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Knowledge Management Process for Air Quality Systems based on Data Warehouse Specification

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Abstract

Even though several systems for Air Quality (AQ) monitoring have been in existence for over a decade, a research model for Knowledge Management (KM) of AQ data has to be created in order to enhance the decision-making and organize the air quality data collected from the Internet of Things (IoT) consumer devices. This model should be made more performant by ensuring greater flexibility and interoperability between devices and emerging technologies. In this context, we propose an approach for representing Data WareHouse (DWH) schema based on an ontology that captures the multidimensional knowledge of tools, techniques, and technologies used for novel AQ systems. This enhances decision-making by coping with potential problems such as data sources heterogeneity and covering the various phases of the decision-making life cycle.

Keywords: Knowledge Management, Air Quality, Data Warehouse, Conceptual Data Model, Multidimensional Design, Ontology.

1. Introduction

The technologies of information air quality systems have been progressing at a rapid pace. Information systems are now being called upon to support KM, and not just to process data or information. Hence, various methods have been devised to support knowledge organization and interchange [1]. Ontologies further specify the semantics of a domain in terms of conceptual relationships and logical theories. From a computational perspective, a major benefit of such formalizations has been the development of algorithms that support the generation of inferences from a given set of facts about the world, or ones that check for consistency. Such computational aids are clearly useful for KM, especially when one is dealing with large amounts of knowledge. In this paper, we propose a method that uses ontologies for the multidimensional design of DWHs from an operational data source from different IoT sensors of

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AQ parameters. In addition, we present an ontology-based method for data modeling schema that eventually covers different phases of the DWH lifecycle, and takes into account the users by considering their personalized needs as well as their knowledge. This work is organized as follows: The second section presents the related work. The third section defines the knowledge management process based on data flow. The fourth section describes the design approach. Besides, the fifth section defines the advantage of this approach in knowledge. Finally, we end this work with a conclusion and some prospects of future works.

2. Related Work

In this section, we present related work based on two investigations. First, we define the different techniques for the DWH design and then we investigate different systems and architectures related to indoor and outdoor air quality. This helps to collect knowledge about different AQ technologies and classify them.

Table 1: Comparison Indoor and Outdoor Air Quality (IAQ / OAQ) systems

Location	**Paper**	**Year**	**Connectivity**	**Data access**	**Boards**	**Storage**
IAQ	[15]	2020	WiFi	Mobile	Arduino UNO	MySQL
	[15]	2020	WiFi	Mobile	Arduino UNO	MySQL
	[17]	2019	WiFi (ESP8266)	Web and mobile	ESP8266 Arduino Core	SQL server
	[18]	2018	WiFi	Web	Raspberry Pi2	Cloud
	[25]	2018	WiFi	Mobile	Arduino UNO	SQL server
	[16]	2018	Ethernet XBee PRO	Desktop	Raspberry Pi2	Emoncms setup
OAQ	[27]	2020	Web browser or a mobile APP	IEEE 802.15.4 K protocol	General-Purpose Processor (GPP)	Cloud
	[22]	2020	Xbee-ZB	EmonCMS	Raspberry Pi2	Cloud
	[21]	2020	Not defined	SeReNo2 IoT Dashboard at Ubidots	not defined	Cloud
	[19]	2018	LAN	Web service	Arduino UNO	Not defined
	[23]	2019	ZigBee	Web and mobile	-	Cloud server

First, we investigate Indoor AQ (IAQ) [15] [17] [18] [25] [16] and Outdoor AQ (OAQ) [27] [22] [21] [19] [23] systems. Thus, a new era of computing technologies has started based on IoT solutions. This leads to numerous systems in which several models have been developed in order to provide effectiveness for indoor and OAQ monitoring. table 1 shows knowledge of different tools and techniques used for novel AQ systems Second, we investigate different methods for DWH design. Different modeling techniques are used to represent the multidimensional concepts extracted from data sources, as well as the sources themselves. It can be ER diagram, UML diagram or graphs [3], etc. Unlike ontologies, which are ready for computing, these techniques are conceptual formalizations intended to graphically represent the domain and not used for querying and reasoning. This work is a continuation to a previous research [3], [11] and it aims at integrating ontologies in the DWH design process [5]. Therefore, the starting point was the meta-model of DWH scheme [11]. There are other studies that have supported the organizational and informational resource perspectives of the business process. For example, the Authors in cite [9] presented an ontology supporting semantic application for the e-recrutement in the domain of information technology. Authors in [2] proposed a multidimensional business knowledge model using a set of rules that formalize of these dimensions organized around the perspectives of business processes by implementing the whole of formalization rules. This constructs the target model starting from the business process model. The multidimensional ontology [10] is a representation of knowledge dedicated to the decision-making dimension. It specifies the multidimensional concepts and their semantic and multidimensional relations[7]. Its use covers different steps of the DWH lifecycle. During these steps, it assists the designer to solve problems of data source heterogeneity. In the OLAP requirement specification step, the decisional ontology helps to validate the multidimensional concepts (fact, measure, dimension, etc.) and relations between these concepts. It also prevents associations between concepts not semantically associable (e.g. associating fact-to-fact, dimension-to-dimension, hierarchy-to-fact, etc.). This allows us to add as many extensions as needed to the multidimensional ontology to cover the various phases of the life cycle of a decision-making dimension. To demonstrate this aspect, we have proposed an extension that represents the operational data source conceptual schema, in this case, an ER diagram [11].

3. Process of Knowledge flow management for air quality systems

The increasing volume, variety, and velocity of knowledge will keep going to fuel the AQ information exploding. Under the explosive growth of data, many various forms of data appear from a huge number of sources. In order to make entropies finds it so difficult to deal with the raw, semi-structured, and structured data, various system architectures as [20] [26] and [24] are used to handle data flow from an input source to the source of the output that is desired and needed to understand the required data as presented in figure 1. Therefore, we define basic components :

- Data sources: Data is scattered over the network and without any understandable documentation, So it can't be directly explored and used to extract the expected result.
- Data collection: It also known as data sensing or data acquisition is dealing with the collection of data (actively or passively) from the device, system, or as a result of its interactions. For data collection, critical AQ information needs to be available at the right point in a timely manner, and in the right form as mentioned by [12]. The data gathering from different sensory devices with the collection of environmental data or identification of real-world objects needed to incorporate into the system. Therefore, there are two subcomponents for collecting data which are batch processing that aims at acquiring data at rest and stream processing that aims at acquiring data in motion.
- Extract, Transform and Load ETL [13]: BI system has one of the most important components which are extract, transform, and load process. It allows manipulating data from various data sources, to reformat and to store the data in a repository.
- Business analytics: The business analytics will be able to explore data in preparation for data modeling such as service. It includes tools that produce reports and desired outputs to help managers to make decisions. Through tools that produce reports or desired and needed outputs to figure out the data required. It will be able to explore data and to offer a single version of truth [14], increase competitive ability and customer satisfaction and facilitate the alignment with business strategy. This level includes tools that help to produce reports, scoreboards and with high data quality. These data have to be precise, subject-oriented, complete, accessible and time-dependent with respect to security and confidentiality constraints.

- Service: It helps to capture the desired data and their relationships, evaluate and create an intelligent data modeling to provide a visual representation of the data.

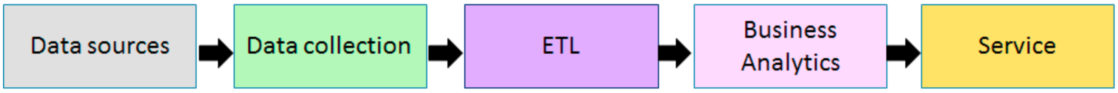

Fig. 1: Process of data flow.

We adopted the KM process developed by in which the process is divided into five stages: create, store, disseminate, use and evaluate knowledge. We suggest fulfilling the knowledge management by [6] dealing with AQ information in DWH such as shown in figure 2. The ERP (Enterprise Resources Planning) aims to build the techno-economic proposal of an offer. In addition, the organizational memory covers the storage of knowledge [4]. Moreover, a DWH will evaluate a set of solutions that make this proposal operational [8] to create and innovate the decision making.

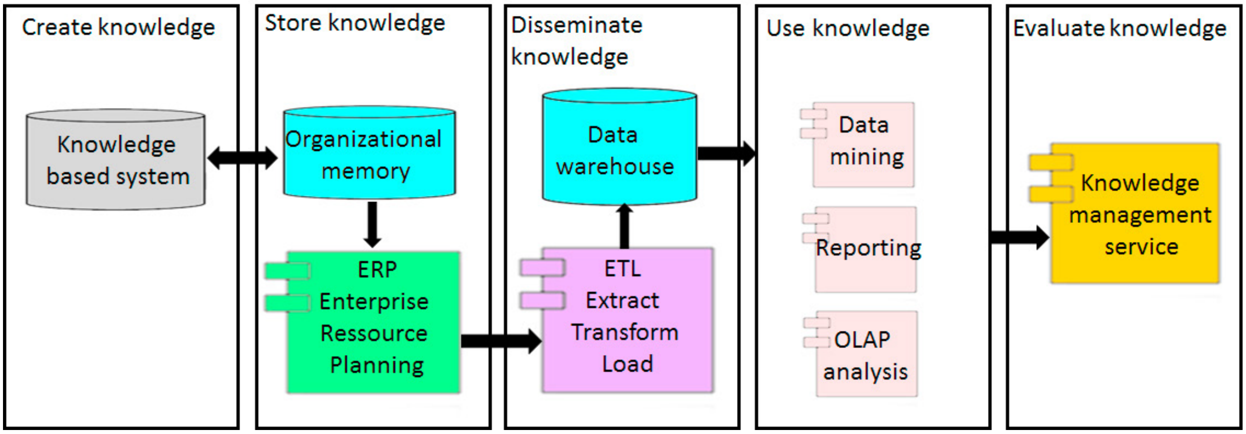

Fig. 2: Process of Knowledge flow management.

4. Ontology-based method for data modeling schema in data warehouse lifecycle

In this section, we present an overview of the first phase of the approach which we adopted. It is progressive and iterative. The assistance of the designer throughout this construction is optional. The approach can be executed autonomously, but the intervening of a designer during validation steps is recommended and will result in better output. A domain ontology contains knowledge that is a semantic representation of multidimensional concepts. This representation is often complete because of its generality. Hence, multidimensional concepts which could be useful for the decision-makers will be contained in the domain ontology. We design the steps of the DWH lifecycle which is an ontology-based method for data modeling schema in Figure 3. As mentioned, domain ontology contains knowledge about a specific domain. This knowledge is a formal and semantic representation of the multidimensional concepts of the domain. Although this representation is general, it is often complete. So if there are other multidimensional concepts, which might be useful for decision-makers, they will be contained in the domain ontology. In addition, we propose a multidimensional schema that contains other multidimensional concepts that do not exist in the data source. This schema, which we will call "suggested multidimensional schema", proposes to introduce new concepts that we recommend to add to the derived scheme in order to improve the DWH. The contribution will be, for example, the addition of a new dimension to an existing fact, or even the addition of a new fact and therefore a new star. The derived multidimensional schema will be contained in the suggested multidimensional schema.

Table 2: Knowledge based emerging technologies for AQ

KM layers	Data flow phases	Examples of existing technologies, tools, and techniques.
Create knowledge	Data source	Sensors (MQ-2, MQ-3B, MQ-4, MQ-5B, MQ-6, MQ-7, MQ-8, MQ-9B, MQ303B, MQ131, ME4-CO, ME4-H2, ME4-H2S, ME3-CL2, ME3-NH3, ME3-SO2, 110-602, SO2, 1528-2509-ND, B5W-LD0101)
		Parameters (Pollutants) (G, C4H10, C3H8, Alcohol, CH4, H2, CO, gas, CH4, Natural, gas, Coal, Propane, H2, CO, Combustibles, O3, O2, H2S, Chlorine, Ammonia, SO2, PM1.0,2.5,10,4, Dust, Density)
	Data collection	Connectivity (LPWAN (LoRaWAN. Sigfox. NB-IoT LTE-M), WiFi for IoT. Cellular (3G/4G/5G), Mesh Protocols (Zigbee),RFID, Bluetooth and BLE. for WSN)
		Boards (SCB: Raspberry, Raspberry Pi2 B, Raspberry Pi. MB: ArduinoUno/Nano, ArduinoLeonardo/micro, Arduino Genuino, Arduino Genuino Zero)
Storage and disseminate knowledge for ETL	Data ingestion	ETL: Apache Kafka, Apache Hive, Apache Spark, Apache Pig. ELT: Apache NiFi. Middleware: REST, .NET, J2EE, CORBA, web services: (SOAP, WSDL, UDDI)
	Data store	Data lake, data warehouse, cloud
	Data wrangling	Spark, Hadoop, Storm, RapidMiner, Mahout, Orange, Weka, DataMelt, KEEL, SPMF, Rattle...
Use knowledge	Data analysis	Teradata, Teradata Aster , Spark SQL, Vertica, Ad-hoc queries (Apache Drill, Hazecast, SAP Hana..), Birst, GoodData, MicroStrategy, SAP Lumira Cloud, Tibco, Spotfire, Cloud, Bime
	Data vizualiztion	Google Charts, Tableau, Grafana, Chartist. js, FusionCharts, Datawrapper, Infogram, ChartBlocks, and D3. js. or 3D
Evaluate knowledge	Application	Smart devices (watch wearable, phone), computer
	Model	Histograms, Conceptual model

Here, we introduce an algorithm to automatically identify the interesting concepts available in the global ontology representing the source. The output of this algorithm is a list of multidimensional concepts existing in the source.

Algorithm 1: ANALYSE ONTOLOGY OF FACT IDENTIFICATION

Data: Domain Ontology
Result: List of fact
Identify(O);
Begin
for *for each class in 0* **do**
    for *each attribut in class* **do**
        if *is_num(attribut)* **then**
            attr_num ++;
        end
    end
    if *r> seuil* **then**
        fact=class; fact.list_measure=list$_n um$; $fact.list\_level = list\_non\_num$;
    end
end
End

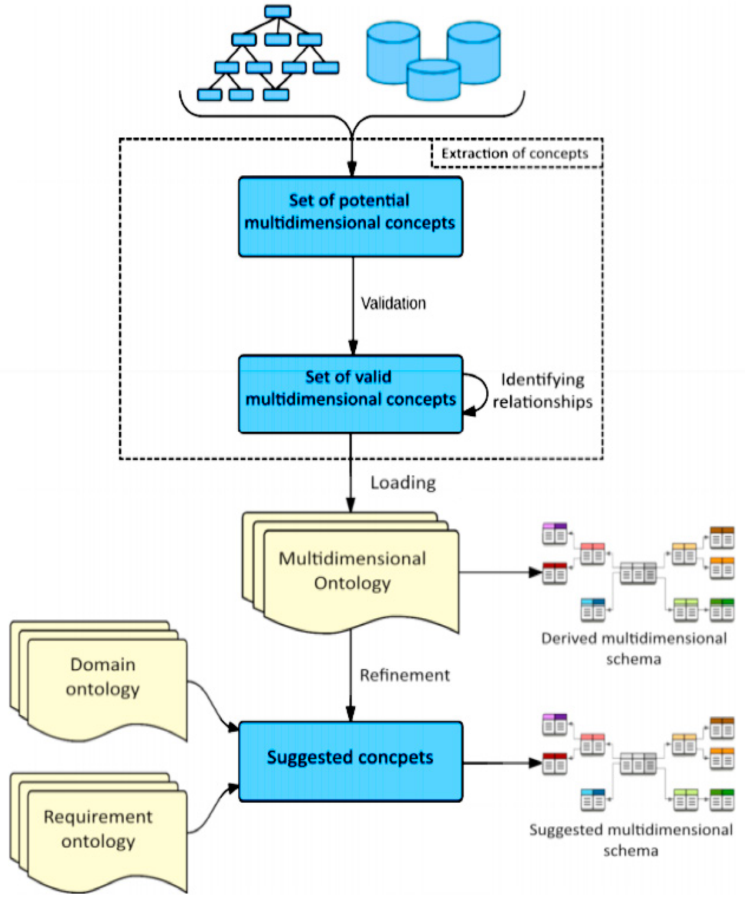

Fig. 3: The data warehouse lifecycle: ontology-based method for data modeling schema [10].

For each attribute (e.g. dataproperty) of the concept class under consideration, we compute the ratio "r" of the numerical attributes with respect to the total number of attributes (r=attr_num / total_attr). Concepts with a ratio above the threshold are marked as facts. The threshold is a numerical value that must be chosen arbitrarily by the designer. The numeric attributes of the fact are identified as measurements (list_num) and the non-numeric attributes (list_non_num) are identified as levels.

Algorithm 2: ANALYSE ONTOLOGY OF DIMENSION IDENTIFICATION

```
Data: Fact
Result: List of dimensions
Begin
Identify_dimensions(fact);
linked_conceptslinked = list_concepts_linked_to (fact);
for each concept in Linked_concept do
    if maxCardinalité == n & minCardinalité == 1 then
        list_dim = list_dim + concept;
    end
end
End
```

Algorithm 2 is used to identify the dimensions of the facts obtained as a result of algorithm 1. The aim is to identify the dimensions of a given fact. This algorithm is applied to all the facts of the list resulting from algorithm 1. We begin by identifying the list of concepts related to "fact". We rely on the cardinalities of relations with "fact" to identify the dimensions. The concepts related to "fact" by a relation 1..n, are added to the list of dimensions of this fact.

4.1. Multidimensional relationships

After defining the concepts of the multidimensional ontology, we need to specify the relationships that exist between them. Each relationship is of the form Relation (X, Y), where Relation is a binary predicate, and X and Y are concepts. We define the relationships described below through the schema given in Figure 4.

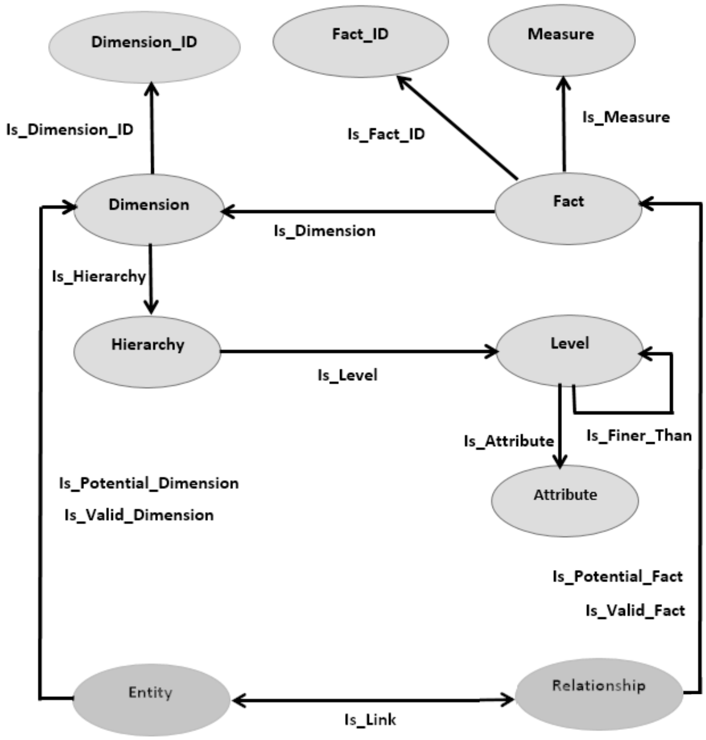

Fig. 4: Graphical representation of multidimensional relationships of ontology.

Both multidimensional concepts and relationships are presented in the bellow:

- Is_Fact_ID (***FID, F***) where Fact_ID (***FID***), Fact (***F***) and ***FID*** is the Id of ***F***.
- Is_Measure (***M,F***) where Measure (***M***), Fact (***F***) and ***M*** is a Measure of ***F***.
- Is_Dimension (***D, F***) where Dimension (***D***), Fact (***F***) and ***D*** is a Dimension of ***F***.
- Is_Dimension_ID (***DID, D***) where Dimension_ID (***DID***), Dimension (***D***) and ***DID*** is the Id of ***D***.
- Is_Hierarchy (***H, D***) where Hierarchy (***H***), Dimension (***D***) and ***H*** is a Hierarchy of ***D***.
- Is_Level (***L,H***) where Level (***L***), Hierarchy (***H***) and ***L*** is a level of ***H***.
- Is_Attribute (***A, L***) where Attribute (***A***), Level (***L***) and ***A*** is an Attribute of ***L***.
- Is_Finer_Than (***Li, Lj***) where Level (***Li***), Level (***Lj***), ***Li*** and ***Lj***are from the same Hierarchy and ***Li*** has a finer granularity that ***Lj***.

With the aim of ensuring the availability of data, we consider the data sources that are represented in a conceptual data model for the production base. In the next step, we extract the multidimensional concepts. It is divided into three stages that are repeated for each multidimensional concept. Thus, we determine a set of potential multidimensional, using extraction rules.

4.2. Fact extraction

As it has been previously shown, KM has four dimensions. Therefore, to distinguish between them, we allocate the different concepts to the corresponding knowledge dimension. Thus, We defined a set of rules. For each activity belonging to the process model, we create functional knowledge situated at the process perspective knowledge of the knowledge model that has the name of this activity. Therefore, facts describe these activities. An object is an entity registering the details of an event such as the payment of the knowledge proposition, etc. These entities are the most interesting for the DWH and are the basis for the construction of the fact tables. However, they are not all-important. Thus, we must choose those that have an interest in the decision-making. Usually, an object can be complex by containing multiple pieces of AQ information. Therefore its modeling requires its decomposition into associated sub-objects. In the ER model, an object may be represented in one of two forms which are an entity connected to an association and two entities linked by an association.In order to determine "***Fp***" (set of potential facts), we define the heuristic ***HF*** for all transaction objects as potential facts. For each identified transaction object identified, we associate a more descriptive name, which will be the name of the fact. These facts are necessarily all pertinent, thus a validation phase where the designer may intervene is essential to retain a subset of valid facts (***Fv***).

4.3. Measure extraction

As we previously stated, a transaction object is the result of the knowledge in companies' activities. Accordingly, the attributes may be measurements of a fact that is encapsulated in the transaction object. The following heuristics determine the potential measures:
Hm1: Mp (***fv***) contains the non-key numeric attributes belonging to the transaction object representing "***fv***".
Hm2: If the attribute is a Boolean, we add to Mp (fv) the number of instances corresponding to the values"True" and "False" of this attribute.

- Fv: a valid fact from the previous step;
- Mp (***fv***): the set of potential measures of "***fv***";
- Mv (***fv***): the set of measures of "***fv***" approved by the designer, which is a subset of "Mp (***fv***)".

The extraction of measures is also followed by a validation step by the designer in order to determine Mv (***fv***) which elements satisfy the following assertion:

$$\forall fv \in Fv, \forall m \in Mv(fv) \rightarrow Is\_measure(m, fv) \tag{1}$$

4.4. Decision extraction

Extraction of dimensions is based on a second type of object called base object. A base object determines the details of an event by answering the questions "who", "what", "when", "where" and "how" related to an object. A base object completes the meaning of the event represented by a transaction object thus providing additional details. Each object corresponding to one of these questions, and directly or indirectly linked to a transaction object is a potential dimension for the fact representing the transaction object. The extraction of dimensions consists of determining the name, **ID** and hierarchy(s) through these heuristics **Hd1** for any base object directly or indirectly connected to the transaction object of "***fv***)" which is a potential dimension of "***fv***" and **Hd2** for all **IDs** of a base object obtained by **Hd1** which is an "***id***" of "***d***". Dp (***fv***) is used for the set of potential dimensions of "***fv***"; Dv (***fv***) is defined bt the set of valid dimensions of "***fv***"; which is a subset of "Dp (***fv***)"; d is used for ***a*** dimension; idd is employed for the "***id***" of a dimension "***d***",

The validation step produces two subsets **Dv** (***fv***) and **IDDv** (***fv***), satisfying the following assertion:

$$\begin{aligned}&\forall fv \in Fv, \forall d \in Dv(fv), \exists dimension\_id(did)\\&\rightarrow Is\_dimension(d, fv) \wedge Is\_dimension(idd, d)\end{aligned} \quad (2)$$

4.5. Attributes extraction

We define the following heuristics to determine the potential attributes:
Ea1: Any attribute belonging to the base object containing "***idd***" is a potential attribute of "***d***".
Ea2: Any attributes belonging to a base object that generated a valid dimension "***dv***" is a potential attribute of "***dv***".
The validation step produces a set of valid attributes "***Av***", satisfying the following assertion:

$$\forall av \in Av(dv) \rightarrow Is\_attribute(av, dv) \quad (3)$$

Each extracted element becomes an individual (i.e. instance) of the concept that represents its role.

5. Advantage of this approach in the knowledge of AQ systems

Working on a KM of AQ data implies the intervention of several collaborators. Certainly, these contributors exchange knowledge and information of AQ flows. However, its environmental differences lead to various representations and interpretations of knowledge. Such failures are described in terms of conflicts: the syntactic conflicts are the results of different terminologies used by stakeholders in the same domain. The structural conflicts are related to different levels of abstraction which aim at classifying knowledge. The semantic conflicts concern the ambiguity that emerges due to the stakeholders' reasoning in the development of the techno-economic proposal. Heterogeneity conflicts are due to the diversity of data sources. The contextual conflicts are mainly from environmental scalability problems. Thus, stakeholders can evolve in different environments. In this context, we can deduce that the multidimensional schemas permit to overcome the problems with these various conflicts and manage the knowledge. Furthermore, these approaches used for AQ systems will be useful and will help future academic researchers, industrial and enterprise stockholders due to the capabilities and the advantages of IoT technologies for the AQ field. In addition, this will ensure semantic and syntactical interoperability between different technologies in each component of data flow processing and organize collected data.

6. Conclusion and Perspectives

To conclude this paper, we presented a solution based on a multidimensional approach to model AQ knowledge collected from IoT systems and approaches. For this purpose, we presented the data flow-based knowledge for AQ systems. This helps to define the AQ knowledge management process-based data flow by using DWH. Besides, we have presented an approach for representing DWH schema based on an ontology that captures multidimensional knowledge. We discussed one possibility for extending the multidimensional ontology to eventually cover different phases of the DWH life cycle. We focused on the design phase and showed how the use of the multidimensional ontology combined with an extension can be beneficial. In the future, we intend to continue to explore the possibility of extending ontologies by considering ontologies as extensions that could be used to improve the resulting DWH schema; in addition to real cases of the implementation of the air quality approach based on knowledge related to Coronavirus Disease 2019 (COVID-19) which can help researchers to create better systems with adequate technologies and techniques.

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