**Data**	*SemanticNotification - Threshold*	**D**
hasSensorValue		*Threshold - Sensor*	**I**

D: Direct, **I**: Indirect

Table 5-1: SENS-IT Ontology Properties

SENS-IT ontology has six main properties that describe relationships between classes and other parts, as shown in Table 5-1. Each property is classified as object that is used to link classes' individual or as data that links individual to its data literal. The relationships show how a reasoning relationship happens between SENS-IT components to generate a semantic notification according to a spatiotemporal context. The SENS-IT properties are considered either a domain relationship that attach to ontology entities or a range relationship that points to other entities. For example, the *SensedBy* property links *Observation* as domain and links *Sensor* as range in which it points to.

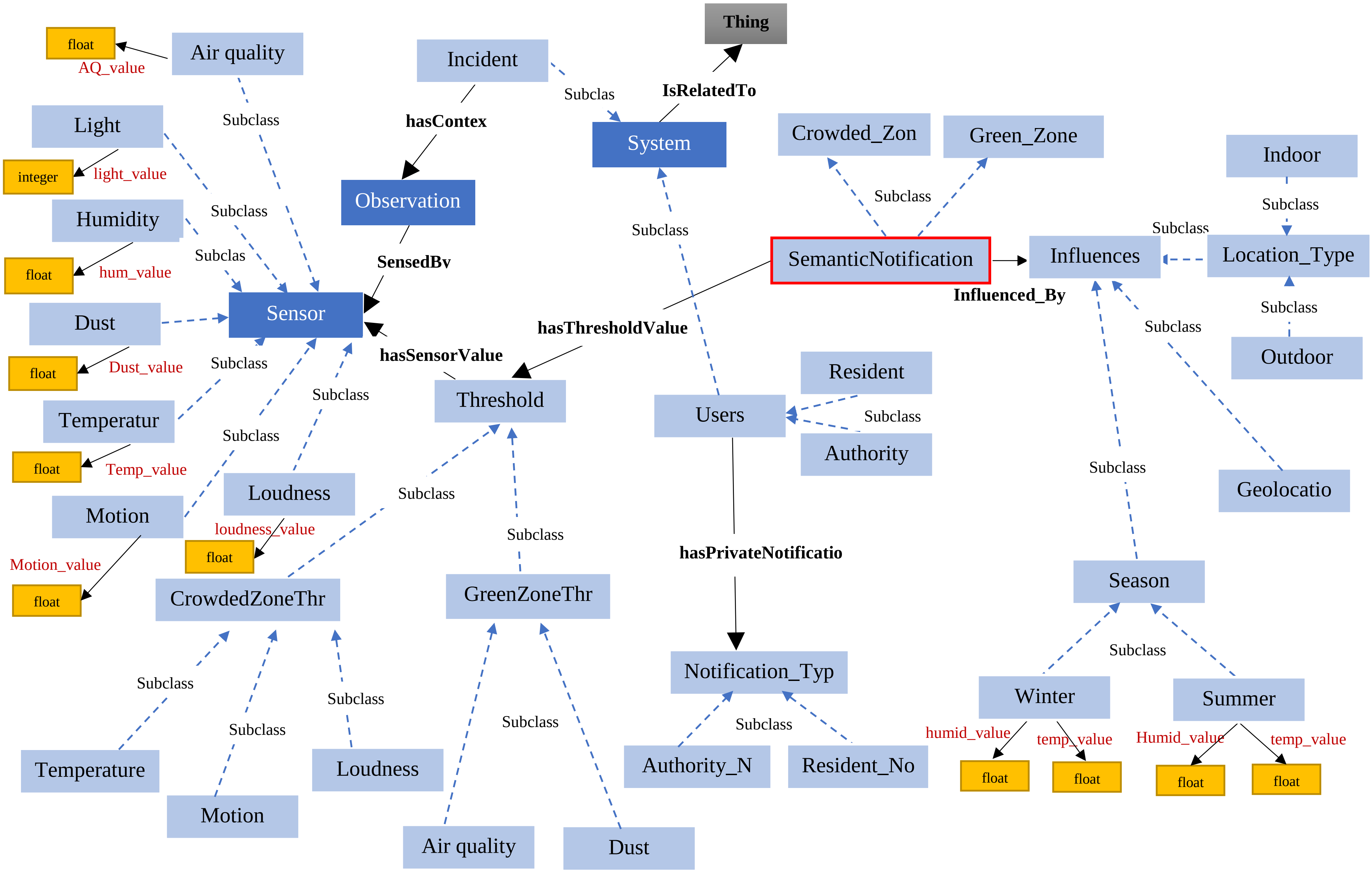


Figure 5-4: A Visualization of SENS-IT Ontology

To make the conceptual ontology clearer, in the next subsection we examine a scenario about an assumed semantic notification that is generated by a combination of two sensory sources, with direct effects of natural influences.

5.3 A Semantic Notification Scenario

Description logics (DL) are used to describe the knowledge and reasoning needed to model ontologies (Horridge et al., 2011). Our SENS-IT ontology uses a simple DL called Attribute Language with Complement (ALC) to describe the sensory data semantically, and to create relationships between individuals in our ontology domain. We used OWLAxiom, the fundamental statements used for OWL expressions, to provide associations between classes and properties (Deborah L. McGuinness, 2004) according to their partial or full characterization. Figure 5-5 depicts a simple scenario of our SENS-IT ontology; that is, a set of raw sensory data converted to meaningful perception of outdoor ambiance status. Each semantic notification has two or more Sensor instances that observed by Observation as a single Incident. To describe a scenario of a semantic notification, we present an indoor *CrowdedZone* feedback that is resulted according to threshold triggers of a combination of multiple sensory data. We will describe it in OWLAxiom format.

The main high-level view of properties that involve in generating a semantic notification are *Senses* that that produces raw sensory data, *Triggeredby* that produces thresholds values, and *InfluencedBy* that illustrates influences around people.

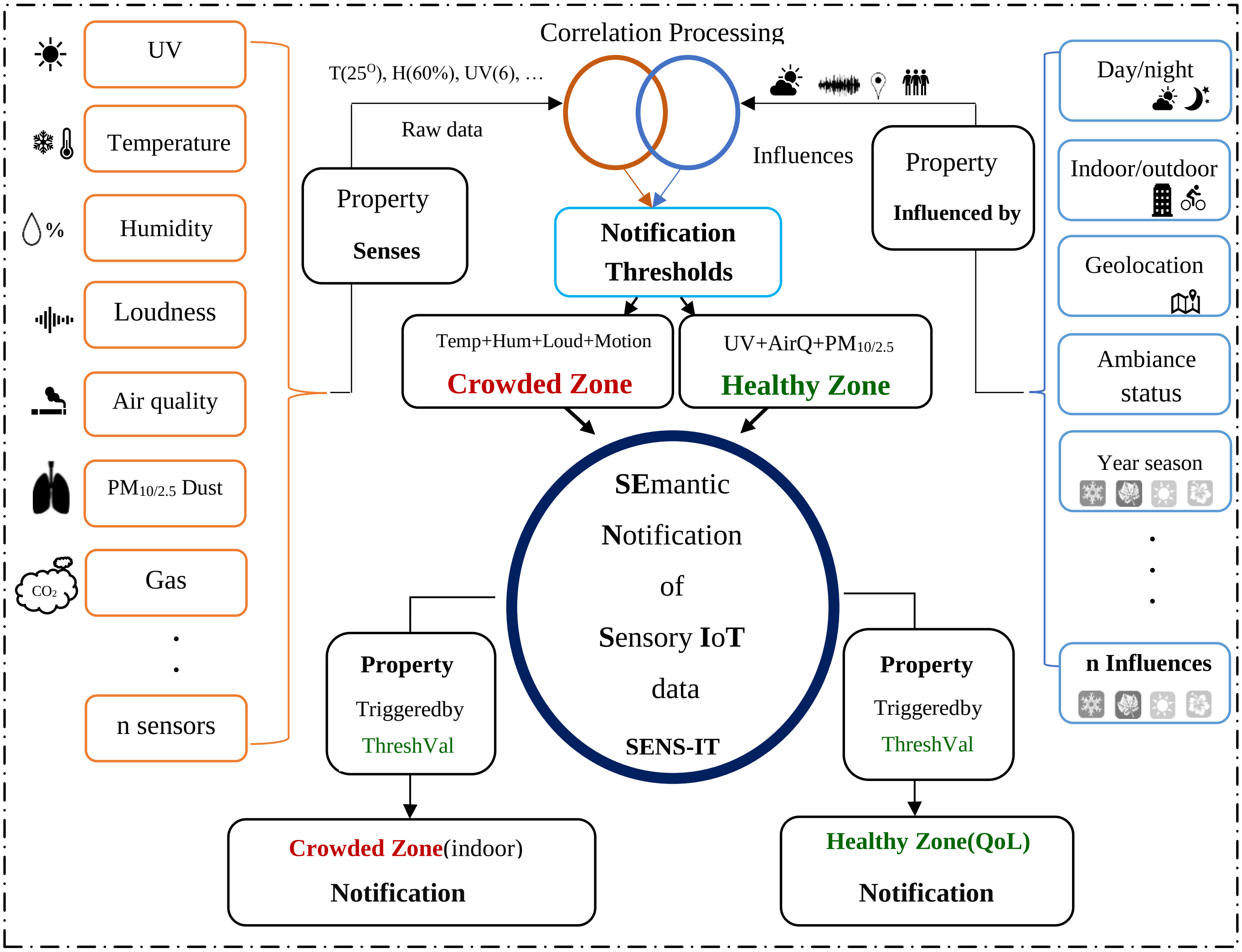


Figure 5-5: Semantic Notification Ontology Approach Example

We start with an individual incident or event of sensory data as a description of a single axiom. An initial *incident* is shown in axiom (5.1) as an *observation* instance. In axiom (5.2), a description of an incident is defined through the *hasContext* property in which a single sensor source (e.g. temperature) represents an observation of ambiance status that has a special context.

$$Observation \sqsubseteq Incident \tag{5.1}$$

$$Incident \sqsubseteq \forall hasContext.Observation.Sensor \tag{5.2}$$

An individual sensor used as an observation is then described through *SensedBy* as a template of sensory observation, as shown in axiom (5.3).

$$Incident \sqsubseteq \forall hasContext.Observation(\forall SensedBy.Sensor) \tag{5.3}$$

Every sensor represents an observation, such as *sin:Temperature*, as described in axiom (5.4). An individual Observation, *TempSensor*, will be sensed by the temperature sensor, as shown in axiom (5.5)

$$TempSensor \sqsubseteq Observation \tag{5.4}$$

$$TempSensor \sqsubseteq \forall Observation \wedge SensedBy.TempSensor \tag{5.5}$$

For our assumption of simple *CrowdedZone* notification at indoor places, temperature, humidity, motion, and loudness sensors are used, each with a predefined threshold value. First, the initial axiom of the notification as a *SemanticNot* is shown in axiom (5.6), and (5.7) is a template of *CrowdedZone* semantic notification that is composed of multiple *hasThreshold* sensor values. This axiom provides a restriction by class property:

$$SemanticNot \equiv CrowdedZone \tag{5.6}$$

$$CrowdedZone\ SemanticNoti. \exists CrowdedZoneThr. (Temp \cap Mottion \cap Loudness) \tag{5.7}$$

Figure 5-6 shows the relating restrictions between *SemanticNot* and *Threshold* classes using Object Property (*hasThreshold*).

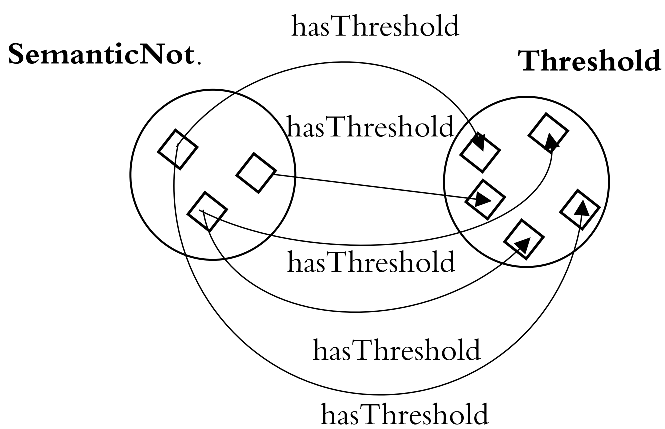


Figure 5-6: Restriction classes using Object Property

Whereas axiom 8 shows a similar notification but using a restriction by object property:

$$CrowdedZone \sqsubseteq \forall hasThresholdValue. CrowdedZoneThr \tag{5.8}$$

The aforementioned will work for all semantic notifications if a *hasThresholdValue* is properly chosen, and notification sensors are involved. The influences class is vital, in case a semantic notification is affected by impacts such as Season and Geolocation for outdoor context. The *InfluencedBy* property and class restriction affects the semantic notification (SemanticNot). In axiom (5.9), the class restriction shows the *influences* subclasses with specific individuals.

$$\exists influences.(Season\ \cap geolocation) \tag{5.9}$$

Also, in axiom (5.10), the restriction of object property *InfluencedBy* shows how one or more of influences affect choosing the potential notification.

$$\exists InfluencedBy\ influences \tag{5.10}$$

In this subsection, we highlighted all SENS-IT properties via a semantic notification scenario. We used descriptive logic restrictions to restrict individuals belonging to a class or subclass starting from a single incident along to a plain semantic notification and a semantic notification under influence of spatial feature.

As we have already mentioned, the ontological approach is characterized by a logic restriction to build a reasoning knowledge which means it is supposed to make sharp decisions that follow strict rules. For this reason, we think we need to structure a much generic optimization that make our system agile to receive any vagueness of sensory data that might not captured by the ontological part.

5.4 Summary

We covered in this chapter our SENS-IT ontology that was extended from SSN ontology. The need to include an ontology in our system is to translate the numerical format of multiple sensory feedbacks to a textual and descriptive format of people's surroundings. Therefore, this translation needs to build a knowledge-based of linguistic format to generate a semantic representation of environmental status of people's indoor and outdoor places. We used a well-known tool called Protégé for designing and developing ontologies. The knowledge base formalization involves rules restrictions that might not cover new sensory environmental events, therefore we come up to investigate the agility of fuzzy rules as it will be covered in the next chapter.

Chapter 6 THE SYSTEM DEVOLPMENT USING FUZZY LOGIC

6.1 Introduction

The real world doesn't have strict measurements or observations but instead has approximate boundaries in regard to relationships between things. Also, although people regularly observe numerous real-world phenomena, these occurrences could be explained in a more descriptive manner, in order to increase understanding. That is what led us to come up with a better representation of the sensory data, by investigating the fuzzy rules, so that our ontology could be agile enough to positively impact our SENS-IT performance. Therefore, we propose a fuzzy inference system (FIS), as a part of our approach, to provide people with clear descriptions and allow them to have a broad understanding of their environment. This will ensure that any vagueness or uncertainty of the context reasoning can be avoided. Thus, this chapter presents an FIS overview, the SENS-IT FIS, a scenario of SENS-IT and its relevant mathematical model.

6.2 Fuzzy Inference System Overview

Fuzzy computing has been adopted in the literature to overcome uncertainty or vagueness in a variety of applications that are used regularly by many people. Fuzzy logic refers to solving uncertain human's needs belonging to different domains of examination by mapping the space between inputs and outputs (Dubois, Nguyen, Prade, & Sugeno). In other words, it is a fuzzy set that has overlap edges between its objects (L. a. Zadeh, 1965, 1968, 1976, 1978). Fuzzy inference systems are leveraged in many applications and uses (Elizabeth J. Chang, Omar K. Hussain, 2013), one of which is to enrich smart environments as part of the IoT applications, in order to provide awareness of environmental status, e.g. quality of location.

Any aim to generate an inference involves building knowledge. This leads us to build rules based on a set of inputs to represent the desired knowledge. We adopted the Fuzzy Markup Language (FML) (Acampora, Gaeta, Loia, & Acampora, 2010) as our modelling tool to describe generated raw notifications of multiple environmental sensory data, in case of any imprecise representation. As depicted in Figure 6-1, the FML format is structured according to a generic fuzzy control as: a Fuzzifier that accepts the variables as a fuzzy set, an Engine that contains Knowledge Base and Rule Base, and a Defuzzifier that produces a fuzzy set as output values.

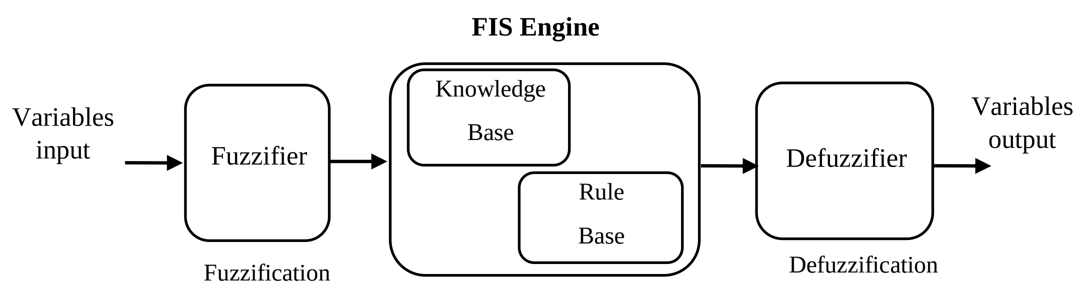


Figure 6-1: Main FML Components Block Diagram

The fuzzy approach makes our system as agile as possible and therefore able to accept sensory feedback that might not be captured by the ontology. We initially constructed a knowledge base of the commonplace sensory data sources using fuzzification variables and the relevant membership functions.

6.3 SENS-IT FIS

In this section, we present a generic fuzzy inference system (FIS) of a semantic notification structure, as depicted in Figure 6-2. As already mentioned, and shown in the diagram, an FIS block has embedded knowledge-base and rule-base components, both are needed to generate proper semantic notifications.

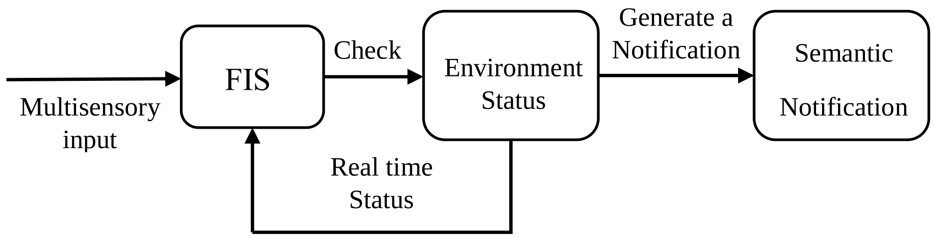


Figure 6-2: A Generic FIS of a Semantic Notification Generation

A semantic notification of an environment status needs to have two or more sensory data sources as fuzzification inputs. Therefore, the basic membership of any semantic notification should follow the algorithm shown in **Algorithm 3**.

In our FIS, we used FML to model the fuzzy memberships and the relevant rules. Two widely known approaches in the literature for modeling inference systems, are the Mamdani Model (L. A. Zadeh, 1968) and the Sugeno Model (also called the TSK fuzzy model) (Dubois, Nguyen, Prade, & Sugeno). We used the former since it is more useful when modeling knowledge reasoning approaches (Santamaria et al., 2016).

Algorithm 3: Simple SENS-IT FIS algorithm

```
In1 ← Sensor1 value                          // In1: Sensor1 linguistic variable
In2 ← Sensor2 value                          // In2: Sensor2 linguistic variable
SN ← StatusOutput                            //SN: Semantic Notification
procedure Membership(sensorySet)
    while In1 & In2 do                       (1)
        if In1 = High & In2 = Low then
            return true
            SN is High
            convert SN to nonfuzzy inference
        else if In1 = Low & In2 = High then
            return true
            SN is Average
            convert SN to nonfuzzy inference
        else
            SN is Low
            convert SN to nonfuzzy inference
        end if
        goto (1)
    end while
```

Each fuzzy rule is considered a relation between one or more antecedent(s) and its consequent. A typical rule in a Mamdani fuzzy model has the following format:

$$\boldsymbol{IF}\ (input\ \mathrm{A})\ (\ \mathbf{AND}\ ,\mathbf{OR}\ )\ (input\ B)\ \boldsymbol{THEN}\ (Consequence\ C)$$

Each FML instance is implemented in an XML tags format, which is needed to model a fuzzy controller. The main FML tags needed to form fuzzy inference engines are shown in Table 6-1, along with a use for each tag:

FML Tag	Usage
<FUZZYCONTROLLER>	Root tag of an FML System that has all FML components
<KNOWLEDGEBASE>	Combines all fuzzy concepts
<FUZZYVARIABLE>	An instance of a fuzzy instance
<FUZZYTERM>	A linguistic describing a fuzzy concept
<XXSHAPE>	Fuzzy tag shape used to define the relevant fuzzy set. XX represents the shape type.

Table 6-1: Main FML Tags

An FML template is shown in Appendix **FML template**. The fuzzy engine of an FML representation is constructed based on a fuzzy controller according to a tree-leaves structure, as depicted in Figure 6-3. The controller starts in a Knowledge-Base and a Rule-Base. The former is to build the fuzzy terms from each variable or input, whereas the latter is to build the antecedent-and-consequence (A&C) rules. We will show an FML representation for each of our scenarios.

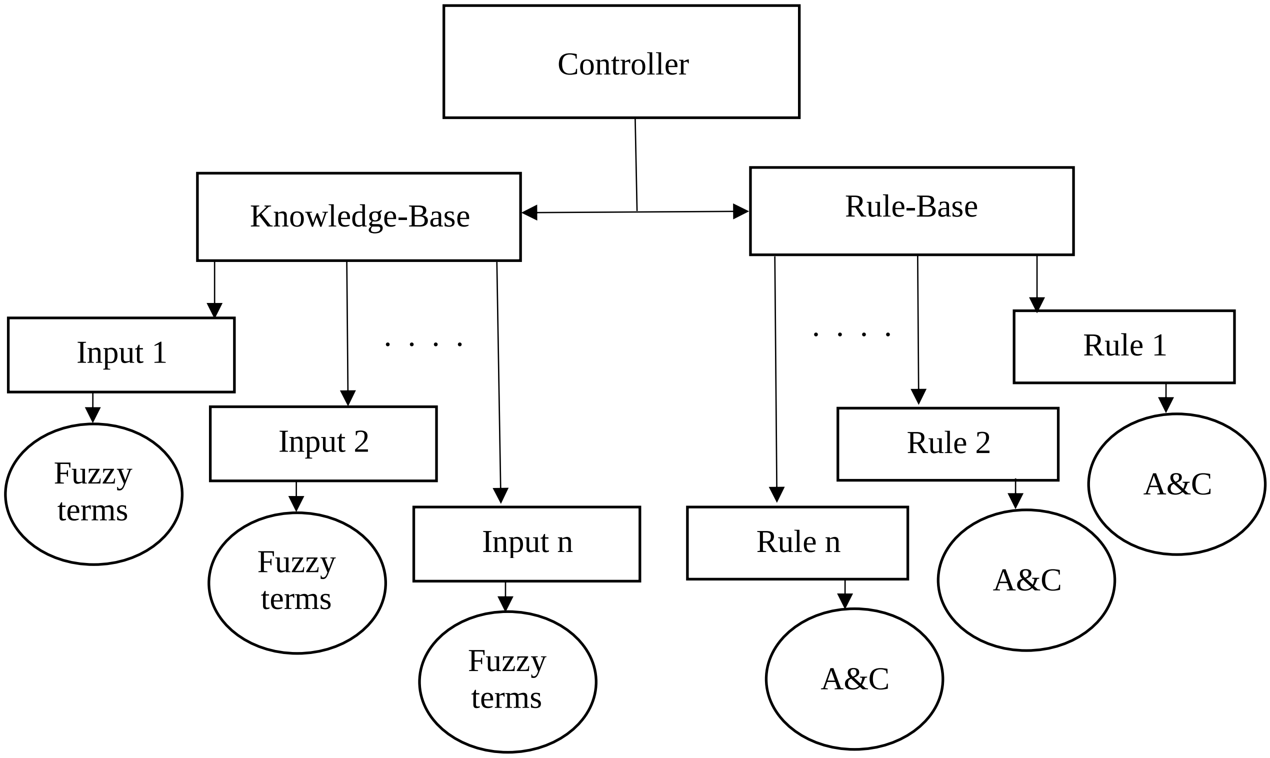


Figure 6-3: FML Controller Structure

6.4 SENS-IT FIS Scenario

We show in this section a scenario that describes inputs, output, rules and memberships of an FIS semantic notification, e.g. quality of location (QL), which is composed of two or more sensory data sources. This section aims to simplify the concept of modelling the FIS mathematically, which will be presented in the next section. We adopted a development environment tool called the VisualFML to model our FIS (Acampora, Loia, & Vitiello, 2013). The environment tool is compatible with any Java Runtime Environment (JRE) platform.

We classify an assumption of quality of location QoL level (weight) for choosing suitable indoor places (Café, restaurant, banks, library, etc.) based on two classifications:

1) **The actual QoL of indoor locations:** Here indoor places are quantified based on a standard QoL level that provides the real status of an indoor place based on the most suitable IoT environmental sensory sources like noise, motion, temperature, humidity, just to name a few. Figure 6-4 depicts a standard category block of a QoL semantic notification.

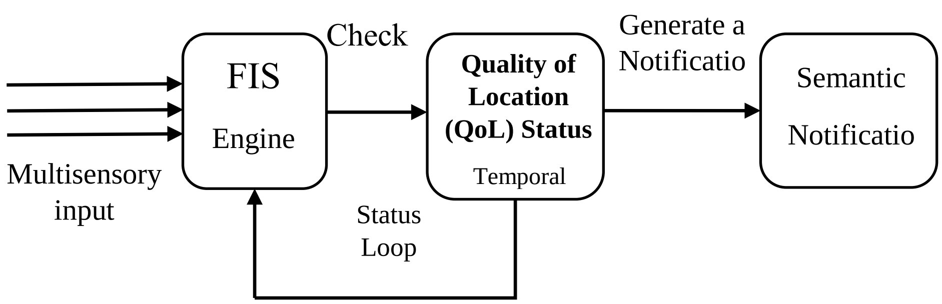


Figure 6-4: Standard Category of a QoL Semantic Notification

2) **Customizable QoL preferences:** This is based on users' preferences of location status (quiet, air quality, odor, etc.), according to temporal contexts. The semantic notification is sent based on predefined rules that were selected by users according to their preferences of a set of environmental sensory data sources. Figure 6-5 shows how a set of preferences are chosen in advance, based on actual readings and historical measurements references. The preferences are determined based on what people can observe in their environment. The combination of sensory data sources is translated into semantic notifications based on the user's preferences.

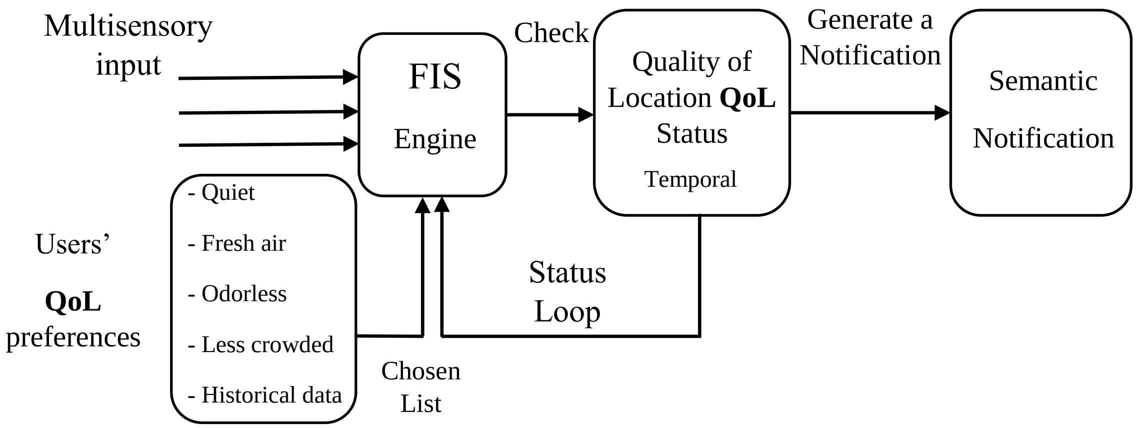


Figure 6-5: Customizable QoL Preferences

The scenario's objective is to provide an idea of quality of location, based on multiple sensory sources, for example air quality and noise level measurements. The input linguistic variables and the terms of the sensory set are shown as follows:

• Air quality: AQ = {Low, Mild, High}.

• Noise: N = {Low, Average, High}.

And the output linguistic variable of the QL notification is:

• QL = {Low QL, Average QL, High QL}.

Figure 6-6 shows a high level of FIS QoL notification, but Section 7.4 will describe the whole FIS of QL semantic notifications, which include a two sensory set input, fuzzy rules for both sets, and the output, including a surface visualization along with its temporal information.

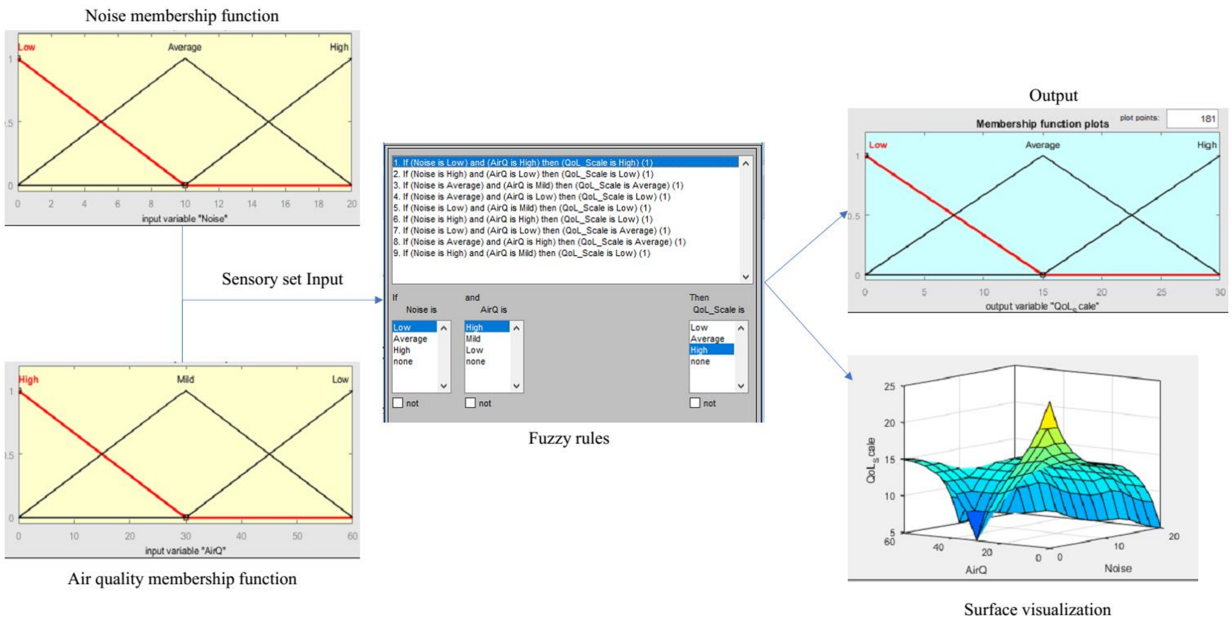


Figure 6-6: FIS of QoL a Semantic Notification

6.5 Mathematical Model

This section presents a simple mathematical model for our fuzzy system inference. The model is composed of multisensory events coming from two sources; events based on user preferences and events based on accumulative sensory data.

Given N sensory events, represented by two vectors: the user preference events vector (X) and the accumulative sensory events vector (W). Vector (X) is derived directly from the user (shown in Equation 1). Vector (W) combines current sensory events and the history of these events over a definite time interval (shown in Equation 2). The objective is to provide a recommendation that best matches user preferences, given current and historical events.

$$X = [x_1, x_2 \dots, x_N]^T \tag{1}$$

$$\mathrm{X} = [\mathrm{x}_1, \mathrm{x}_2 \dots, \mathrm{x}_\mathrm{N}]^\mathrm{T}$$

$$W = [w_1, w_2, \ldots, w_N]^T \tag{2}$$

Vector (X) represents the static sensory events of the model; its values are only updated by the user. On the other hand, vector (W) is dynamic and is computed according to sensory events captured in real-time, and the history of these events over time. At a general instance of time (t>0), vector (W) is calculated as the weighted average of the current events vector and the history of events vector (Equation 3).

$$w_i(t) = a_i \times w_c(t) + \beta_j \times \frac{1}{N} \sum_{j=1}^{N} e^{-j} \times w_i(t-j) \tag{3}$$

Where:

a_i is the weight of the current value of the i^{th} sensory event.

$w_c(t)$ is the current value of the i^{th} sensory event.

N is the window of previous values to be considered for the accumulate sensory events.

β_j is the weight of the history of sensory events.

$w_i(t-j)$ is the j^{th} previous value of the sensory events.

In order to rank the sensory events in accordance to user preferences and system prioritization, a cost function $C_j(t)$ is defined. The cost function $C_j(t)$ is defined as the Euclidean distance between w_j and x_j, minus the prioritization factor $P_j(t)$, as shown in Equation 4. The sensory events are then ranked in increasing order based on their cost function. The sensory event with the lowest cost function will be ranked as the first choice option and suggested as such to the user.

$$C_j(t) = D\left(x_j(t), w_j(t)\right) - P_j(t) \quad (4)$$

Where:

$D(w_j, x_j)$ is the Euclidean distance between w_j and x_j.

$\boldsymbol{C_j(t)}$ is called the prioritization factor. It is used to enforce media prioritization.

6.6 Procedure

The procedure used to determine the ranking of the sensory events and eventually a selection is composed of three steps: compute the prioritization factor, compute the cost of each sensory event and select sensory notification according to the minimum cost, and update the accumulative sensory event values according to the following steps:

Step 1: The prioritization factor ($P_j(t)$) is computed first. This is a function that can describe any relevant parameters not included in the user preferences (cost, location, timing, social connections, etc.). This function is not defined here since it is scenario dependent.

Step 2: Calculate the cost function $C_j(t)$ for each input sensory event (represents the Euclidean distance between w_j and x_j, minus the prioritization factor), as shown in Equation 4. The sensory event with minimal cost is selected as the first choice for the user.

Step 3: Read the current sensory events and update the $w_j(t)$ values for all the input sensor events, according to Equation 3 (t>0).

6.7 Summary

In this chapter, we proposed utilizing a fuzzy inference system (FIS) to support our ontology solution that is already covered in Chapter 5. The aim of proposed FIS is to make our ontology much agile, so people's surroundings statuses can be presented in broader descriptive feedback. We first presented a generic structure of FIS needed for a semantic notification. Then, it is followed by a scenario, an initial mathematical model and procedure of ranking sensory events. The FIS will be evaluated based on an empirical study that both will be covered in Chapter 7.

Chapter 7 EVALUATION AND RESULTS

7.1 Introduction

In the current chapter, we show the results of three evaluations of our system. The first evaluation is an empirical study and an impact analysis of a sensory data set in selected locations in the city of Ottawa, Ontario. The study was conducted over a two-month period, where the raw data was collected by our running IoT deployment. The second evaluation is about our ontology that was extended from SSN and the third is evaluation of our fuzzy inference development of the system.

7.2 Empirical Study of a Sensory Data Set Analysis

In this section we evaluate our SENS-IT deployment by presenting a statistical analysis that aims to support our objective of using multisensory sources for better insights of people environments. Therefore, for proof of concept, we examined the relationship between the sensory set based on the impact of different conditions like sensors' location characteristics and timeframes as shown in Table 7-1 and Table 7-2. The results can help in building a plausible semantic notification of ambiance notification, according to people's desires. Also, we conducted T-Value and P-Value for further statistical analysis, in order to show the correlation significance between the sensory set readings. Each sensory data event is published in a JSON format, as shown in **Algorithm 2** in Chapter 4. The timestamp field is generated and appended by the IoT platform for each published event data.

Figure 7-1 shows a sequence chart of the empirical study. The study starts by collecting the environmental sensory data from the deployed locations. As depicted in the chart, each node has to satisfy two main conditions before publishing the sensory data. First, it needs to enable a bridge communication between the microcontroller and the Linux operating system.

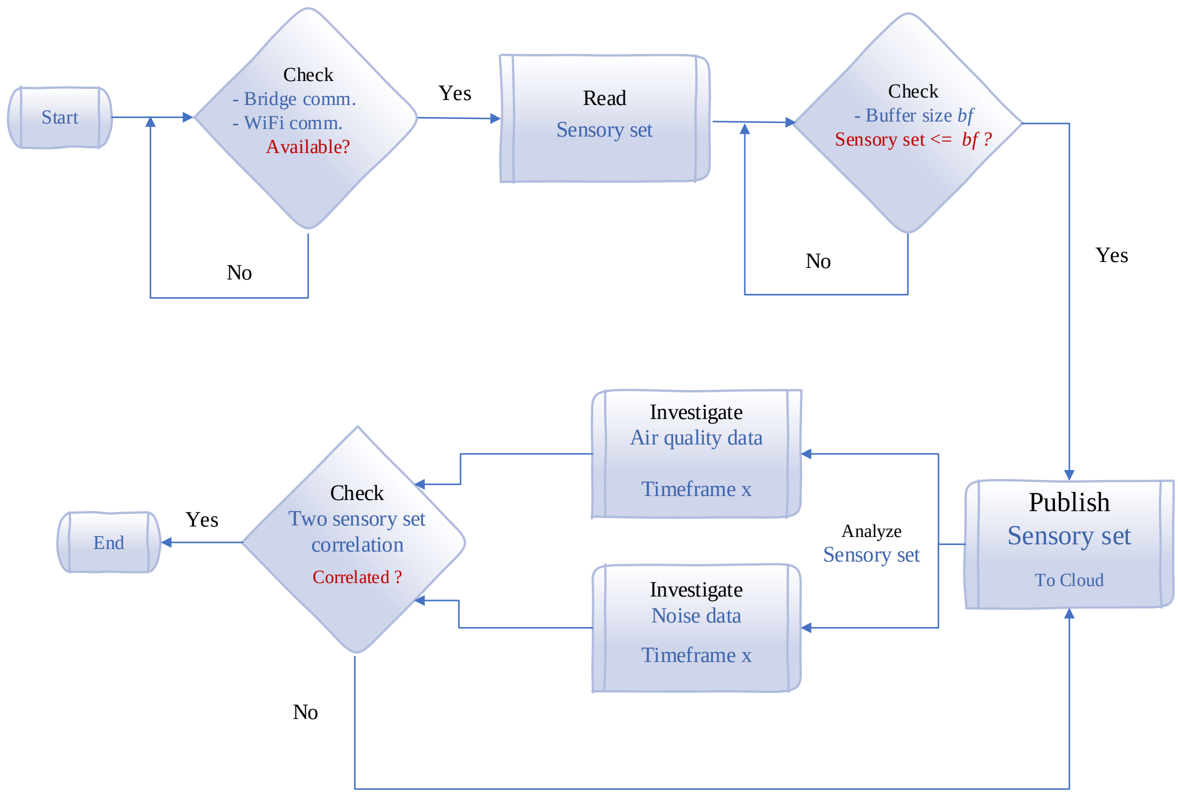


Figure 7-1: Empirical Study Sequence Chart

Second, WiFi access is necessary for the node to have Internet connection. Once both conditions are satisfied, the node has the ability to read the sensory set. The microcontroller needs a specific buffer size to hold a single sensory measurement. Once a complete sensory data event is collected, it will be published to the cloud. The analysis is done manually by investigating both sensory sets to see whether or not there is a correlation between air quality and noise, at a specific time. When there is a correlation between the sensory sets, the correlation value will be recorded, along with its time frame. Otherwise, the investigation will continue for another sensory set and time frame.

7.2.1 Study Impact

Our platform is built based on a mixed scalable approach of cloud and edge computing solutions, to provide real-time streaming and monitoring of IoT sensory data. We intentionally used the cloud platform for two main reasons, as follows:

- To enable people, whether residents or city authorities, to monitor the measurements of the environment ambiance in a real-time fashion.
- To maintain a scalable and timely IoT sensory system of environmental status variations.

We have four nodes installed in different neighborhood locations to collect environmental status variations, and each location has its unique characteristics, as detailed in Table 7-1. Each node is comprised of five or six environmental sensors, publishing a total of approximately 6,900 messages per day. Since the impact of noise and air quality pollution on chronic diseases (e.g. Asthma, strokes) has been emphasized in several research works ((ATS), 2013; Andersen et al., 2011; Hoek, Brunekreef, Goldbohm, Fischer, & Van Den Brandt, 2002), we evaluate our IoT deployment statistically to explore the correlation efficiency between these two sensory sets in different places. The results can enable people with health difficulties to determine their optimal residence based on the quality of life perspective.

Node ID	Location Characteristics	Image at location
node01	- Condensed neighborhood. - Schools nearby.	
node02	- Frequent road traffic nearby. - Suburban location.	
node03	-Very condensed neighborhood.	
node04	- Frequent bus traffic. - Airport nearby. - Very active road nearby.	

Table 7-1: Node Location Characteristics

7.2.2 Correlation Co-Efficiency

We used a correlation coefficient method to investigate whether or not there was a relation between the values of our platform for noise and air quality, in the selected locations. If so, to what degree is there a correlation, according to the relevant time frame samples. It is worth noting that the closer the correlation value is to one, the better. We first calculated the covariance of the noise and air quality samples, as follows:

$$Cov = \frac{\sum_{i-l}^{N} (n_i - \bar{n})(a_i - \bar{a})}{N - 1} \tag{7.1}$$

For each sample of noise $\boldsymbol{n}$ and air quality $\boldsymbol{a}$, we calculated the means $\bar{\boldsymbol{n}}$ and $\bar{\boldsymbol{a}}$ respectively. Then each sample was quantified via the variation amount of the selected time portion using the following:

$$\sigma = \sqrt{\frac{\sum_{i-l}^{N}(x_i - \mu)}{N-1}} \tag{7.2}$$

Where $\boldsymbol{\sigma}$ is the sample standard deviation, and $\boldsymbol{x}$ is the noise or air quality data set sample along with its mean. We found that the relatedness of noise and air quality is very strong. Periods of hours, days, and weeks were chosen to calculate the correlation efficiency values (CEV). The relation between noise and air quality was investigated using the following formula:

$$CEV = \frac{Ce_{NA}}{Ce_N Ce_A} \tag{7.3}$$

Where *CEV* is the Correlation Efficiency Value, *n* is a single element in noise values, *a* is a single element in air quality values, Ce_{NA} is the covariance of noise and air quality samples, and Ce_N Ce_A is the sample standard deviation of each sensory data. We monitored the two sets of sensory data over a two-month period to find out the impact of noise and air quality in four outdoor locations in the city of Ottawa. We made our observations based on the following considerations:

- By analyzing the data for air quality and noise for particular weeks within the two-month period, we can infer from the results that there is a strong correlation between these two sensory data sources.
- We clearly realize that whenever the noise reading increases, the air quality reading decreases at that specific time and location of the study period. However, this inference might differ from location to another.

- The data analysis is carried out during weekdays because of the clear impact of people's activities during weekdays rather than on weekends.

- Since the analysis was carried out over an 8-week period, we chose four weeks per month and combined each week's correlation values as a single one-week value, to simplify the analysis. More precisely, due to the massive number of captured sensory data, we chose our sample according to the highest CEVs of noise and air quality, which are considered the highest impact periods in the analysis.
- The chosen time frames have a more significant impact on weekdays than on weekends.

The chosen time frames have a more significant impact on weekdays than on weekends.

Month 2017	**Week#**	**5am**	**9am**	**12pm**	**4pm**	**Mean μ** per week
July	1	0.72	0.77	0.81	0.49	**0.71**
	2	0.74	0.94	0.91	0.81	**0.81**
	3	0.85	0.78	0.67	0.67	**0.74**
	4	0.86	0.85	0.61	0.56	**0.72**
August	5	0.92	0.88	0.37	0.41	**0.64**
	6	0.81	0.91	0.51	0.86	**0.77**
	7	0.72	0.96	0.61	0.61	**0.72**
	8	0.79	0.94	0.71	0.66	**0.75**
Mean μ per time-frame		**0.72**	**0.87**	**0.65**	**0.63**	**0.73**

Table 7-2: Noise and Air Quality Correlation Efficiency

As was explained in Equation 6-3, we calculated the correlation efficiency values (CEV) of noise and air quality at the times that showed the strongest correlation between the two sensory data sources, as shown in Table 7-2. Our study is based on different times during an 8-week period in July and August 2017 and based on different location characteristics. The times chosen were 5 a.m., 9 a.m., 12 p.m. and 4 p.m. The table shows each timeframe's mean per week for the whole study period. Also, it shows in the bottom the total mean per timeframe and the total mean for the whole timeframes. We intentionally chose the correlation function to investigate whether there is a degree of relation between noise and air quality values. In the following subsection we will show the results in detail.

7.2.3 Results and Discussion

Correlation Significance Measurements T-value / P-value				
	5am	**9am**	**12pm**	**5pm**
July	1.9624/2.56E-215	1.9627/1.05E-215	1.9627/5.15E-206	1.9627/1.13E-223
August	1.96826/~ 0	1.96823/4.65E-294	1.96826/~ 0	1.96863/~ 0

Table 7-3: T-Value & P-Value Measurements

We can infer from the last table that the correlation is based not only on the timeframe but also on the node location as noticed that the mean correlation 0.41 is low accordingly to its location characteristic. To test the statistical degree of noise and air quality CEVs, the Paired Sample type of T-test was chosen for our analysis. This type of statistical analysis is important to compare the samples' means from similar groups at different times. Table 7-3 shows the T-values and P-values according to the significance of the correlation mean of the samples' measurements throughout the study period. As noticed in P-values, the CEV of both sensory data sources has a clear significance since all the P-values of the four-time frames are either zero or below. This indicates that the correlation between noise and air quality values did not occur by coincidence but instead is very sound. We also noticed that both months have revealed similar CEV values. The concentration of noise and air quality variations is observed at specific times and values.

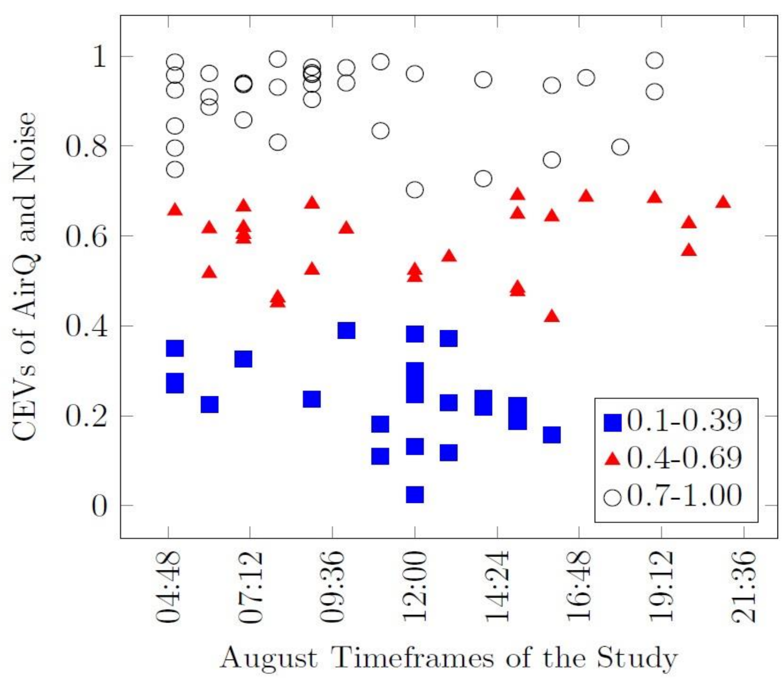


Figure 7-2: Scattered Concentration of Noise and Air Quality CEVs in July 2017

In Figure 7-2 and Figure 7-3, the scattered values of noise and air quality correlations are clearly tied to people's activities, especially at 9 a.m., as depicted by the circles. The circles here are meant to show the correlation values that are above 0.7, which represents the third of the overall correlation values, as shown in the legend. Both figures show that most of the values of the correlation efficiency of air quality and noise in the study period are above 0.5, thus proving our assumption.

We have come up with a number of observations based on the results of the study, including:

- Each time sample of the study period has its unique CEV, depending on people's activities at specific times of the day. For example, the highest noise and air quality CEVs were in the 9 a.m. time frame for both months, as is revealed by the mean total of the study period.

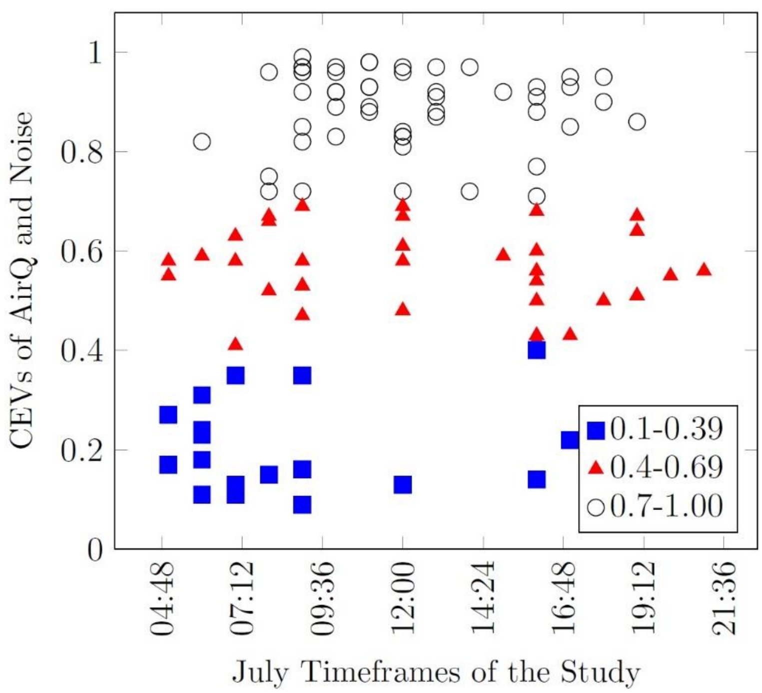


Figure 7-3: Scattered Concentration of Noise and Air Quality CEVs in August 2017

- The CEVs of the data transmitted from node04 had the highest impact due to its location near global transportation zones.

To sum up, we noticed that based on the results and measurements obtained from our IoT real-time deployment and the analysis of the data that was captured during a two-month study period, there is a strong correlation between noise and air quality. This observation shows that it is possible to describe an outdoor location status using multi-sensory data sources in a meaningful and semantic notification, according to the spatio-temporal context.

7.3 SENS-IT Ontology Evaluation & Results

In order to optimize the ontology's performance and ensure that the relationships between properties, classes and other parts of the ontology can function properly, we needed to evaluate it from two perspectives. First, to make sure that the ontology is of high quality and that it can fulfill our specific aim with the least number of pitfalls. Second, based on the enhanced quality, the ontology should be widely accepted and adopted in the semantic web space. The ontology evaluation process is defined as the measuring role of an ontology quality (Vrande, 2010). In the next section, we will show the evaluation of our ontology using two categories that are widely known: Automatic diagnosis and Semi-automatic diagnosis.

7.3.1 Automatic Diagnose

We call this type of evaluation a *within ontology-based* evaluation. Through Protégé, we used a plug-in tool called Hermit (Shearer, Motik, & Horrocks, 2008) as a reasoner that is known for ontologies written in OWL. The reasoner's function is to investigate an ontology's validity by diagnosing the status of its logical consistency and classes hierarchy. Therefore, any classification incoherence or pitfalls can be detected. Two types of classification hierarchies are used within ontology development platforms (Horridge et al., 2011). The *inferred hierarchy* is used by the reasoner to automatically infer a class hierarchy, whereas the *asserted hierarchy* is used manually by having developers construct the classes. Figure 7-4 shows the two hierarchy classifications, with *inferred hierarchy* on the left and *asserted hierarchy* on the right of our SENS-IT ontology.

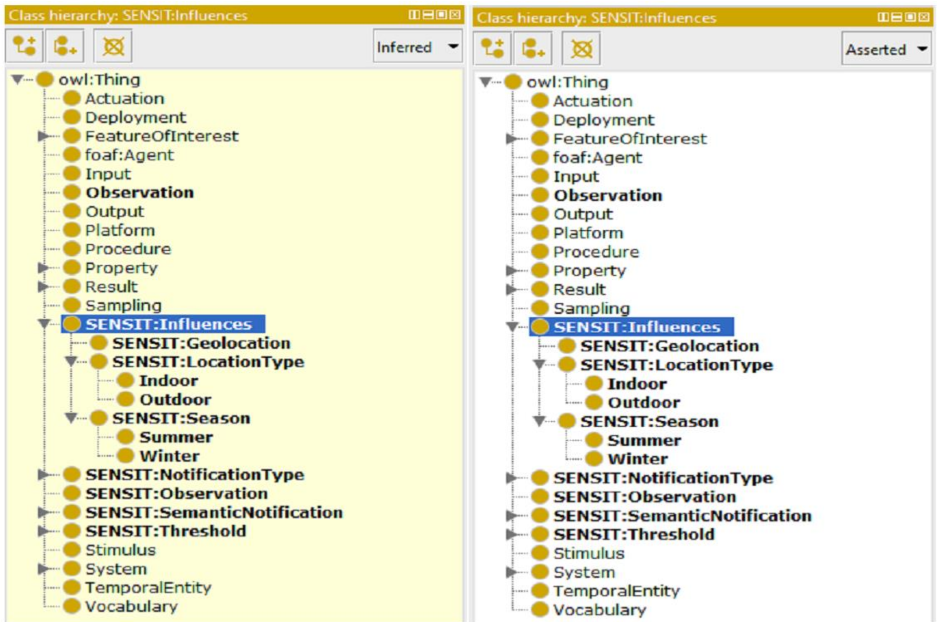


Figure 7-4: The Inferred and Asserted Hierarchy Classifications

Several criteria used in the evaluation of ontologies are discussed in the literature (Brank, Grobelnik, & Mladenić, 2005; Vrande, 2010), however we will focus on the consistency aspect of our ontology's evaluation. According to Gómez (Gómez-Pérez, 2001), the consistency of an ontology refers to the condition that an ontology has valid definition inferences and that its expression parts are sound. Also, it should not have any conflicts between its classes and individuals. We did the first evaluation run using the reasoner. As shown Figure 7-5 the answer according to the evaluation query is provided by the reasoner and states that the ontology is coherent and consistent. The Input Ontology View shows the results of the Correct axioms of the SENS-IT ontology; however, the reasoner assumes that there is a problem with the Knowledge Base (KB) that leads to a list of Possibly Faulty Axioms, as shown in Figure 7-6.

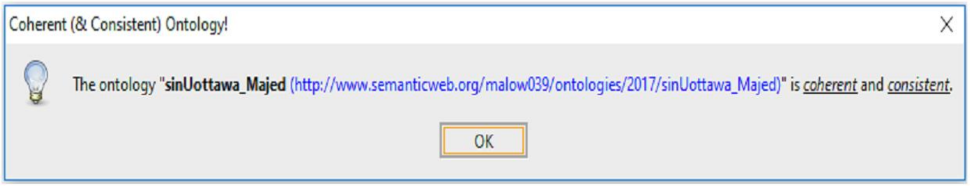


Figure 7-5: The Consistency Result of the SENS-IT Ontology

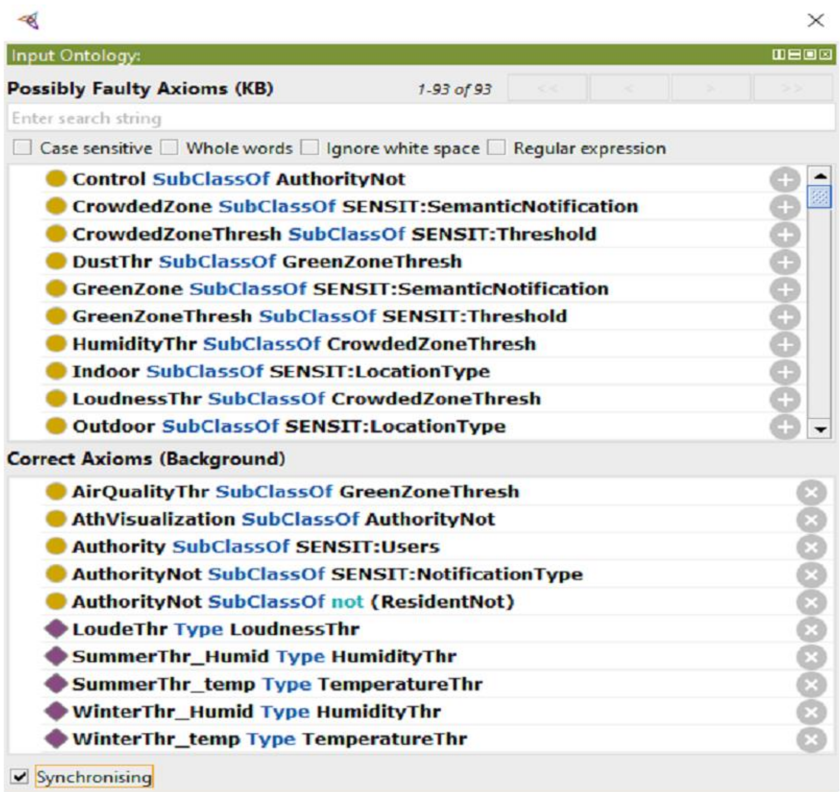


Figure 7-6: The Possibly Faulty and Correct Axioms

This faulty list shows the errors that might cause inconsistencies in an ontology. Since our ontology is a new ontology, extended from an existing one, by default whole axioms are supposed to be erroneous. So, according to this case, we assume that our ontology is correct by adding the axioms to the Correct Axioms list. We then run the second evaluation round to see the result we get from the reasoner after having applied the modifications needed to solve the faulty axioms. The evaluation result of the SENS-IT ontology is consistence and coherent and all axioms are now correct, as shown in Figure 7-7.

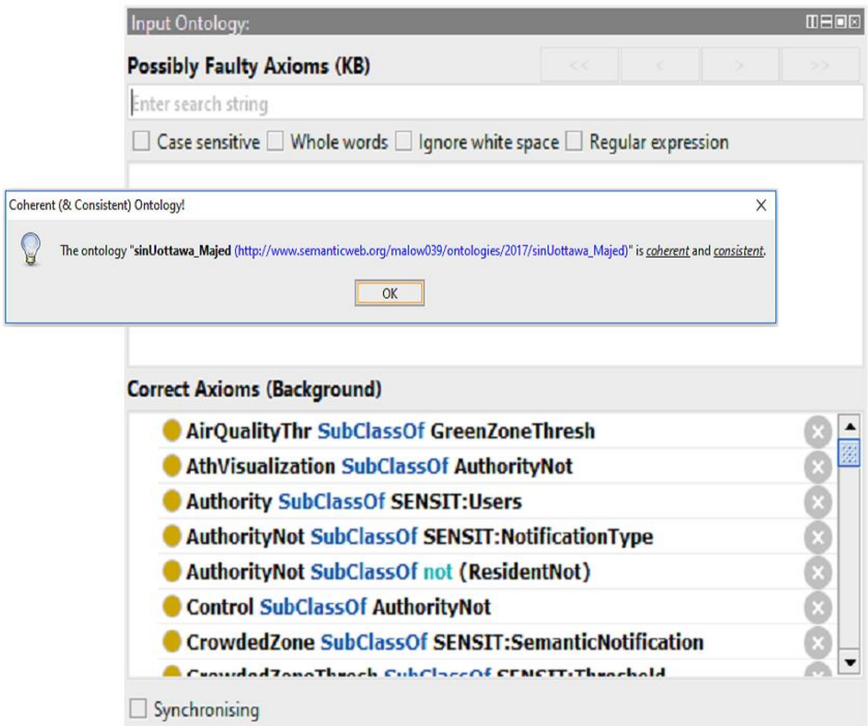


Figure 7-7: The Evaluation Result of the SENS-IT Ontology

7.3.2 Semi-Automatic Diagnosis

We call this type of evaluation an *off-ontology-based* evaluation that is based on a RESTFul web diagnosing service. Using this type, we can choose a custom evaluation set of potential pitfalls through a pitfall checking tool that is not part of our ontology engine.

We used an evaluation checking tool called the Ontology Pitfall Scanner! (OOPS!) (Poveda-Villalón, Suárez-Figueroa, & Gómez-Pérez, 2012) to diagnose our ontology. This tool is an open source and has been widely used in several academia projects (Poveda-Villalón et al., 2012), so developers can track their ontology's validity before it is fully presented to the public. OOPS!'s function is to parse an ontology using the Jena API, searching for mistakes according to a list of pitfalls of ontology components. This tool provides the option to scan the ontology through its URI or use a direct input of the ontology as an xml format. Based on a classified significance level that shows the degree a pitfall affects the ontology, the evaluation results generated by OOPS! are classified into one of three levels, as follows (Poveda-Villalón, Suárez-Figueroa, & Gómez-Pérez, 2015):

- **Critical:** This type of pitfall affects the ontology's consistency, usability or other critical factor and must be corrected.
- **Important:** This type of pitfall is not critical, but it is nevertheless highly recommended to correct it.
- **Minor:** This type of pitfall doesn't affect the ontology, although it is still advisable to correct it.

For the validation of our ontology, we did some evaluation runs to solve the three pitfall types that were related to our ontology. The evaluation could be conducted for all of the ontology's components or only for some, by selecting a specific pitfall or category of evaluation.

Listing 1 shows the metadata of our ontology that will be evaluated in the upcoming evaluation runs. We started by investigating our entire ontology, so all of the pitfalls and evaluation categories are examined, using the direct input scanner method for diagnosis. Table 7-4 shows the results of the first evaluation run of our SENS-IT ontology by listing the pitfall type, the ontology in which the pitfall appears, the number of cases, and the pitfall impact category. The results show that the ontology doesn't have any critical pitfalls but that it does have some pitfalls in the important and minor pitfall categories.

```
<owl:Ontology
  rdf:about="http://www.semanticweb.org/malow039/ontologies/2017/si
  nUottawa_Majed">
  <owl:imports rdf:resource="http://www.w3.org/ns/ssn/"/>
  <terms:rights>Copyright 2018</terms:rights>
  <terms:created>2017-11-01</terms:created>
  <terms:license>MCRLAB - uOttawa</terms:license>
  <terms:title>Semantic Notification of Sensory IoT</terms:title>
  <rdfs:comment>In case of any errors, please provide us with the error to
  MCRLAB @uottawa.ca</rdfs:comment>
  <owl:versionInfo>SENS –IT version 0.01</owl:versionInfo>
  <terms:description>The SENS –IT ontology aims to
  describe people' s surrounding in much perceptible status by
  aggregating the corresponding sensory data into a textual format.
  </terms:description>
  <terms:creator> - SSN - Majed Alowaidi</terms:creator>

</owl:Ontology>
```

Listing 1: Metadata of SENS-IT Ontology version 0.0.1

By investigating the evaluation results, we show in the following the detected pitfalls, along with their code according to the OOPS! pitfall catalogue (Poveda, 2016), and their possible corrections:

- **Three pitfalls** of type P04, showing that there is isolation between parts of the ontology. From the table we see that these pitfalls appear in components that are not related to our ontology, so we will omit them.
- **Fifty-seven pitfalls** of type P08, showing that certain ontology components are not annotated. Fifty-four pitfalls out of this list are related to our ontology, therefore, we

will annotate all of these elements. The table shows that three of the pitfalls in the list are unrelated to our ontology.

- **Thirty-eight pitfalls** of type P11, showing that a property has not identified a domain or range in the ontology (Villalon, 2016, p.79). However, we noticed from this list that these pitfalls are related to the ontology from which we extended our SENS-IT ontology. We will ignore these pitfalls since they don't affect our ontology.
- **Nine pitfalls** of type P13, showing that an inverse relationship has not been identified for each relationship inside the ontology (Villalon, 2016, p.149). There are only six pitfalls that are related to our ontology and the rest are from the initial ontology, as the table clearly shows. We solved this pitfall issue by adding the inverse relationship for each ontology relation.
- **One pitfall** of type P24, showing that an element of the ontology uses a recursive definition (Villalon, 2016, p.92). By investigating this pitfall, we found that it was related to one of the SSN extension components. Since we don't use these components in our ontology, we left it as is.
- **Two pitfalls** of type P30, showing that equivalent classes are not defined explicitly (Villalon, 2016, p.97). These pitfalls are not related to our ontology's components, so we will leave them as is, especially since we did not use the relevant classes in the extension.
- **One pitfall** of type P40, showing that the ontology lacks a description to declare the corresponding ontology license (Villalon, 2016, p.106). We solved it by identifying the relevant information, as shown in **Listing 1**.

Pitfall Type	Appearance	Cases no.	Impact Category
P04: Ontology parts are not linked properly.	FOFA, OWL-Time, VOAF	3	Minor
P08: Ontology components are not annotated.	SENS-IT(55), FOFA, OWL-Time, VOAF	58	Minor
P011: Domain or range of property is not identified.	SOSA(23), SSN(15)	38	Important
P013: Inverse relationship is not declared.	SENS-IT(6), SOSA(1), SSN(2)	9	Minor
P22: Naming conventions of the ontology are different.	SENS-IT	G*	Minor
P24: An ontology element uses recursive definition.	SSN	1	Important
P30: Equivalent classes are not explicitly declared.	SSN	2	Important
P40: License of ontology is not identified.	SENS-IT	G*	Important
D: Direct, **I**: Indirect			

Table 7-4: The Evaluation Result Using OOPS!

The second evaluation run was conducted according to a list where specific evaluation criterion where selected in advance for the ontology's evaluation. Consistency checking is a major factor in the evaluation of any ontology's structure. So, we started this evaluation by investigating the criteria pitfalls that might be related to inconsistency issues. As shown in Figure 7-8, the consistency criterion includes five pitfalls that all lead to a wrong inference.

Consistency

The pitfalls that share in this type of evaluation are:

P05, P06, P07, P024

Figure 7-8: Consistency Criterion Evaluation

The P05 pitfall (Villalon, 2016, p.73) refers to a reverse relationship problem between ontology objects, which might lead to an improper inference. The P06 pitfall (Villalon, 2016, p.74) shows a loop problem in the hierarchical structure of a class, which finally leads to reasoning and logical misconceptions. The P19 pitfall (Villalon, 2016, p.87) is caused when more than one domain or range is defined for each relationship, possibly leading to an incorrect interpretation. We have already covered pitfall P024.

In Figure 7-9, we notice that the evaluation run shows only one pitfall of type P024, defined as a recursive definition problem that only appears in the SSN ontology, meaning that it is not related to our SENS-IT ontology. According to the consistency evaluation output, our ontology is consistent in ensuring that there are no wrong inferences.

Consistency Result:

Pitfall P024

1 case | rate: Important ●

This pitfall is appeared in the following components:

➢ http://www.w3.org/ns/ssn/system

Figure 7-9: The Result of the Consistency Evaluation Run

7.3.3 Results & Discussion

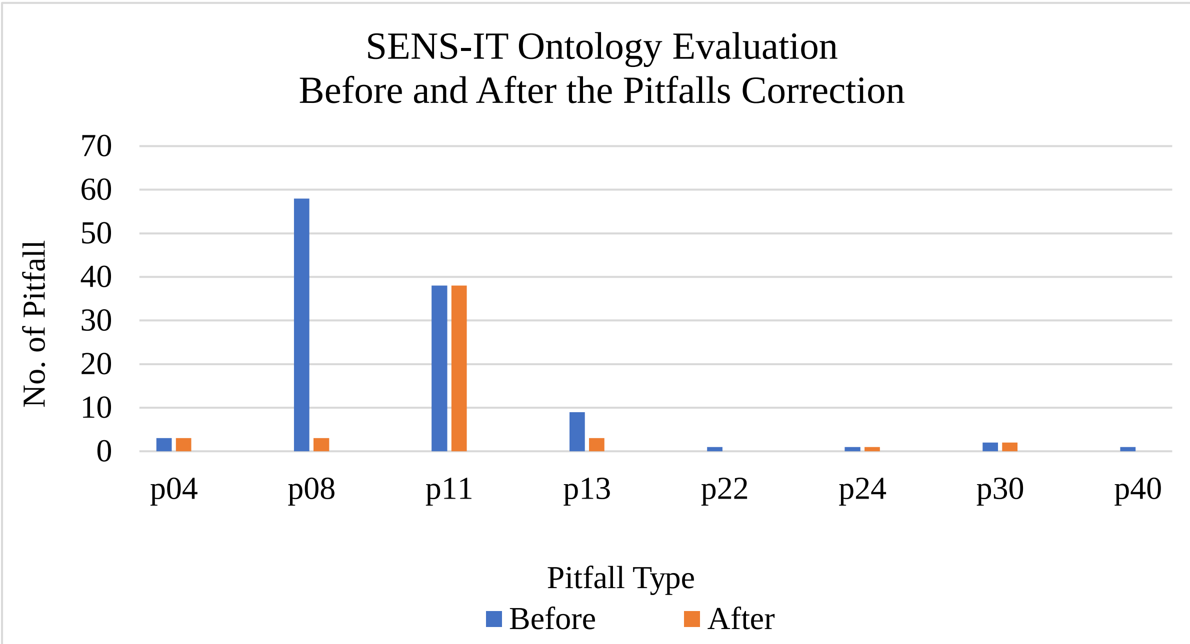


Figure 7-10: The Ontology Evaluation Before and After Pitfall Correction

We present here a conclusion from the evaluation runs part. Figure 7-10 shows a comparison chart of our SENS-IT ontology evaluation before and after applying the relevant modifications. The chart shows two bars for each pitfall that was discovered by OOPS! tool in the evaluation runs. We present here a summary and conclusion of the evaluation runs. Figure 7-10 shows a comparison chart of our SENS-IT ontology evaluation before and after applying the relevant modifications. The chart shows two bars for each pitfall that was discovered by the OOPS! tool during the evaluation runs. We can see that the pitfalls that were related to our ontology have been corrected, as shown in the after bars of pitfalls P08, P13, P022, and P40 pitfalls. The other pitfalls are related to the other ontology from which our ontology was extended. However, those pitfalls don't affect our ontology's consistency since their sources of extensions are not used in our ontological structure. To sum up, after we conducted several evaluations runs and applied the relevant optimization to our ontology, we can emphasize that our SENS-IT ontology is consistent and coherent in eliminating erroneous or improper classifications of ontological parts, which might affect the inference of optimal semantic notifications.

7.4 Fuzzy Inference System SENS-IT Evaluation & Results

7.4.1 Multivalued Correlation Degree (MCD) Impact

Any aim to generate an inference about an action requires building an appropriate knowledge. This leads us to build rules based on a set of inputs to represent the desired knowledge. We used the FML approach via VisualFMLTool to model and evaluate our fuzzy inference system (FIS).

The impact of air quality and noise has been known for its risk on human health ((ATS), 2013; Andersen et al., 2011; Hoek et al., 2002). The association between air quality and noise from multiple sources is measured in many research works and confirmed its effect on people's daily and long-term health (Cai et al., 2017; Davies, Vlaanderen, Henderson, & Brauer, 2009).

Each sensory data is streamed with a timeframe that represents a timestamp of the recorded data. Based on the measurements of the correlation efficiency that was presented in (Alowaidi, Karime, Aljaafrah, & Saddik, 2018), it was found that there is a tight relationship between noise and air quality as two significant pollution indicators. Therefore, the proposed fuzzy inference approach is assumed to address the relationship value in the domain [0,1] that represents a gradual correlation value according to the study timeframe. The statistical results shown in the study indicates a two-value correlation. As shown in Figure 7-11 , the article proposes a multivalued correlation degree (MCD) using the FIS memberships as shown in the next section.

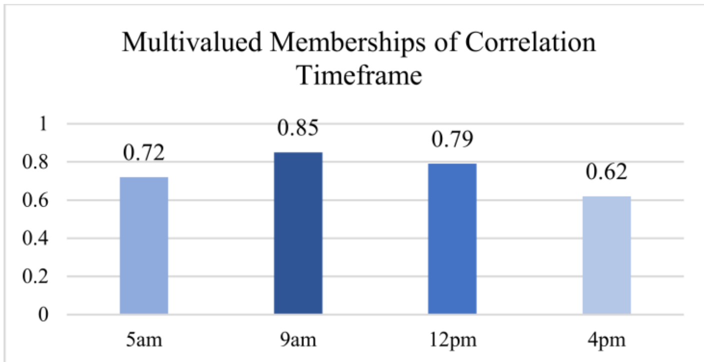


Figure 7-11: Degree of Multivalued Membership Correlation

7.4.2 Initial Knowledge Block

The obtained output when comparing two sensory set values is a binary-value result that clearly indicates whether these sensory sets are correlated or not, as this rule explains:

IF n **AND** a both increased (or decreased), **THEN** there is a correlation q

As a Standard Strict implication, we can employ the two sensory sources correlation as follows:

$$n \rightarrow a \begin{cases} 1 & if\ q \\ 0 & otherwise \end{cases}$$

Where n and a are instances of noise and air quality sensory data sources. The membership function of this relation is a sharp membership that produces 1 when there is a correlation or 0 otherwise, as shown in Figure 7-12.

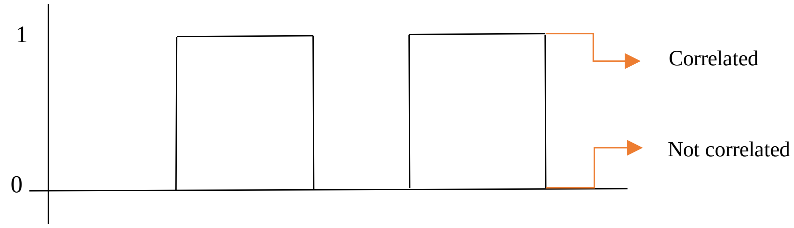


Figure 7-12: Binary Value Membership of Correlation

In previous work, the extent of the correlation degree was not mentioned explicitly. So, we built a linguistic list of correlation degrees representing the function memberships of linguistic terms. We might consider correlation degrees according to the quintuple form:

$$(z, S(z), N, J, V) \tag{5}$$

Where:

z is the correlation variable.

$S(z)$ is the term of the terms set related to *correlation* as linguistic values of z, that defined in N as a fuzzy variable.

J is a syntax rule for values of z, and,

V is another rule to associate a value to its meaning.

In our case, the linguistic variable used is *correlation* and the set of terms is assumed as follows:

$$S = \{low, slightly\ average, average, high\} \tag{6}$$

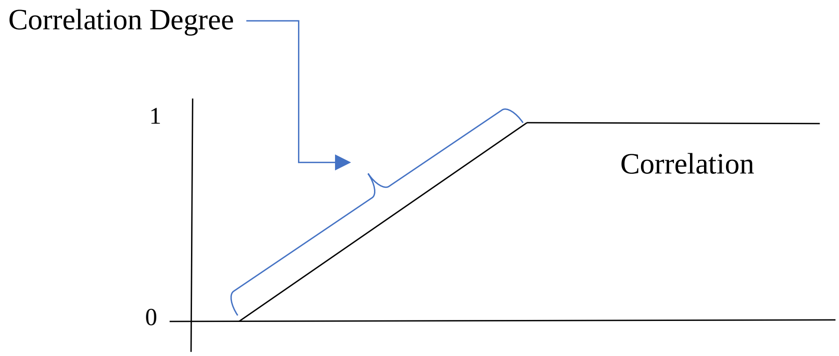


Figure 7-13: A Multivalued Membership of Correlation

Where each term in S (Correlation) is featured by a fuzzy set. The discourse domain per linguistic term is $N = \{0,1\}$, as shown in Figure 7-13. Here it is obvious that the correlation between the two sensory data is not crisp, instead it has a gradual shape as each time frame of a sensory data has its own impact. Therefore, the Standard Strict implication is changed to reflect the gradual domain of correlation concentration between the sensory set as follows:

$$\boldsymbol{n \rightarrow a\ (or\ a \rightarrow n)} \begin{cases} \mathbf{1} & \boldsymbol{if\ q\ Very\ correlated} \\ \mathbf{0.5} & \boldsymbol{if\ q\ slightly} \\ \mathbf{0} & \boldsymbol{Otherwise\ Not} \end{cases}$$

For example, as shown in Figure 7-11, the mean value of 9am time produces a higher correlation value that all other time frames because people are more active in weekdays than weekends.

7.4.3 Results and Discussion

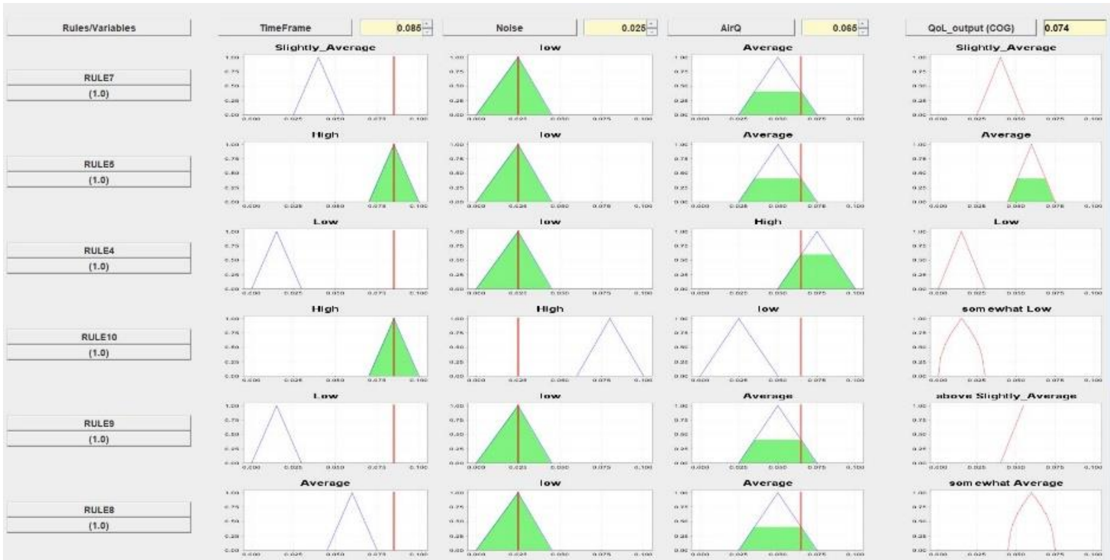


Figure 7-14: Membership Functions of QoL FIS

For a proof of concept, we assume our FIS output is considered as a quality of location notification according to inputs $\boldsymbol{n}$, $\boldsymbol{a}$, and timeframe. Figure 7-14 shows clearly the membership functions of all FIS inputs. The time-frame plays a key role in identifying the correlation degree according people's activity. The output of the defuzzification process is shown in Figure 7-15. We can notice that the impact on choosing a high QoL value is based on the output of the optimal value of each sensory source along with its relevant timeframe as shown in Rule 1.

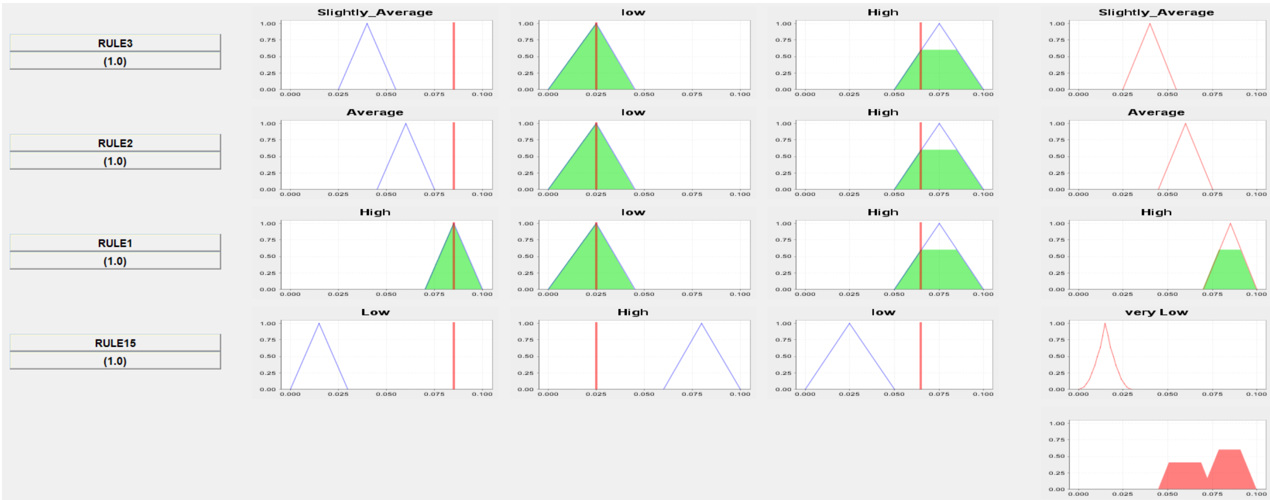


Figure 7-15: Remaining Membership Functions and QoL FIS Output

```
<RuleBase activationMethod="MIN" and Method="MIN" name="QoL" or Method="MAX"
type="mamdani">
      <Rule connector="and" name="RULE1" operator="MIN" weight="1.0">
                  <Antecedent>
                      <Clause>
                          <Variable>AirQ</Variable>
                          <Term>High</Term>
                      </Clause>
                      <Clause>
                          <Variable>Noise</Variable>
                          <Term>low</Term>
                      </Clause>
                      <Clause>
                          <Variable>TimeFrame</Variable>
                          <Term>High</Term>
                      </Clause>
                  </Antecedent>
                  <Consequent>
                      <Clause>
                          <Variable>QoL_output</Variable>
                          <Term>Average</Term>
                      </Clause>
                  </Consequent>
       </Rule>
```

Figure 7-16: FML Rule-Base Block

7.4.4 Modifier terms of the FIS rule-base

In order to modify the correlation between the two sensory data needed for inferencing the result as the quality of location notification, a list of modifiers has been used in the FIS that plays an important role in defining the gradual degree of quality of location needed per people's health preference. Table 7-5 shows a list of modifiers including examples that used in the FIS inference system. Figure 7-16 shows clearly the membership functions of some FIS rules of each input's components.

Modifier used in the FIS rules-base	**Example**
Slightly(somewhat)	• RULE3: If (AirQ is High) and (Noise is low) and (TimeFrame is **Slightly**_Average) then (QoL_output is **Slightly**_Average); (1.0)
Very(extremely)	• RULE15: If (AirQ is low) and (Noise is High) and (TimeFrame is Low) then (QoL_output is **very** Low); (1.0)

Table 7-5: Modifiers List of the FIS

7.4.5 Main FIS characteristics

To build an FIS, two widely known approaches in the literature are used to model inference systems namely the Mamdani Model (L. A. Zadeh, 1968) and the Sugeno Model (also called the TSK fuzzy model) (Dubois, Nguyen, Prade, & Sugeno). The former one has been used because it is useful when modeling knowledge reasoning approaches (Santamaria et al., 2016). As shown in the previous figures, the triangular shape type is used in building the fuzzy variables and terms as created by the VisaualFML tool. The FIS of correlation degree between the sensory set of the study is depicted in Figure 7-17 showing the main parts of the knowledge base and fuzzy control for inferring a quality of location status as follows:

- The fuzzy rules as quality of location (QoL) linguistic combination.
- The linguistic terms for each variable *air quality*, *noise* and *TimeFrame*.
- The QoL output that results from the fuzzy rules.

Fuzzy Input Variables	**Fuzzy linguistic terms**	**Membership function type (Triangular) (a, b, c)**
Noise	Low	(0.0, 0.025, 0.05)
	Average	(0.025, 0.05, 0.075)
	High	(0.05, 0.075, 0.1)
Air quality	Low	(0.0, 0.025, 0.05)
	Average	(0.025, 0.05, 0.075)
	High	(0.05, 0.075, 0.1)
Timeframe	Low	(0,0, 0.015, 0.03)
	Slightly Average	(0.025, 0.04, 0.055)
	Average	(0.045,0.06,0.075)
	High	(0.07, 0.085, 0.1)

Table 7-6: FIS Membership Parameters

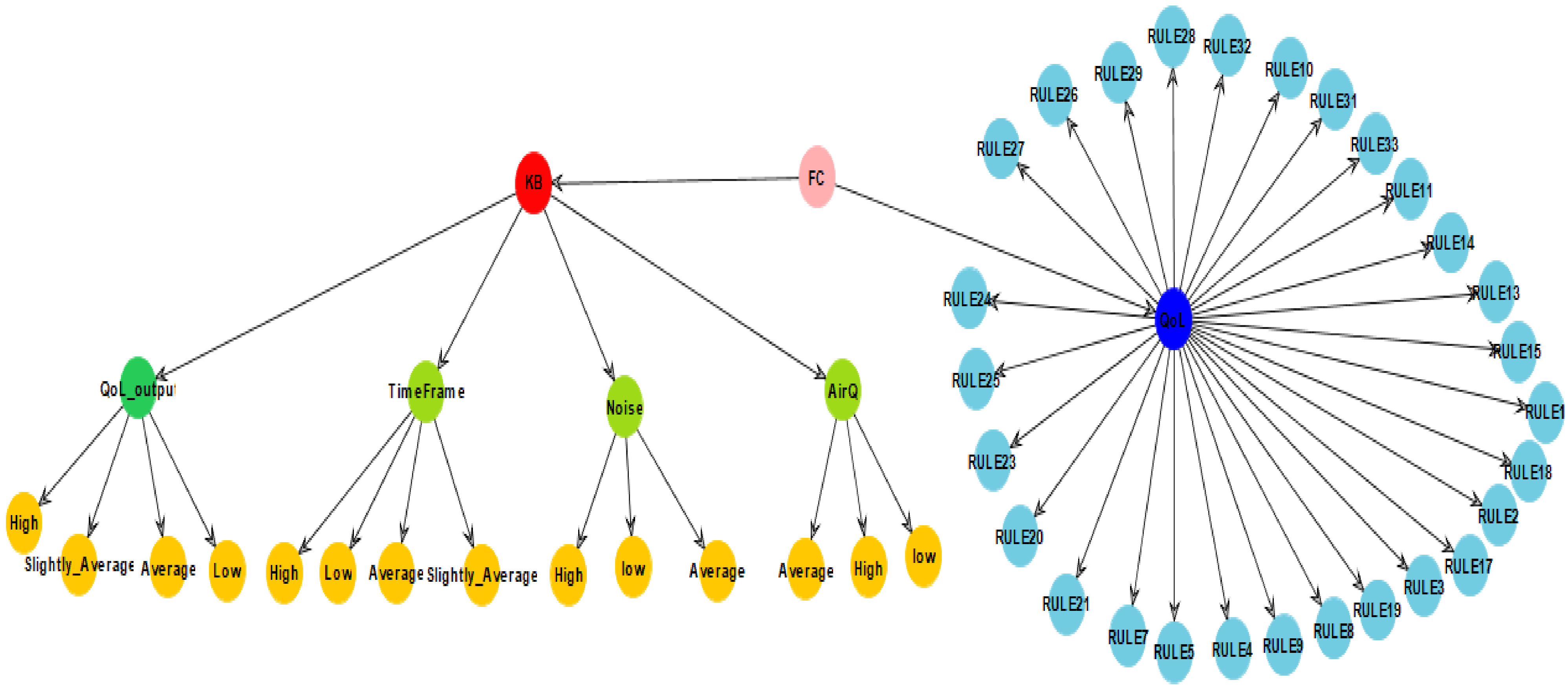


Figure 7-17: FIS Implementation

Table 7-6 shows a detail of the FIS membership functions including the variables and the linguistic terms of air quality, noise, and timeframe as inputs used in inferring the quality of location notification. The timeframe of each sensory data plays a key role in identifying the correlation degree according to people's daily activity. In Table 7-7, we show some of our FIS Rules base along with the applied time-frame.

FIS Rule	**The study timeframe**
• RULE1: If (**AirQ** is High) and (**Noise** is low) and (**TimeFrame** is High) then (**QoL**_output is Low); (1.0)	9am
• RULE2: If (**AirQ** is High) and (**Noise** is low) and (**TimeFrame** is Average) then (**QoL**_output is Average); (1.0)	4pm
• RULE11: If (**AirQ** is slightly Average) and (**Noise** is low) and (**TimeFrame** is Slightly_Average) then (**QoL**_output is Low); (1.0)	5am
• RULE13: If (**AirQ** is low) and (**Noise** is High) and (**TimeFrame** is Average) then (**QoL**_output is somewhat Low); (1.0)	12pm

Table 7-7: Some Linguistic Rules of QoL FIS

7.4.6 Actual and predicted timeframe

In a previous work, the correlation between the two sensory data has been calculated, which is adopted in this work to indicate the actual QoL value. On the other hand, the predicted correlation between the two sensory data is calculated based on the Fuzzy Inference Mechanisms as a crisp output of the FIS which is used to refer to the inferred QoL value. The membership functions of fuzzy output variable have been utilized with four linguistic terms which are Low, Slightly Average, Average, High. Consequently, those timeframes that have the most affected correlation degrees are highlighted in Table 7-8 along with its relevant FIS linguistic rules and triangular membership functions.

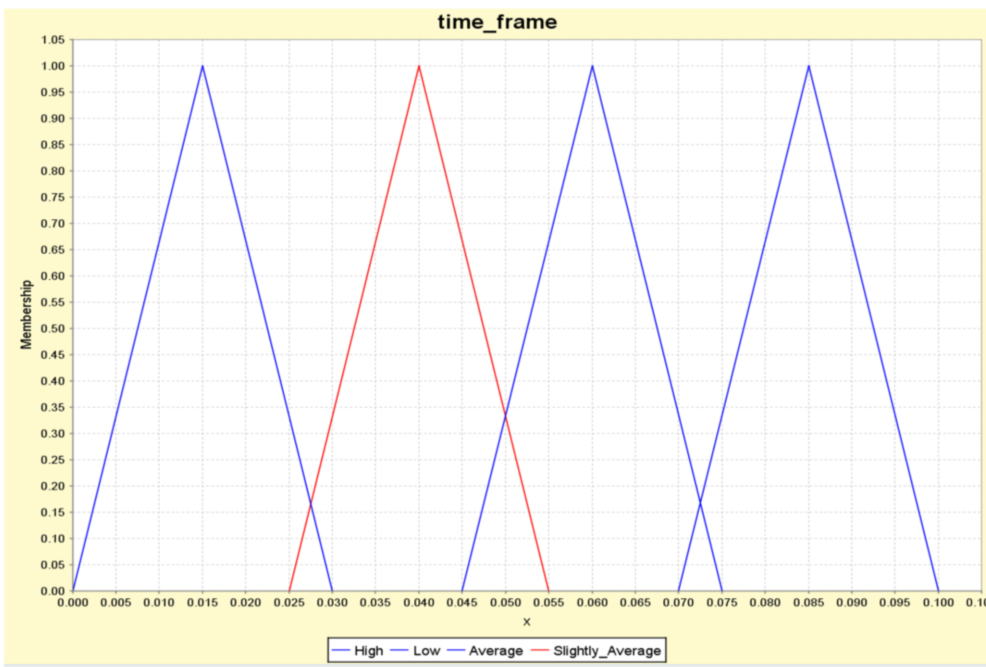
Timeframe Domain Legend		Timeframe Membership Function
Domain	**Term**	
0.0 - 0.03	Low (not active time)	
0.025 - 0.055	Slightly average	
0.045 - 0.075	Average	
0.07 - 0.099	High (Very active time)	

Table 7-8: Description of Time frame Discourse Domain

To show the impact of timeframes on the correlation degree, the relative/percent error, mean square error (MSE) and root mean square error (RMSE) methods (Equations 7, 9) are used to compare the actual value (calculated) QoL and the output of the FIS i.e., predicted (inferred QoL) respectively.

$$Re_{ave} = \frac{1}{n}\sum_{t=1}^{n}\frac{QoL_A - QoL_P}{QoL_A} \qquad (7)$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(QoL_A - QoL_P\right)^2 \qquad (8)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(QoL_A - QoL_P)^2}{n}} \qquad (9)$$

Where:

$(QoL_A - QoL_P)$ are the variables difference of the observed and predicted values of the all QoL values.

n is the number of samples used per measurement

The usage of errors square is important to statistically weight any irregular values that might affect the results. Based on Equation 7, 8 and 9, Table 7-9 shows the measurements of errors based on both the actual (calculated) and predicted (inferred) values demonstrating how it is significant to consider the captured timeframe in each fuzzy inference. Also, samples of the membership functions (MFs) of the calculated FIS errors are also shown respectively. In addition, each MF illustrates the relation between the two sensory sources that is influenced by the relevant time-frame as observed for each sensory set.

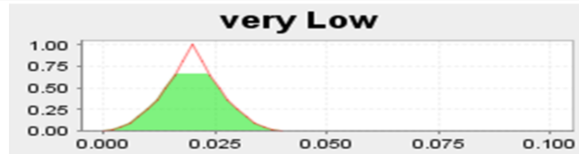
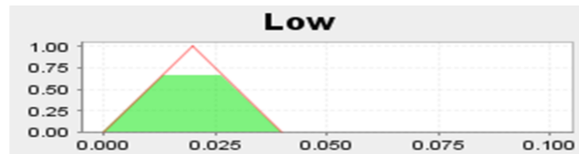
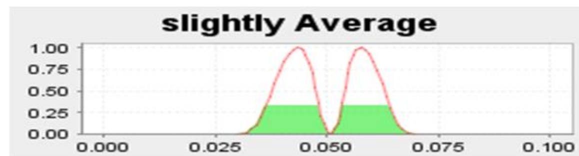
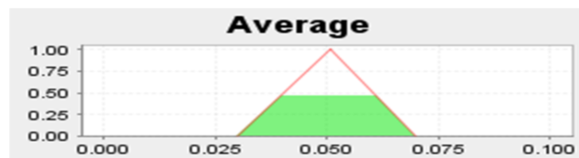
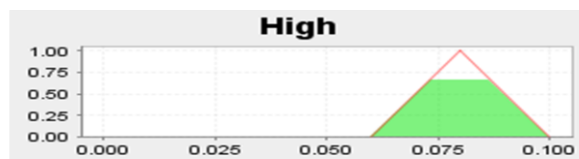
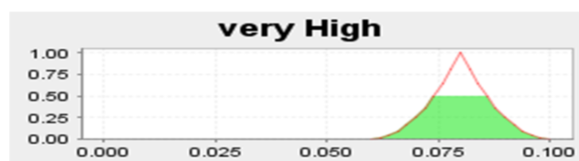
FIS Input (0,1)			Output (0,1)			Error	Square of Error
Time-frame	Noise	Air quality	(Actual) QoL_A	FIS Inferred QoL_P	Membership function output		
0.08	0.08	0.017	0.015	0.02		-0.005	0.000025
0.055	0.08	0.02	0.023	0.034		-0.011	0.000121
0.048	0.012	0.045	0.051	0.05		0.001	1E-06
0.06	0.02	0.07	0.074	0.05		0.024	0.000576
0.035	0.02	0.07	0.072	0.079		-0.007	4.9E-05
0.01	0.012	0.07	0.096	0.08		0.016	0.000256

Table 7-9: QoL Output MF of Timeframe Significance

As can be noticed from the output of the membership functions, the degree threshold of quality of location is affected by the two sensory data along with its relevant time. The lower air quality value and the higher noise value results in low QoL as shown in the output of the membership functions. The vice versa happens for a high QoL status when air quality value is high and noise value is low. In other words, the QoL threshold is affected according to the tied (strong) relationship of the two sensory data with the timeframe variation during hours of weekday.

Even though, MSE method performed quite well in indicating the average model prediction error between QoLA and variable QoLP. The usage of error square is important to statistically weigh any irregular values that might affect the results. As such, RMSE performed better in term of error prediction accuracy and monotonicity since it has the advantage of penalizing large errors in predicting observation according to variables of previous time periods. RMSE measures the difference between the predicted value of an estimator and the actual outcome. The idea is to calculate how far the FIS output is from the general category of the results. In our case the average RMSE = 1.28%. This is an absolute and not a relative value. This indicates that on average, the estimator (FIS) value deviates from the original value (QoLA) by approximately 1.28 points on a scale of 100. According to Table 7-10, which highlights the average MSE and RMSE of the FIS output, it is obvious the errors between calculated and inferred QoL value are so small, implying the importance of including timeframe parameter in the people's environmental health aspect. Furthermore, it can be certainly deduced that the quality of location inference is not only affected by the sensory source's location but also the time that was involved in each environmental sensory event triggering.

MSE	RMSE
0.00018	0.00128

Table 7-10: MSE and RMSE Measurements of Calculated and Desired QoL

The comparison chart in Figure 7-18 shows a visualization of the measured ACT and APT of the conducted study where both values are so close. The perception of the strong tie between the two values indicates a significant impact of QoL in people's surroundings that can help them for choosing the convenient environments according to different perspectives.

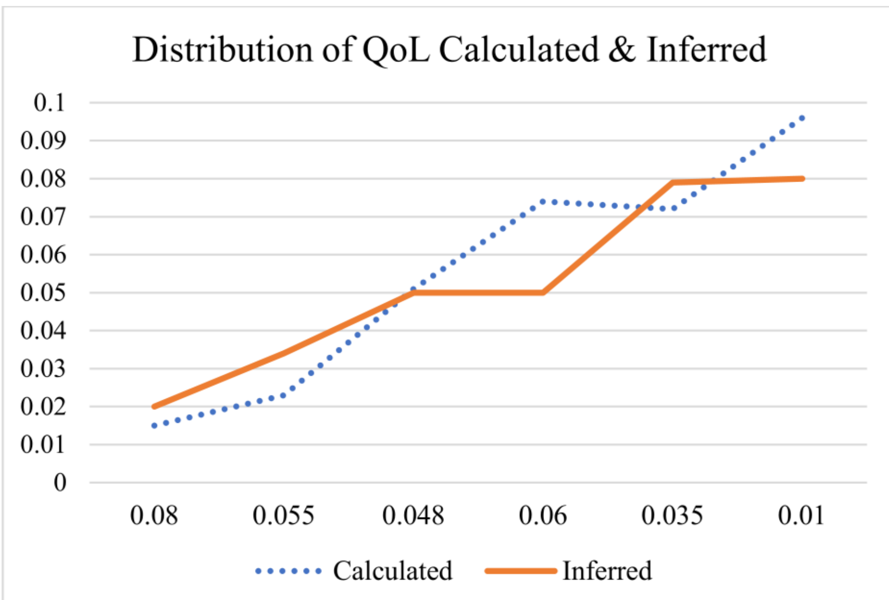


Figure 7-18: Calculated and Inferred Distribution of QoL Timeframes

7.4.7 Impact nodes' locations on QoL outcome

Based on the FIS approach mentioned in Table 7-9, we exploited the FIS outcome that was obtained from the statistical study result in a way that can infer the QoL status according to the characteristics of the nodes' locations in the deployment process. In this manner, we can support the aim that was explained in the previous section.

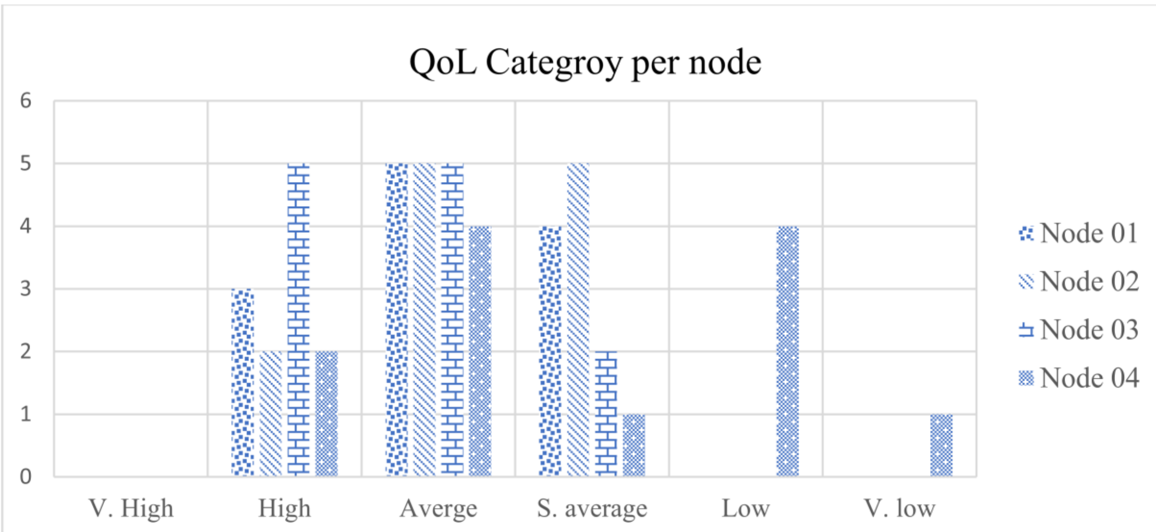


Figure 7-19: QoL Category of Nodes' Location

First, as a proof of concept, we collected 12 sensory data samples per node that represent part of the study data as shown in Figure 7-19. Since each node's location is featured differently according to its location factors, this gives each one a distinguishable FIS set of rules. However, this can be applicable to more than one node because of nodes' locations similarity of traffic activity. Table 7-11 shows the QoL output per node/location that resulted from inferencing different live sensory parameters that were captured over several weeks through the FIS engine. It is clear that an FIS rule of QoL might have an output in multiple locations that have similar characteristics.

QoL Category	FIS Inference Rule			QoL hits per node			
	Air quality	Noise	Timeframe	01	02	03	04
V. High	High	High	High	0	0	0	0
High	High	Average	High	3	2	5	2
Average	Average	Average	High	5	5	5	4
S. Average	Average	S. Average	High	4	5	2	1
Low	Average	High	High	0	0	0	1
V. Low	Low	High	High	0	0	0	1

Table 7-11: QoL Status hits per Node's Location

For each node, the number of QoL hits output shows how many rules are applicable during the study period.

Based on the node's location characteristics, it shows gradually how good or bad a node's location status is at specific times according to a triple FIS rule. For example, node 04 is located in a frequent bus and automobile traffic. Thus, by measuring the sensory data of noise and air quality at a specific activity time and after applying the FIS rules, it becomes clear that this node's location is the worst among all others since the output indicates a bad QoL status (i.e. QoL hits per node is 0 for both low and V. low). On the other hand, a location where traffic is minimal such the location of node 01 shows that the QoL is always good.

This also, implies that this location has lower traffic activity compared to the previous one. This section's aim is to emphasize the importance of FIS in providing a meaningful and intuitive feedback of people's surroundings.

7.5 Summary

This chapter presents our SENS-IT evaluations of the three implementations as covered in the three previous chapters. We first evaluated our framework implementation through deploying, collecting, monitoring, and analyzing the sensory data based on different locations in the City of Ottawa. We calculated the correlation means of two sensory data because of the clear relationship that was observed in different timeframes. We also calculated T-Value and P-Value as further statistical to show the correlation significance between the observed sensory set measurements. We evaluated the ontology to make sure the relationships between its components are valid. So, we did some evaluation rounds to check the consistency and coherence to discover of any pitfall using two types of checking, namely automatic and semi-automatic diagnoses. The former one is conducted by using a built-in feature in Protégé tool and the latter is achieved using a RESTFul called OOPS!. Both evaluation methods concluded that our ontology is coherent and consistent. The FIS evaluation was conducted by using an FML tool named VisualFMLTool that was used to model and evaluate our FIS. For proof of concept, we calculated two values, ATV and PTV, to evaluate our fuzzy inference model to find oud if there is a relationship between a two sensory set as two major pollution indicators. The comparison result of ATV and PTV shown that both values are close which emphasizes the significance of timeframes in the different locations.

Chapter 8 CONCLUSION AND FUTURE WORK

8.1 Conclusion Remarks

The IoT is a key component of the digital twin vision that aims to bridge the gap between the physical and the virtual worlds. Thus, simultaneous feedbacks from both worlds can improve and enrich our day-to-day life and wellbeing. In this thesis, we reviewed the literature and found that although other's work addressed some criteria related to raw sensory data, they lack some important aspects for semantic reasoning and representation of user ambiance that facilitates the perception of multiple sensory data sources as a meaningful and environment-aware notification. Therefore, based on the criteria analysis we introduced a platform called SENS-IT with the goal of providing people with a meaningful understanding of their indoor and outdoor environments, allowing the public and the authorities to obtain semantic notifications from multiple sensory data sources. SENS-IT is a three-layer architecture that aims to address the perception complexity of outdoor environmental status variations caused by having only one sensory source and raw data feedback. The approach has three main components: IoT environmental sensory nodes, edge computing services/devices, and IoT cloud-based services. The IoT nodes component involves the deployment of four sensory nodes in the city of Ottawa, Ontario, to measure the environmental status of outdoor ambiance. We intentionally placed the nodes in locations where they would have different characteristics, as shown in Table 7-1: . Each node is composed of a microcontroller board (MCB) and a typical set of environmental sensors, and it publishes approximately 6,900 event messages to the cloud per day, using an API and a MQTT protocol. Each message will be wrapped in a JSON format, with tagged geolocation information for further processing and visualization. The MQTT broker will handle the reception of the messages to be stored in a

NoSQL database, whether in a local or cloud-based repository. The edge part is responsible for partial processing, for instance applying certain rules in advance, like making fuzzy inference decisions before the whole sensory data is forwarded to the cloud. This solution has many optimizing benefits such as reducing network traffic.

We chose to deploy our SENS-IT to stream the sensory data to a cloud service because of its scalability and therefore its ability to work with more sensory data per node. As mentioned, a huge quantity of sensory data is published to the cloud every day, which may lead to complications related to resources, network processing delays, unwanted stored data, security issues, etc. To prevent these problems and optimize our system, we added an on-edge service and device. So, the sensory data from all of the locations will first be published to the edge for local storage and partial processing before being pushed to the cloud. As mentioned in Chapter 2, adding on-edge services or devices can bring many advantages to IoT deployments like reducing operational costs and processing high frequency actions at device locations, just to name a few.

Since air quality and noise are factors that have an impact on people's daily lives, we did a proof of concept empirical study to support our objective of using multisensory sources to perceive people's environments. Using our SENS-IT approach, a two-month study was conducted to measure the correlation between two sources of pollution, noise and air quality. We collected outdoor environmental events from four node locations. After statistically analyzing the results using CEV, T and P-values, we found a significant relationship between noise and air quality at the times when people are typically active. This proves that two or more sensory data sources can help measure outdoor environmental status changes by combining several sensory data and converting them into meaningful notifications. Applying a reasoning and descriptive method to perceive people's environments involves modeling a knowledge concept of objects and their relationships. Thus, we created an ontology extension of SSN that describes environmental status changes using multiple sensory data in semantic notifications. By reviewing the literature, we found that no previous work has been conducted on this subject.

In order to provide an optimal context for better integration, analytics and environmental perception of people surroundings, the relationships between entities or concepts are important to structure for better choices and much efficiency of people's interactions. Therefore, we developed the SENS-IT Ontology to build a reasoning and knowledge structure between the environmental sensory components. The extension is based on Semantic Sensor Network (SSN) Ontology where six classes were adopted for our SENS-IT ontology. We presented a scenario of our SENS-IT ontology using a description logic (DL) method known as the Attribute Language with Complement (**ALC**), which identifies the axiom usage of the assumed scenario and describes the relationships between individuals and the relevant ontology.

We adopted the agility of the fuzzy rules in our SENS-IT system. Therefore, we proposed a fuzzy inference system (FIS) to make our semantic notification approach generic enough so it covers a broader understanding of people's environments. We utilized the empirical study result on FIS approach by building a scenario implementation of the two sensory as a multivalued quality of location (QoL) outcome instead of a binary value. The result shown a significant role of FIS approach on time frame in identifying the degree of QoL over time.

8.2 Forecasts of Future Work

The growth of the IoT impacts a core part of people's perception of their environment. Many smart environment applications rely on the way events and data are processed and analyzed. Semantic IoT brings simplicity in identifying and interpreting people's environment in a much-augmented way.

We are in the process of optimizing the current version of our ontology by adding more components and deriving the needed classes from other ontologies, in order to ensure better reasoning and representation of people's various environments. These improvements will also make our ontology much more likely to be accepted by other academia and research institutions.

We aim to synchronize the SENS-IT ontology with the fuzzy inference system, so we can provide a simultaneous, automatic and very descriptive interpretation of people's environments using a combination of heterogeneous environmental sensory sources. The plan is to start by processing the sensory data streaming through the ontology and then to pass the results through the fuzzy inference to remove any ambiguity or uncertainty of data that might not have been solved by the ontology. Finally, we aim to optimize our mathematical model, so it can infer location status according to the cost of variables that affect the choice of people's desired locations.

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APPENDENCIES

1- FML template

```
<?xml version="1.0" encoding="UTF-8"?>
    <FuzzyController name="newSystem" ip="127.0.0.1">
        <KnowledgeBase>
            <FuzzyVariable name="var1" domainleft="0.0"
                 domainright="10.0" scale="" type="input">
                 <FuzzyTerm name="term1" complement="false">
                 <LeftLinearShape Param1="5.5"
                  Param2="10.0"/>
                 </FuzzyTerm>
                 <FuzzyTerm name="term2" complement="false">
  <TriangularShape Param1="0.0" Param2="2.0" Param3="5.5"/>
                  </FuzzyTerm>
            </FuzzyVariable>
                      <TriangularShape Param1="5.0"
                      Param2="10.0" Param3="15.0"/>
                   </FuzzyTerm>
  <TriangularShape Param1="0.0" Param2="5.0" Param3="10.0"/>
   </FuzzyTerm>
   <FuzzyTerm name="term3" complement="false">
   <TriangularShape Param1="10.0" Param2="15.0" Param3="20.0"/>
   </FuzzyTerm>
   </FuzzyVariable>
  <KnowledgeBase>
   ...
  </FuzzyController>
```

2- Attribute Language with Complement (ALC) constructing concepts:

Process	Description
$A \sqcup B$	Instances in A or B
$A \sqcap B$	Instances in A and B
$\forall A . B$	Instances of A with some relations to B
$\exists A . B$	Instances of A with all relations to B