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Deliverable Summary

Around the world, water utilities are building Smart Water Networks (SWNs) by integrating various solutions and systems that enable remote and continuous monitoring and diagnosis of problems, manage maintenance issues and optimize the water distribution network by utilising data-driven and knowledge-driven approaches. The gradual deployment of data-enabled Internet of Things (IoT) devices, such as smart sensors and actuators, by water utilities have offered an opportunity to build a cohesive 'overlay network' in Smart Water Network (SWN). Once applications and IoT devices of a SWN are networked they can start communicating and exchange of information. However, their interoperability (*exchange and make use of information*) can not be successful without the syntactic (*structure*) and semantic (*meaning*) interoperability of the data/information they share. For instance, at the point of decision-making, a Decision Support System (DSS) relies on the understanding of every bit of data/information that is available from every single IoT device and database, otherwise it would not be able to advice correctly.

This document delivers a literature review of interoperability in the IoT and water domains. At first, this report presents the related technologies (IoT, Multi-Agent System (MAS), and semantic web technologies) and concepts (protocols, interoperability and Data Information Knowledge Wisdom (DIKW)) due to their relevance in an IoT-enabled SWN. Subsequently, it investigates the approaches to knowledge management, semantic modelling, and interoperability in the IoT and water domain projects. Interoperability of applications remains a hot topic in industry and academia and one can still find new approaches and solutions that are published recently to address interoperability. In the reviewed IoT projects, the interoperability solutions are based on the transitive conversion model for data protocols, e.g. converting Message Queuing Telemetry Transport (MQTT) to/from Constrained Application Protocol (CoAP) and CoAP to/from Representational State Transfer (REST) then achieving interoperability of MQTT to/from REST. Similar interoperability approach is adopted in the water related projects, at first a base ontology (e.g. Water analytics and Intelligent Sensing for Demand Optimised Management (WISDOM) ontology) is aligned with all possible standards and ontologies then it is used to convert from one standard/ontology to another. In all projects, semantic web technologies are utilized to build semantic models with ontologies. Achieving automation and orchestration of services with MAS is observed in some water related projects. Thereafter, this deliverable highlights the key challenges for achieving interoperability in IoT-enabled SWN that are identified during literature review. Finally, this document finishes with a concluding summary of the work.

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Introduction

Around the world, growing population, industrialisation, urbanisation, and climate change are leading us to the water scarcity and water quality crisis. Due to these concerns worldwide, each year billions of dollars are being invested in integrated water resource management to meet the water demand with the supply of affordable, sustainable, and pure water to consumers (Sensus, 2019). Water utilities are building SWNs by integrating various solutions and systems that enable remote and continuous monitoring and diagnosing of problems, manage maintenance issues and optimize the water distribution network by utilising the data-driven approach in real-time. The gradual deployment of data-enabled IoT devices, e.g. smart sensors and valve controllers by water utilities have offered an opportunity to build a cohesive 'overlay network' in SWN. However, the IoT-device-generated heterogeneous and dynamic data regarding leaks, the status of pipes, and the water quality cannot be shared and used among various applications due to lack of data and information interoperability thus related systems can not run information analysis and make decisions or operate appropriately in real-time.

In (S. Howell et al., 2017), Howell et al. recount reason of interoperability failure from (IEEE, 2011) as *(i) lack of machine communication protocols, (ii) lack of common data formats, and (iii) lack of common meaning of exchanged content.* In IoT-enabled SWN. Some of the existing solutions in this direction are the HyperCat specification (IGO Consortium, n.d.) that can be used as a common communication protocol to discover information about IoT assets over the web and WaterML2 that can be exploited as a common data format. However, based on the literature review presented in this document semantic aspects are not sufficiently addressed in the literature.

Additionally, diversity in data syntax and communication protocols of IoT-products remains an open issue, as the industry will keep on bringing new smart products with different proprietary standards in the market. Hence, a solution to share and use information IoT-devices should be based on the interoperability of data and information and without necessarily being integrated at the time of deployment in SWN. Interoperability of IoT-enabled applications is still a subject of research as cited in (Kalatzis et al., 2019), *one of the main obstacles towards the promotion of IoT adoption and innovation is data interoperability.*

The following parts of this document is organised in sections as. *Related Technologies and Concepts* discuss the innovative technologies and concepts that are in focus of the research and are influencing the smart water domain. *Literature Review* investigates the recent research work of the related technologies and their approaches to knowledge management, semantic modelling, and interoperability in the IoT and water domain projects. *Research Challenges* highlight the key points for achieving interoperability in IoT-enabled SWN that are identified during literature review. *Conclusion* summarizes the work and goal of this document.

Related Technologies and Concepts

Before we start with the literature review in the next chapter, it is important to understand the definition and the architecture of a SWN and discuss existing SWN solutions that the challenges of the water domain. A SWN is a result of the integration of many innovative technologies, such as IoT for smart sensors, MAS for autonomous activity, and semantic web technologies for managing and sharing data. Thus, the following sections of this chapter discuss these related innovative technologies. Additionally, the fundamental terms (data, information, and knowledge) and the concepts (communication and interoperability) of SWN are introduced, as they are defined and explained in the literature because they are very frequently used by researchers in the literature.

2.1 Smart Water Networks

There are many definitions of SWN in the literature. Quiñones-Grueiro et al. cite Lee (Lee, 2008) to define Cyber physical system (CPS)s as physical processes interacting with embedded systems in a networked environment and recite Rasekh et al. (Rasekh et al., 2016) to present SWNs as CPSs formed by the distribution system of pipes together with sensors, actuators, Programmable Logic Controller (PLC)s and Supervisory control and data acquisition (SCADA) system (Quiñones-Grueiro et al., 2019). According to Wu et al., a SWN is capable of monitoring/sensing with instrumentation, data management, data analytics for useful/actionable information retrieve or extraction, systematic analytics including simulation and optimization modelling for decision-making, and finally the automation control for triggering/communicating the instruments in the field. A truly smart water network needs to be 'smart' at each of the steps to achieve the best outcomes of water network management and operation (Wu et al., 2015).

In the industry, Sensus defines a SWN as a fully integrated set of products, solutions, and systems that enable water utilities to remotely and continuously monitor and diagnose problems, preemptively prioritize and manage maintenance issues, and remotely control and optimize all aspects of the water distribution network using data-driven insights (Sensus, 2019). In the water domain community, a widely accepted architecture of smart water is shown in figure 2.1. It is built from bottom to top of five layers, *(1) The physical layer* is comprised of data-less physical elements with mechanical, hydraulic or chemical functions e.g. pipes, pumps, valves, and Pressure Reducing Valves (PRV)s. *(2) The sensing and control layer* is the interface between the net-

Figure 2.1: SWAN Architecture Layers (SWAN et al., 2016)

work operator's data systems and the physical layer that enables the connection of the "smarts" of the Smart Water Network to the real, physical network. It is comprised of electronic devices and sensors. Sensors measure parameters (e.g flow, pressure, water quality parameters, reservoir levels, water temperature, etc) of the water delivery and distribution. Remote-controlled devices (e.g remote-controllable pumps, valves, and pressure-reducers) enable remote operation of the network. *(3) The collection and communication layer* is the interface between the underlying communications infrastructure and a human operator or with other central data systems. It has two main responsibilities, first is discrete data point collection, transmission, and storage and second is to enable communication (e.g wired and wireless network technologies) for the instruction of sensors and actuators about what data to collect or which actions to execute. *(4) The data management and display layer* is the interface between underlying communications infrastructure and human operators or with other central data systems e.g. SCADA. In this layer data collected from various sources may be preprocessed, stored in repositories, transferred, and accessed by Geographic Information System (GIS) or network schematic visualisation tools. This is also responsible for converting human operator commands or instructions from higher-level systems into concrete device settings (e.g. switching several pumps on or off, changing valve states, etc.). *(5) The data fusion and analysis layer* is responsible for the integration of raw input data and the creation of inferred information by applying domain knowledge. The resulting information may be displayed to a human operator, passed on to further analysis within the layer, or trigger automatic action through the data handling layer (or directly via the communications layer). Online hydraulic modelling systems, network infrastructure monitoring, smart pressure management, smart (not fixed feedback) pumping or energy optimisation systems, and DSSs exit in this layer to build a Smart Water Grid (SWG).

Table 2.1 lists the major challenges in the water domain and the possible SWN solutions developed by the SWAN Forum to addresses them. For example, figure 2.2 represents a smart wastewater network management solution, in which each level represent its corresponding layer in the SWN architecture of figure 2.1. At level 3

Table 2.1: Challenges and SWN solutions in the water domain (SWAN, n.d.)

Challenge Focus	**SWN Solution**
Leakage	Leakage Detection, Pressure Management, Water Network Management, Customer Metering
Water Quality	Water Quality Monitoring, Water Network Management, Wastewater Network Management
Energy Efficiency	Energy Management, Pressure Management, Wastewater Network Management
Bursts	Leakage Detection, Pressure Management, Water Network Management
Ageing Infrastructure	Energy Management, Pressure Management, Leakage Detection, Water Network Management, Water Quality Monitoring, Wastewater Network Management
Water Scarcity & Drought	Leakage Detection, Pressure Management, Water Network Management, Customer Metering
Apparent Losses	Customer Metering

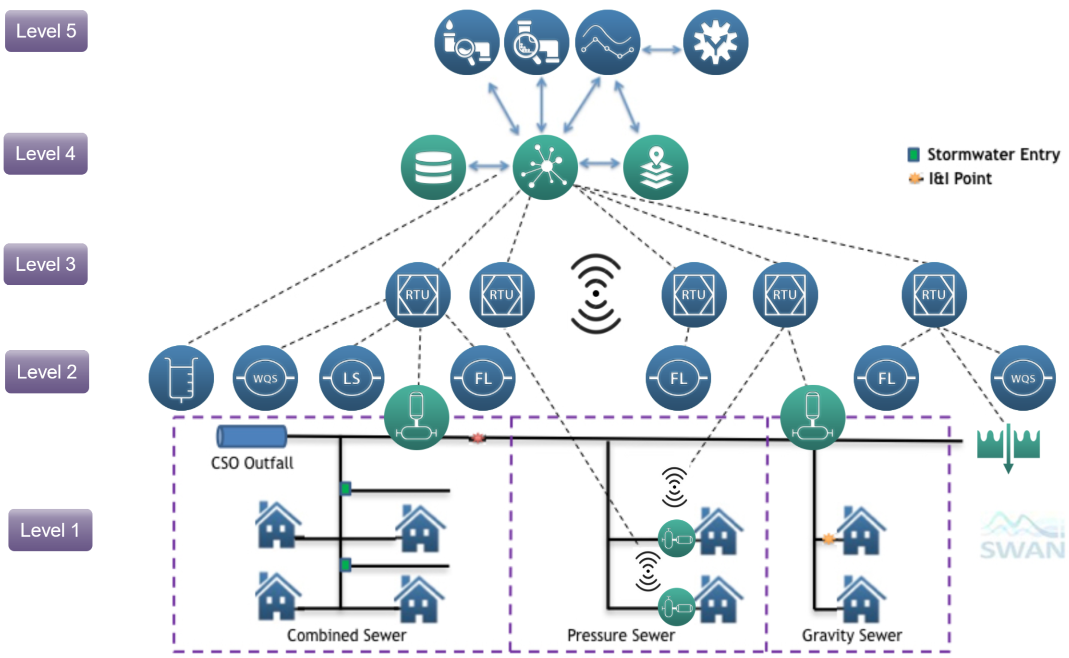

Figure 2.2: SWN architecture for wastewater-network-management (SWAN, n.d.)

and 4 of wastewater network, monitoring and detecting anomalies (e.g. blockage or infiltration) help operating companies to effectively manage the flows of sewage at level 5 (SWAN, n.d.). At level 5, a DSS is required for the wastewater management, since it helps decision makers use communications technologies, data, documents, knowledge and/or models to identify and solve problems and make decisions (Power and Kaparthi, 2001).

Figure 2.3 displays the SWN's convergence of multiple technologies that play their roles in different contexts and at different layers of a SWN architecture. In the left part, the layered architecture of SWN is presented and is associated with the key context (devices, software artefacts) at each layer. In the right part of the figure some key tech-

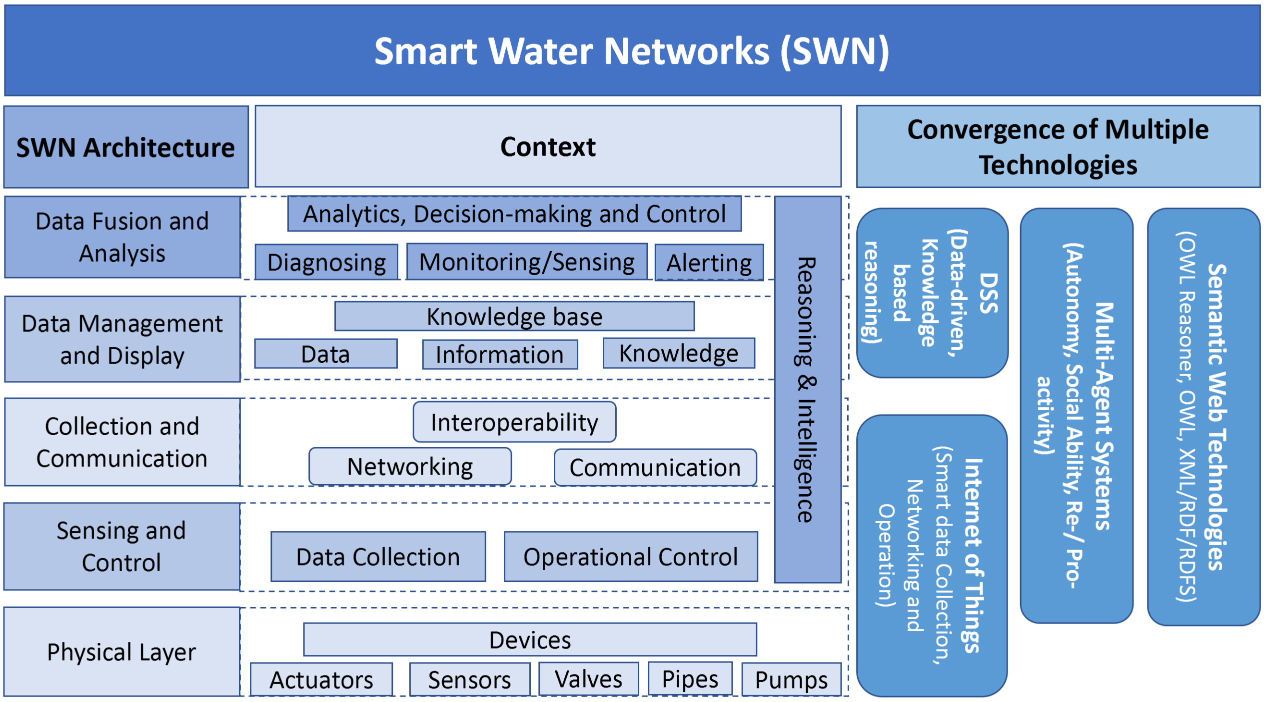

Figure 2.3: Relevence of other technologies and concepts in SWN

nologies are identified and positioned across the layered architecture indicating their contribution in the different SWN layers. Whilst a traditional water network infrastructure where assets (e.g. mains, reservoirs, and pumps) are controlled by a SCADA system, IoT devices encapsulates these assets at physical layer and offer data collection and operational control at sensing and control layer in an IoT-enabled SWN. Smart IoT devices bring the ability to network and communicate with other applications and IoT devices in the collection and communication layer. Since, decentralized and distributed control schemes are required for managing and operating the distributed smart devices in a SWN, as an Information and Communications Technology (ICT) paradigm MAS technology provides a good solution for an intelligent distributed control, monitoring, and automation. MAS technology can be applied in all layers of a SWN architecture when applications and devices are modelled as agents that can interact, cooperate with other agents, change their behaviour through Artifical Intelligence (AI)-based strategies to accomplish their goal. In Machine to Machine (M2M) communication, smart devices and applications (e.g. decision-making and analytics) require homogeneous machine readable data format to cooperate with each other and this is where semantic web technologies (Web Ontology Language (OWL), reasoners, Resource Description Framework (RDF)/Resource Description Framework Schema (RDFS)) come in to represent, share, and reason the data of a SWN. Thus they exists in all layers of a SWN architecture. DSS can utilize semantic web technologies to build knowledge-base with ontologies authored in OWL. Collected data and real-world entities of a SWN can be stored as facts in RDF. Once data and domain expert knowledge is authored in a computational model, DSS can apply data-driven and knowledge-based approaches to reason about the collected data and support/help the decision-making applications and human operators at data management and display layer to data fusion and analysis layer.

The following sections introduce these technologies and concepts while discussing their definitions and traits, as they are presented in the literature.

2.2 Internet of Things

Today, we are living in a digitally networked world, where there are more connected things than humans. The networking of the devices started, when a modified Coke machine at Carnegie Mellon University was connected to a smart appliance in 1982, it was able to report its inventory and temperature. According to the Business Insider Intelligence (BII) report, there will be more than 55 billion IoT devices by 2025 (Newman, 2018). The Internet of Things technology enables us to build a network of physical objects that are connected with the Internet of Things through various kinds of sensing equipment (sensors) to carry out information exchange and communication to realize intelligent identification, positioning, tracking, monitoring, and management. The Internet of Things is an extension and expansion based on the convergence of Internet, telecommunication network and radio and television network, and the key to triple-play (*offering data, voice, and video to a subscriber via a single telephone or cable connection*) is to realize the full IP of the triple play. Therefore, for the Internet of Things, based on the Internet Protocol (IP) protocol, a layered network communication protocol similar to the Internet Transmission Control Protocol/Internet Protocol (TCP/IP) protocol can be used to provide services for various applications in the application layer, while the protocol allows various heterogeneous networks under the IP protocol to run on the optimized network (Sun, 2020).

Communication

The International Organization for Standardization (ISO) has introduced a conceptual model, called Open Systems Interconnection (OSI) model, to achieve the interoperability of diverse communication systems with standard communication protocols. The OSI model characterises and standardises the communication functions of a telecommunication or computing system regardless of its underlying internal structure and technology.

A *communication protocol* defines a system of rules, syntax, semantics, synchronization and error handling so that it allows two or more entities of a communications system to transmit information via any kind of variation of a physical quantity. Protocols may be implemented by hardware, software, or a combination of both. In a computer network of interconnected devices and applications, communication protocols can be classified into two main categories i.e. network and data protocols.

Network protocols enable to build a network of computing devices and applications. Each telecommunication network technology can be classified as wired or wireless and it has its network protocols, that in general differentiate with others in data transmission speed, coverage, limitation, cost, availability, and dedicated applications. Wired networking is realised with technologies Integrated Services Digital Network (ISDN), Digital Subscriber Line (DSL), and fibre internet Fiber to the Home (FTTH)/Fiber to the Premises (FTTP) for stationary units and very high data transfer speed. Wireless/mobile networking technologies like Bluetooth, Zigbee, Wifi, Near-field communication (NFC), and cellular 3G/4G/5G are used by mobile computing devices to build a network and exchange data with variable data transfer rates with certain coverage ranges.

Data protocols enable sharing data among networked computing devices and applications at the application layer. In IoT platforms, commonly used data protocols are MQTT, Modbus-RTU/American Standard Code for Information Interchange (ASCII)/Transmission Control Protocol (TCP), Open Platform Communications Unified Architecture (OPC UA), Simple Network Management Protocol (SNMP), REST/JavaScript Object Notation (JSON) (JSON), Advanced Message Queuing Protocol (AMQP), CoAP, Extensible Messaging and Presence Protocol (XMPP), Simple Object Access Protocol (SOAP), and Universal Plug and Play (UPnP). A comprehensive survey of IoT messaging protocols with detailed structure and functionality description is done in (Al-Fuqaha et al., 2015). Data protocols support standard messaging patterns *publish/subscribe* and *request/response* to exchange data with a network. Data protocols can also be categorised in *(i) data-oriented, (ii) message-oriented (iii) resource-oriented* protocols (Meng et al., 2017).

In computer networks, computing devices may use any of telecommunication networking technologies to build a network, but there three basic types of communication connections: *(i) Point-to-point* connection allows one device to communicate with one other device. *(ii) Broadcast/multi-cast* connection allows a device to send one message out to the network and have copies of that message delivered to multiple recipients. *(iii) The multi-point* connection allows one device to connect and deliver messages to multiple devices in parallel.

2.3 Interoperability

Both research and industry communities have studied the interoperability with mature approaches in diverse domains, as such the term "Interoperability" is also defined variously. In general, the Institute of Electrical and Electronics Engineers (IEEE) defines interoperability as *the ability of two or more systems or components to exchange information and to use the information that has been exchanged.* (Manso et al., 2009) refer interoperability to, "the working together of diverse autonomous entities to achieve a common goal, requiring the entities to possess the ability to exchange information about system function and domain content." The Information Technology Vocabulary (ISO/International Electrotechnical Commission (IEC) 2382:2015(en)) of fundamental terms defines the interoperability as, *"capability to communicate, execute programs, or transfer data among various functional units in a manner that requires the user to have little or no knowledge of the unique characteristics of those units".*

Integration should not be interchanged with the interoperability (Roberts, 2020), as according to (ISO/IEC 2382:2015(en)), system integration is the progressive assembling of system components into the whole system. System interoperability is the ability of the systems or devices, which are engaged in an ecosystem, not only to exchange real-time data between systems without a middleware but also to interpret incoming data and present it as it was received, preserving its original context. Unlike system integration, where multiple applications and devices are combined into a system to function together as a unified whole, system interoperability requires single common communication language from multiple disparate and entirely independent systems to understand and communicate data without any added complexity and delay.

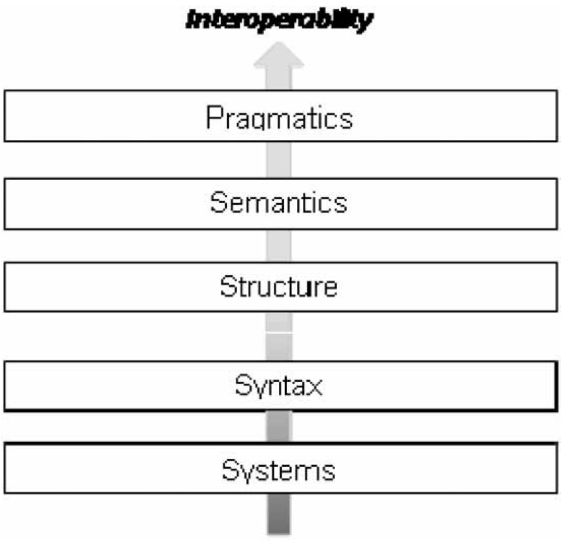

Figure 2.4: Interoperability levels for the message transformation (J. Brodaric, 2007)

In (B. Brodaric et al., 2015), *Brodaric et al.* refer to the data interoperability to collaboration among data providers in which their goal is to exchange, deliver, or use data through sending messages in a coordinated way. Such messages must typically be transformed at each interoperability level, either by the sender or receiver, to a construct that can be readily consumed and thus understood by the receiver – this process is often referred to as message alignment.

Levels of Interoperability

By abstracting over the interoperability stacks presented by (Manso et al., 2009) and (J. Brodaric, 2007), figure 2.4 describes the common levels of data interoperability within a data network or data networks from bottom to top.

1. **Systems interoperability** is the ability to overcome the heterogeneity of hardware or software elements required for core functions such as message passing or data manipulation, and largely involve platform aspects such as operating systems, transmission protocols, or particular database limits.

2. **Syntax interoperability** is the ability to overcome differences in abstract or concrete syntaxes of languages that are to encode a message, including requests for data as well as the actual data content. The syntax defines a language's alphabet, words, and grammar.

3. **Structure interoperability** is the ability to overcome diverse structures for

data or related web services, via alignment of associated schemas that are used in messaging.

4. **Semantic interoperability** it the ability to overcome inherent meaning differences (semantic heterogeneity) in some components of a message's schema or data content. Inherent meaning is typically represented as digital definitions, e.g vocabularies or ontologies in structured form or free-form text in unstructured form

5. **Pragmatic interoperability** is the ability to overcome contextual factors, e.g. legal, organizational, and economic, to ensure that the message sender and receiver share the same expectations about the effect of the exchanged messages and the context where this exchange occurs plays an important role (Tolk and Muguira, 2003).

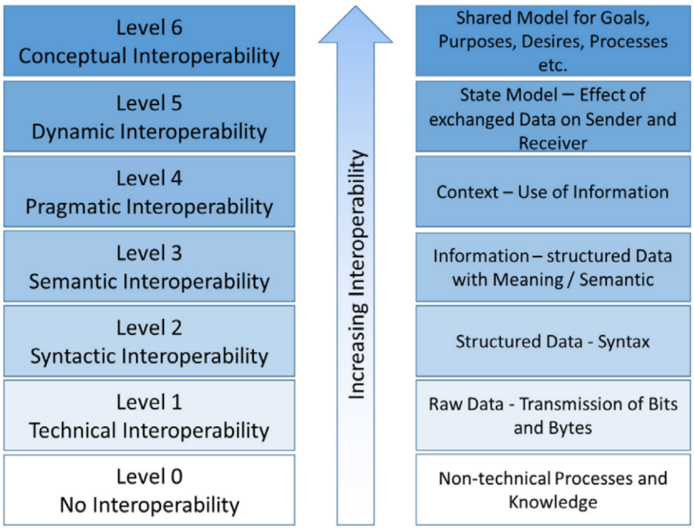

Figure 2.5: Interoperability conceptual model (Wassermann and Fay, 2017)

A conceptual interoperability model, as shown in figure 2.5 is based on the consecutive interoperability layers and achieving interoperability at higher layer is only possible, if the predecessor layer offers interoperability. Since, systems interoperability deals with the hardware or software, for the interoperability of data and information syntax, structure and semantic interoperability are crucial.

Cross-domain Interoperability

According to Network Centric Operations Industry Consortium (NCOIC), cross-domain interoperability refers to the ability of systems and organizations to interact and exchange information (inter-operate) among different areas, markets, industries, countries or communities of interest (domains). As displayed in figure 2.6, cross-domain interoperability enables systems, users, and organisations to seamlessly communicate and conduct an activity, despite their reliance on different technical environments or frameworks.

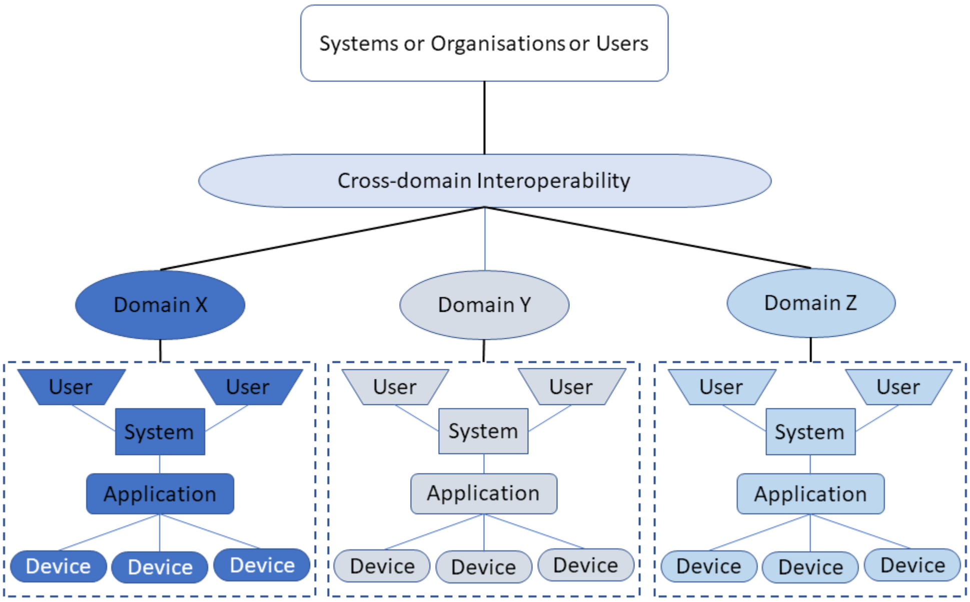

Figure 2.6: Cross-domain interoperability

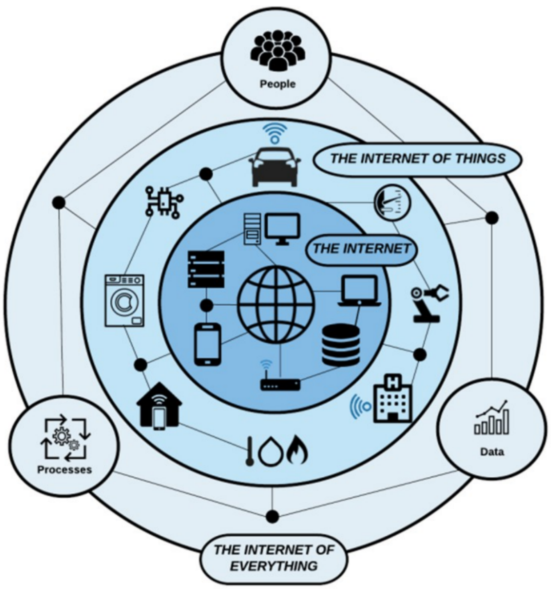

Figure 2.7: Cross-domain data interoperability (Kalatzis et al., 2019)

Figure 2.7 illustrates cross-domain data interoperability as the key enabler for the evolution of the IoT to the Internet of Everything (IoE), hence stating that the next generation of the IoT computing paradigm cannot be realised unless cross-domain data interoperability is facilitated.

2.4 Knowledge Hierarchy

Figure 2.8 shows Achoff's *knowledge hierarchy or knowledge pyramid*, in which he defines *data* as symbols that are properties of observables, and *information* as descriptions. The difference between the two is not structural, but functional, and information is inferred from data. *Knowledge* as know-how is acquired from learning, i.e., by instruction or from experience, and adaptation, i.e., the correction of the learned in accordance with new circumstances.

Knowledge acquisition process requires understanding what error is, why the error occurs, and how to correct it. According to him

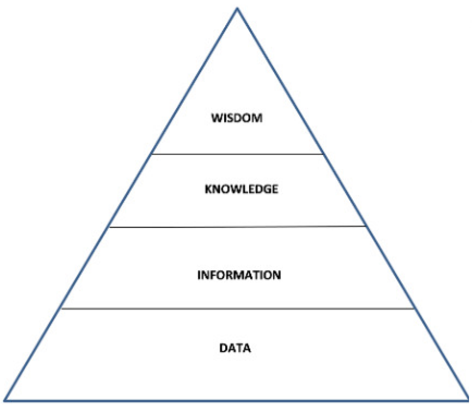

Figure 2.8: DIKW hierarchy (Rowley, 2007)

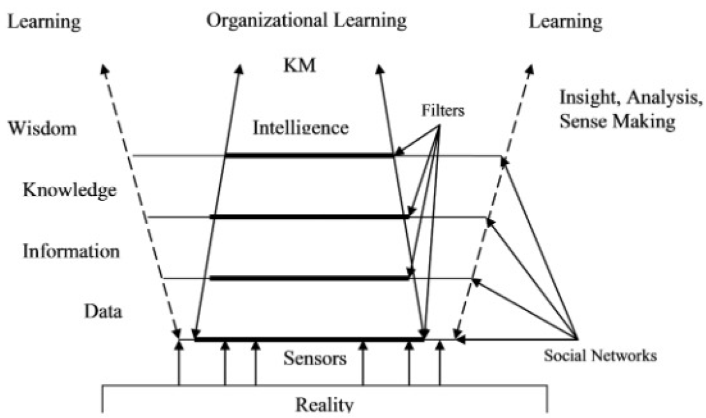

Figure 2.9: The revised Knowledge-KM pyramid (Jennex and Bartczak, 2015)

- *information systems can be automated and generate information out of data,*
- *that computer-based knowledge systems require higher-order mental faculties; "they do not develop knowledge, but apply knowledge developed by people", and*
- *that wisdom adds value, endures forever, and will probably never be generated by machines.*

Figure 2.9 shows the revised knowledge-KM pyramids, in which the following terms are proposed for consensus working definitions:

- *Intelligence* refers to specific actionable knowledge required to make a specific decision in a specific context in a specific organization.
- *Learning* refers to the acquisition of DIKW that leads to a change in behaviour or expectation within the individual or group that is doing the learning.
- *Organizational Learning* refers to learning that leads to quantifiable improvement of activities, increased available knowledge for decision-making, or sustainable context. An organization learns if, through its processing of DIKW, its potential behaviours are changed.

Table 2.2: Explanations of DIEK by (Dammann, 2019)

Concept	What is it?	How produced?	By whom?	Goal?
Data	Numbers, Symbols, Text, Images, Sound recordings, Unit values	**Collected** from field research, database, measurements in experiments, from individuals, populations	Data Collector	Use as raw data or for information generation Storage, curation, retrieval
Information *is data contextualized*	Data in context	**Contextualization** by making data useful, and using them, for specific tasks	Informatician, informaticist, statistician, data scientist	Use as a source for answering questions Storage, curation, retrieval
Evidence *is information compared*	Useful, contextualized information	**Comparison** with standards, reference values, reference information	Scientist, theoretician, philosopher Interventionist, policymaker	Use for analysis and hypothesis-testing to support claims/hypotheses and decision-making
Knowledge *from evidence*	Evidence-based, (predictive, testable, consistently successful) belief	**Consensus** based on reasoning and discussion		Justification

- *Social networks* refer to formal or informal, direct, or indirect methods used to share DIKW among users.

- *Filters* refer to KM processes that limit access and separate and capture that Data Information Knowledge Wisdom/Intelligence (DIKW/I) which is required from that and which is not.

Dammann reviews Achoff's approach of knowledge and revises it with new term *evidence* as shown in table 2.2. He overlooks Ackoff's definition of *wisdom - the addition of value to knowledge that requires judgement* because he thinks knowledge is more important than wisdom and wisdom requires judgment at all levels of the hierarchy. Further, he believes that knowledge can be defined, in the context of informatics and data science, as predictive, testable and consistently successful belief, if there is a causal connection between the facts represented by the data, information, and evidence on the one hand, and our beliefs on the other (Dammann, 2019).

Knowledge-base and Ontologies

According to Murdock and Bassbouss, the vision of interoperability requires *designing ontologies and enabling the sensors, devices, and systems to express their contextual information and data by applying the designed ontologies* (Murdock and Bassbouss, 2016).

"An ontology defines the basic terms and relations comprising the vocabulary of a topic area, as well as the rules for combining terms and relations to define extensions to the vocabulary" (R et al., 1991).

The consensual knowledge of a domain captured by humans in inter-related logic statements forms the basis for machine-readable ontologies, hence enables sharing and reuse of knowledge between humans and machines. Ontologies are often used to overcome semantic heterogeneity in data, by aligning concepts and terms to deal with meaning differences and achieving data interoperability (B. Brodaric et al., 2015).

2.5 Semantic Web Technology

In (Hendler et al., 2002), the Semantic Web is defined as an extension of the current Web in which information is given well-defined meaning (i.e. *ontology*), better-enabling computers, and people to work in cooperation. And the data on the Web is defined and linked such (i.e. *annotated*) that it can be used for more effective discovery, automation, integration, and reuse across various applications.

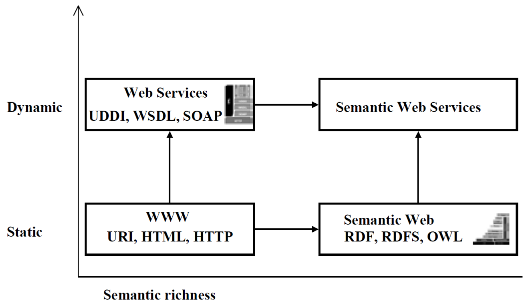

Figure 2.10: Semantic web and semantic web services (Gómez-Pérez et al., 2004)

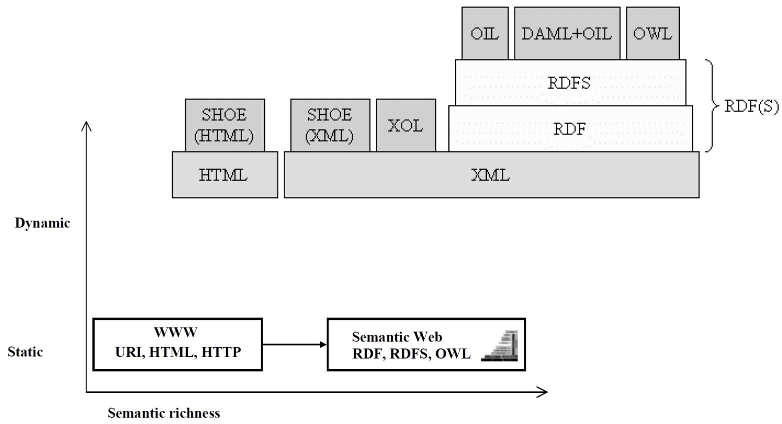

Figure 2.11: Semantic Web Languages (Gómez-Pérez et al., 2004)

Figures 2.10 and 2.11 depict World Wide Web Consortium (W3C)'s vision of semantic web by offering semantic web services and semantic web languages that will support people to create data stores on the Web, build vocabularies, and write rules for handling data, hence realizing a "Web of linked data". W3C's technology stack provides the following fundamental semantic web standards:

- OWL and RDFS to build vocabularies, or ontologies and Simple Knowledge Organization System (SKOS) for designing knowledge organization systems. Rule Interchange Format (RIF) is focused on translating between rule languages and exchanging rules among different systems.
- RDF provides the foundation for publishing and linking of the web data.
- SPARQL Protocol and RDF Query Language (SPARQL) is a query language to send queries and receive results from a RDF-store (*triplestore*), e.g., through Hypertext Transfer Protocol (HTTP) or SOAP or REST.

These standards have been implemented as open-source frameworks, e.g. Jena for RDF and SPARQL, by Apache software foundation, hence we can use these frameworks to build proof-of-concept prototypes. Linked Data (LD) is a set of web technologies based on the Semantic Web that enables the consolidation of different data sources, as well as the efficient querying for feeding Business Intelligence processes. Linked Open Data (LOD) is the LD that can be distributed and freely used by anyone on the web. LOD has five main characteristics: *(i) on the web, (ii) machine-readable data,* *(iii) non-proprietary format, (iv) uses RDF, and (v) is linked with RDF* (Berners-Lee, 2006).

2.6 Multi-Agent Systems

The MAS paradigm is based on a bottom-up description of systems, in which the global system behaviour is not only the sum of the individual agent's behaviours but also result of the interactions between agents (Urbani and Delhom, 2006). In a MAS model, the identification of the system's agents and their behaviour is crucial to building relatively autonomous and intelligent agents. Even in computer science, one can find plenty of definitions of the word *agent*. However, an agent is commonly defined as a hardware or software-based computer system that can be static (permanently located in some computer) or mobile (moving across the computer network, such as the Internet) with following properties (Badjonski et al., 1999):

- *Autonomy* is the ability of agents to operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state
- The *Social ability* of agents to interact with other agents (and possibly humans) via some kind of agent-communication language.
- *Reactivity* is the ability of agents to perceive their environment (which may be the physical world, a user via a graphical user interface, a collection of other agents, the Internet, or perhaps all of these combined), and respond in a timely fashion to changes that occur in it.
- *pro-activeness* is the ability of agents do not simply act in response to their environment, they can exhibit goal-directed behaviour by taking the initiative.

Java Agent DEvelopment Framework (JADE) is an Foundation of Intelligent Physical Agents (FIPA) specifications compliant open source software framework developed by Telecom Italia for Multi-agent Systems (MAS) in a distributed FIPA environment. A JADE-based system can abstract over different operating systems, those are used to run different computing devices if the Java run-time environment is installed on them.

Literature Review

This part of the document reports on the reviewed literature. It presents the current knowledge and works on knowledge management and semantic modelling in the water domain. It displays a portray of chronicle evolution of proven standards and ontologies for the measurement and observation in the water domain. It summarizes the motivation and structural description of these standards and ontologies. Furthermore, it also discusses the DSS types and their role in decision making. Stream reasoning has been reviewed due to its importance in IoT-enabled systems. Finally, it lists the currently influential projects and methodologies of IoT and SWN domain. The approaches of these projects are discussed with the focus on data and information interoperability.

3.1 Water Knowledge Management and DSS

In recent years, ICT and the innovative technologies, IoT, and Semantic Web (SW) have been applied in the SWNs to achieve intelligent sensing and smart water management. DSSs play a crucial role in the operation of clean- and waste-water networks and the management of assets in a more efficient, sustainable, and reliable manner. Many research projects and initiatives, such as ICT4Water, EIP-water, WISDOM, and Water Enhanced Resource Planning (WatERP), have been initiated under the European Commission Seventh Framework Programme (EC FP7) to investigate the challenges and the impact of integrating these technologies in SWN. In Horizon 2020 programme, there are also several projects to address interoperability in IoT and water domain, such as INTER-IoT, Ocean Data Interoperability Platform (ODIP-2), Worldwide Interoperability for SEmantics IoT (Wise-IoT), Bridging the Interoperability Gap of the Internet of Things (BIG IoT) and Smart End-to-end Massive IoT Interoperability, Connectivity and Security (SEMIoTICS).

In SWAN et al., 2016, SWAN Interoperability Workgroup highlights the requirement of pervasive interoperability to integrate and implement innovative technologies in SWNs, because many different communication protocols being used in smart water applications. The primary cause is identified as the retro-fitting of new smart applications on top of existing/proprietary network management systems, which were designed from an automation/vertically integrated point of view, rather than using cross-domain interoperability.

S. Howell et al. propose a water knowledge management platform which extends the Internet of Things towards a Semantic Web of Things, by leveraging the semantic web to address the heterogeneity of web resources (S. Howell et al., 2018). The platform supports the main approaches of DSS, data-driven and knowledge-based, by offering programming interfaces and utilizing in a comprehensive rule-based ontology that developed by industry experts. The Model-Driven DSS approach focus on analyzing data stored in databases/warehouses by using GIS functionalities, On-Line Analytical Processing (OLAP) or quantitative models that permit to extract patterns. The Knowledge-Driven DSS approach utilizes a knowledge-base to reason about a problem to find a solution by using an inference engine (Serrat-Capdevila et al., 2011).

A generic decision support system framework based on MAS and GIS was proposed by Urbani and Delhom in (Urbani and Delhom, 2006). Anzaldi et al. identify the issue of not combining multiple inference engines in a single tool, instead of handling different water managements situations with specific reasoning models or procedures. To address this issue they propose an intelligent decision support system Knowledge-Driven Water DSS (WDSS) that combines the Rule-Based Reasoning (RBR) and Case-Based Reasoning (CBR) engines to meet the water supply and distribution chain management needs. WDSS can integrate the produced knowledge and information by other platforms and systems, as it supports many standardized ontologies and data format that is aligned with Open Geospatial Consortium (OGC)® (Anzaldi et al., 2014).

Table 3.1 displays the DSSs that have been applied in wastewater treatment plants to support the decision-making process regarding quality, operational, design, energy and sustainability aspects. Mannina et al. give a comprehensive review of DSS in (Mannina et al., 2019) and classify them in four main types: Life Cycle Assessment (LCA), Mathematical Models (MM), Multi-Criteria Decision Making (MCDM), and Intelligent Decision Support Systems (IDSS).

According to Escobar Esteban et al., the next,-generation decision-making software tools in SWNs require the integration of multiple and heterogeneous data sources of different knowledge domains for the efficient and sustainable maintenance of water reservoirs and supply networks. To address this challenge they propose the utilization of LD and SW to harmonize data from different data sources and querying efficiently for feeding to the upper-level Business Intelligence (BI) processes (Escobar Esteban et al., 2020).

Data generated in IoT-enabled SWNs is not only heterogeneous but also of highly dynamic nature, as mobile smart sensors or IoT devices in particular with wireless connectivity may be sending data stream constantly while being connected or break transmission when they are disconnected from the network. Therefore to bridge the gap between reasoning over data and data stream processing, stream reasoning is required (Margara et al., 2014). Margara et al. present models as research areas for representing, processing, and retrieving information in stream reasoning systems. Representation models are time, historical, and uncertainty models. Processing models are querying and reasoning model and Uncertainty propagation model. Retrieval models deal with Big data, dynamic data and distributed data. While reviewing the state-of-

[5] Design
[6] Energy consumption
[7] Operational optimization
[8] Improvement of the effluent Quality
[9] Environmental Sustainability

Table 3.1: List of applied DSSs in WWTPs around the world (Mannina et al., 2019)

DSS Type	**Scope**	**Application Description & DSS Ref.**
IDSS	O[7]	Supervision of a WWTP located in the Barcelona region, Catalonia (Pascual-Pañach et al. (2018))
IDSS	D[5]	Optimal design of WWTPs in view of reducing resources and operational costs (Ye et al. (2019))
IDSS	S[9]	The IDSS has been applied to Danube River, consequently the WWTPs effluent quality has been optimized by means of IDSS (Oprea (2018))
IDSS / MCDM	E[6]	Two real conventional activated sludge system (CAS) WWTPs in Germany and in The Netherlands (Torregrossa et al. (2017))
IDSS / MM	Q[8]	Real WWTP of Tabriz, Iran (Nadiri et al. (2018))
LCA	S[9]	Real WWTP located in Copenhagen, Denmark (Yoshida et al. (2014))
LCA	O[7] S[9]	Applied to Betanzos and Calafell WWTPs, both located in Spain. (Lorenzo-Toja et al. (2016))
LCA	S[9]	Applied to Tarragona WWTP, Spain (Pintilie et al. (2016))
LCA / MCDM	D[5]	Applied to two different WWTPs (La Garriga and Granollers), located in Spain (Morera et al. (2015))
LCA / MM	Q[8]	The plant under study was similar to that proposed in BSM2 (Jeppsson et al., 2006) (Bisinella de Faria et al. (2015))
LCA / MM	E[6] S[9]	Real wastewater infrastructure of Delhi, India (Singh and Kansal (2016))
LCA / MM	O[7]	Plant data were generated with the STOAT simulator, that has been set-up to replicate the operational conditions of the WWTP of Solingen-Burg, Germany (Torregrossa et al. (2018))
MCDM	S[9]	Applied for two extensive technologies (constructed wetlands and pond systems; and five intensive technologies (extended aeration, membrane bioreactor (MBR), rotating biological contactor, trickling filter, sequencing batch reactor. No specific location was mentioned in the paper (Molinos-Senante et al. (2014))
MCDM	D[5]	Applied to a laboratory scale municipal WWTPs (Bertanza et al. (2015))
MCDM	S[9]	Large WWTP which serves 1,000,000 person equivalents, in order to enable the exploration of a wide variety of alternative (Garrido-Baserba et al. (2015))
MCDM	S[9]	Two case studies for the application of several scenarios: 1) selection of technology for an upcoming township project in Mumbai, Índia; 2) lake rejuvenation project in the suburbs of Thane, Índia (Kalbar et al. (2016))
MCDM	D[5]	Presents a conceptual DSS to assess fit-for-purpose wastewater treatment and reuse and is applied to an hypothetic case study. (Chhipi-Shrestha et al. (2017))
MCDM	D[5]	Applied for two extensive technologies (constructed wetlands and pond systems; and five intensive technologies (extended aeration, membrane bioreactor, rotating biological contactor, trickling filter, sequencing batch reactor (Arroyo and Molinos-Senante (2018))
MCDM	O[7]	Real WWTP located in Whyalla, south of Australia (Chow et al. (2018))
MCDM	D[5]	Real WWTP of Minnesota, United States (Xin et al. (2018))
MM	S[9]	Real advanced hybrid WWTP (Kyung et al. (2015))
MM	O[7]	Hypothetical structure as the catchment described in ATV A 128 (ATV, 1992) (Saagi et al. (2016))
MM	O[7] Q[8]	China's urban WWTPs (Zeng et al. (2017))
MM	O[7]	Real WWTP located in the province of Alicante, Spain (Díaz-Madroñero et al. (2018))
MM	S[9]	Thirty small WWTPs from Spain were sampled between 2014 and 2016, featuring three different secondary treatment technologies: CAS system, rotating biological contactors (RBC) and trickling filters (TF). (Gémar et al. (2018))
MM	S[9]	Real data obtained from WWTP located in the Lake Taihu region, China (Jiang et al. (2018))
MM	Q[8]	Seawater obtained from a clean coastal site in Saint John's, Canada (Jing et al. (2018)))

the-art of stream reasoning, Dell'Aglio et al. conclude that stream reasoners should offer richer query languages, which include a wider set of operators to encode user needs, and the engine to evaluate them. Reasoners are now capable of deductive and inductive reasoning techniques. Reasoning frameworks should be scalable and able to integrate and reason over huge amounts of heterogeneous data while guaranteeing time requirements. Additionally, reasoner must be able to cope with issues such as noise (faulty/inaccurate output of sensors) and heterogeneity. Internet of Things and Industry 4.0 could the real-world application domains of stream reasoning. They also stress on developing benchmarking and evaluation activities, to compare and contrast the current solutions (Dell'Aglio et al., 2017).

3.2 Semantic modelling

Table 3.2 is an extended version of (S. Howell et al., 2018) and it depicts the common ontologies, formats, and standards that are being used in the water domain to conceptualize the domain knowledge. Here, we can identify that is no commonly agreed or standard representation of these ontologies, although these ontologies utilize semantic web technologies for knowledge and information sharing. However, there have been attempts to recycle and merge existing standards and ontologies rather than build something from scratch.

WaterML 2.0 is an international standard developed by OGC to harmonize various OGC and ISO standards. It utilizes the Observations and Measurements (O&M) data model (ISO 2011) for its core definitions and for the enablement of delivery and consumption of observations data using systems that conform to the Sensor Observation Service (SOS) standard. Furthermore, it enables the integration of water observations data with other environmental sciences domains, e.g. geology and meteorology. Yu et al. present an architecture for WaterML 2.0 validation that combines (document structure) and semantic (e.g.domain and business concepts in the content) validation (Yu et al., 2015).

Smart Appliances REFerence (SAREF) unifies 23 ontologies, by supporting alignments in systems with 3 or more smart appliance ontologies. The SAREF ontology has been adopted by the European Telecommunications Standards Institute (ETSI), giving significant precedence to its reuse.

The Semantic Sensor Network (SSN) ontology has also been broadly adopted in the water and IoT domain to describe sensors and their observations, the involved procedures, the studied features of interest, the samples used to do so, and the observed properties, as well as actuators. SSN follows a horizontal and vertical modularization architecture by including a lightweight but self-contained core ontology called Sensor, Observation, Sample, and Actuator (SOSA) for its elementary classes and properties.

In the WaterWorX solution for water management, Semantic Water Interoperability Model (SWIM) is developed by Aquamatix to offer interoperability to the water domain apps, such as pumpWorX, sewageWorX and netWorX. SWIM consists of domain ontology and applied ontologies that define Things and instance types of the Things that exist in an IoT-enabled SWN.

WISDOM project proposes a semantic model for intelligent water sensing and analytics through a domain ontology that is created by using Izssa's ontology integration approaches. The WISDOM model integrates heterogeneous data sources, various ontologies, thus identifies the necessity of validation. At first, they validate the domain model as an accurate, sufficient, and shared conceptualization of the domain by domain experts, then they validate the ontology instantiation and deployment as a web service within a cloud-based platform, through software testing (S. K. Howell et al., 2016).

WatERP Water Management Ontology (WMO), described in (Varas, 2014), is constructed to match the supply and demand in the water domain. It aligns to major ontologies, standards, and formats. Additionally, it contains concepts for observation, measurement, actions, and alerts.

In the INTER-IoT project, Generic Ontology for IoT Platforms (GOIoTP) is developed as a core ontology and reference meta-data model for IoT platforms. It offers modular data structures for description of entities like device structure, platform, observation, actuation, units, measurements, location, service, and user. Generic Ontology for IoT Platforms Extended (GOIoTPex), also developed in the INTER-IoT project, extends and fills the stub classes/concepts from GOIoTP with more specific classes, properties and individuals.

Both top-level ontologies, GOIoTP and WISDOM brings complementary concepts and domain knowledge, thus an IoT-enabled SWN will require such kind of ontologies to build a semantic model that represents data and information of IoT and water domain. Therefore, an issue of ontology integration arises and this can be solved by Izssa's ontology integration approaches (Izza, 2009): *(i) Ontology mapping* to establish correspondence rules between concepts of two ontologies. *(ii) Ontology alignment* to bring two or more ontologies into a mutual agreement. *(iii) Ontology transformation* to change the structure of the ontology to make it compliant with another. *(iv) Ontology fusion* to build a new ontology from two or more existing ones.

3.3 Data and Information Interoperability

Table 3.3 uses simplified OSI-model and specifies the applications and protocols that may be utilized in analytics communication of a SWN. The table also describes the requirements of the corresponding application and protocols.As it is stated in (SWAN et al., 2016) that there is no single protocol that best suits all the SWN applications and communication infrastructure and the application layer is dependent on the purpose for the data acquisition. A variety of application protocols for specific purposes are required since a general application protocol would be too complex to support efficient business processes.

Although through a middle-ware approach of using common protocols and interface description languages, e.g. CORBA, Distributed Component Object Model (DCOM), and Web Services can help to overcome communication barriers, but data format heterogeneity remains an issue in middle-ware solutions. To solve this issue various approaches were applied: *(i) software bridges* to achieve one-to-one mapping between

[2]Standard
[3]Not verified yet
[4]Ontology

Table 3.2: A chronological list of ontologies and standards in the water domain

Acronym/ Name	**Owner: Authoring Format: Description: Weblink**	**Supported Standards & Ontologies**	**Publish Date**
GOIoTP[4]	INTER-IoT: OWL: GOIoTP is developed as part of the INTER-IoT project; it offers modular data structures for the description of entities most commonly appearing in IoT in the context of interoperating various IoT artefacts (platforms, devices, services, etc). : Weblink	SSN and SOSA	2018
SWIM[4]	Aquamatix: OWL: Device-level IoT semantic model for the water industry.	-[3]	2016
WISDOM[4]	Cardiff University: OWL: Cyber-physical and social ontology of the water value chain. : Weblink	INSPIRE, Industry Foundation Classes 4 (IFC4), SWIM, glssaref, SSN, WatERP WMO, CityGML, Syndromic Surveillance Ontology (SSO)	2016
SAREF[4]	ETSI: RDF/OWL and serialized in Turtle : 'Common denominator" of 23 smart appliance domain models. : Weblink	contains 20 sub ontologies	2015
OntoPlant[4]	Sottara et al.: OWL:Extends the SSN ontology to decouple control logic from equipment choices in wastewater treatment plants. : Weblink	SSN	2014
Utility Network Schemas[23]	EC-INSPIRE: Extensible Markup Language (XML)-[3] : Water and sewer network model; part of a large European directive for geospatial data exchange. :Weblink	-[3]	2013
WatERP WMO[4]	EURECAT-WatERP: OWL-S : Lightweight ontology of generic concepts for water sensing and management. : Weblink	WaterML2.0, HY FEATURES, Semantic Web for Earth and Environment Technology (SWEET)	2013
SSN SOSA[4]	OGC W3C: OWL: An ontology for describing sensors and their observations, the involved procedures, the studied features of interest, the samples used to do so, and the observed properties, as well as actuators. : Weblink	SSN	2017
WaterML 2.0[2]	OGC: XML : WaterML2 is a new data exchange standard in Hydrology to exchange many kinds of hydro-meteorological observations and measurements. It harmonizes a number of exchange formats for water data with relevant OGC and ISO standards. : Weblink	Hydrologic, Water Data Transfer Format (WDTF) and standards of XHydro, CSIRO, CUAHSI, USGS, BOM (AU), NOAA (US), KISTERS (DE), etc.	2012
WDTF[2]	Australian Bureau of Meteorology: XML : Format for transferring flood warning and forecasting data to the governing body. The precursor to WaterML2.0. : Weblink	-[3]	2013
CityGML UtilityADE[23]	OGC: XML[3]: Domain extension for modelling utility networks in 3D city models, based on topology and component descriptions.	-[3]	2012
SSN[4]	W3C: OWL: Ontology Describes sensors and sensor networks, for use in web applications, independent of any application domain.	-[3]	2012
SWEET[4]	NASA: OWL: Middle-level ontology for environmental terminology. : Weblink	-[3]	2011, 2019
Hydrologic Ontology for Discovery[4]	Consortium for the Advancement of Hydrological Sciences Inc. (CUAHSI) : OWL: Supports the discovery of time-series hydrologic data collected at a fixed point. The precursor to WaterML2.	-[3]	2010
HydrOntology[4]	Vilches-Blzquez et al.: OWL : Aims to integrate hydrographical data sources: town planning perspective, top down methodology. : Weblink	-[3]	2009

Table 3.3: SWN Analytics Protocols (SWAN et al., 2016)

Application	Application Presentation Session layer	Transport Network layer	Requirements
SCADA-Server/Analytics	Open Platform Communications Data Access (OPC DA), JSON, RDF, OWL, HTTP/CoAP, RESTful web services, SOAP, Web Services Description Language (WSDL), XML, Comma-separated Values (CSV), Open Database Connectivity (ODBC), OGC, SensorML, WaterML2.0, OpenMI,	IPv6, IPv4, TCP, User Datagram Protocol (UDP)	Web services tend to be proprietary interfaces but can have automatic discovery; secure communication, security, backfill, redundancy, interoperability
Data logger – Server/Analytics	MQTT, HTTP, Lightweight Machine to Machine (LWM2M), CoAP Backfilling	IPv6, IPv4, TCP, UDP, Cellular IoT small data	Secure data exchange; fault-tolerant; command transmission (bidirectional communication);
GIS-Analytics	OGC web services, Geography Markup Language (GML), ISO19139	IPv6, IPv4, TCP, UDP	Secure data exchange, usability

different protocols; *(ii) intermediary-based* solutions to achieve N-one-M mapping, by using an intermediary protocol, between N and M systems that employ various protocols; and *(iii) common abstractions* to enable the interoperation of legacy systems by abstracting their behaviour. DeXMS is introduced as a solution for the interconnection of heterogeneous Things across middleware barriers by automating the synthesis of protocol mediators that support the interconnection of heterogeneous Things Bouloukakis et al., 2019. It builds on Data eXchange (DeX) connector model that comprehensively abstracts and represents existing and potentially future IoT middleware protocols. Table 3.4 compares to the other related frameworks of different approaches, such as Service Oriented Architecture (SOA) to an IoT platform that abstracts Things or their data as services and offers functionalities, e.g. discovery service, the composition of services and access to services; Gateway is a common approach to connect a set of sensors and actuators interacting using Media Access Control (MAC) layer protocols (e.g., Bluetooth, ZigBee, etc.) to the Internet is through Sensor Gateways; Cloud Computing (CC) enables IoT-platforms to store, process, analyze, and retrieve huge amounts of data remotely, reliably and at low cost in a cloud environment; Model-Driven Engineering (MDE) define (i) modelling languages for specifying a system at different levels of abstraction, (ii) model-to-model transformations that translate models into another set of models, typically closer to the final system, and (ii) model-to-text transformations that generate software artefacts, e.g., source code or XML code, from models. Finally, DeXMS's approach is to identify common abstract interaction types across the core interaction paradigms (Client/Server, Publish/Subscribe, Data Streaming and Tuple Space[5]) encountered in the IoT and build DeX Application Programming Interface (API) and connector model that abstracts the underlying heterogeneous IoT protocols

[5] associative memory paradigm for parallel/distributed computing

of a middleware.

Table 3.4: Comparison of DeXMS with related frameworks (Bouloukakis et al., 2019)

Frameworks	Supported protocols	Direct bridging	Software abstractions	Constrained devices	Mediator synthesis
SOA[1]	1-3	few	almost	few	no
Gateways[1]	2-4	all	none	some	no
CC[1]	2-4	all	yes	yes	no
MDE[1]	0	none	none	yes	yes
DeXMS	5	yes	yes	yes	yes

Table 3.5 compares the major European Union (EU) funded IoT research projects in terms of interoperability features. Among the IoT projects, SEMIoTICS not only offers interoperability at four levels but goes 2 steps ahead of its competitors. It utilizes semi-automatic pattern-driven techniques to for the cross-domain operation and interaction of applications.

For IoT ecosystems, BigIoT introduces five interoperability patterns : *(i) cross-platform access, (ii) cross-application domain access, (iii) platform independence, (iv) platform-scale independence, and (v) higher-level service facades.* Although these pattern help to reuse data and services form different platforms of an ecosystem, there is a need for automatic search and orchestration of services (Bröring et al., 2017).

The OpenIoT project provides an open source IoT platform that manages cloud environments for IoT "entities" and resources (such as sensors, actuators and smart devices) and enables the semantic interoperability of IoT services in the cloud. OpenIoT cloud platform uses the W3C SSN ontology as a common standards-based model for semantic unification of diverse IoT systems and offers a versatile infrastructure for collecting and semantically annotating data from virtually any sensor available. It exploits also the LD concept to link the related sensor data sets and provides functionalities for dynamically filtering and selecting data streams, as well as for dealing with mobile sensors (Soldatos et al., 2015).

The INTER-IoT aims at the design and implementation of, and experimentation with, an open cross-layer framework and associated methodology to provide voluntary interoperability among heterogeneous IoT platforms. It considers interoperability across all layers of the software stack in cross-domains of (e/m)Health and transportation/logistics (Ganzha et al., 2017). In this project an ontology alignment format Inter Platform Semantic Mediator (IPSM) is developed to express and do semantic translations in both simple and complex alignments that are expressed in RDF format (Szmeja et al., 2018).

In comparison with IoT interoperability approaches, the WatERP framework from the water domain proposes an architecture that harmonizes the communication between systems that control, monitor, and manage the water supply distribution chain by using a SOA-MAS approach together with a knowledge-base driven by the WMO (Anzaldi Varas et al., 2014). This approach integrates and utilizes innovative technologies, SOA, web services, MAS, and semantic web languages to handle the interoperability issue of monitoring and decision-making applications within SWNs, via offering

[1]considered frameworks in (Bouloukakis et al., 2019)

Table 3.5: Comparison of Features in IoT-Platforms (Hatzivasilis et al., 2018)

Feature / IoT-Platform	SEMIoTICS	BigIoT	OpenIoT	INTER-IoT
Technological interoperability	Yes	No	No	No
Syntactic interoperability	Yes	No	No	No
Semantic interoperability	Yes	Yes	Yes	Yes
Organizational interoperability	Yes	Yes	Yes	No
Pattern-based modelling	Yes	Yes	No	No
Pattern-based semi-automatic management	Yes	No	No	No

a standardized SOA-MAS-based interface and communication interpretation through WMO. Additionally, through SOA-MAS-based approach intelligent orchestration of system functionalities within the architecture is achieved, as agents can be conceptualized with Believe Desire Intention (BDI) (RAO and GEORGEFF, 1998) model to become autonomous and cooperative to achieve their declarative and procedural goals (Winikoff et al., 2002).

The WISDOM project enables the interoperability of things and software in smart water networks through a software platform that utilizes ontology for semantics and web-services for web-enabled sensors to integrate business operations across the water value chain. They define a water value chain as the artifacts, agents, and processes involved in delivering potable water to consumers from natural water sources and safely disposing of foul and runoff waste water. Their approach towards interoperability is to integrate existing data models, which are formalized in different data formats, and often using heterogeneous domain perspectives. They intersect existing models and align them with the WISDOM ontology that is used as a common ontology to support the data interoperability across the existing models. They promote interoperability through semantic web technologies and by performing a schema conversion from a knowledge base of devices instantiated within the WISDOM ontology into another model e.g. SAREF, Infrastructure for spatial information in Europe (INSPIRE), IFC4, SWIM, etc (S. Howell et al., 2017).

Interoperability of applications in IoT-enabled SWN remains an issue, as current solutions do not apply on all interoperability layers and they do not build appropriate semantic models for the interoperability, management, reasoning and sharing of heterogeneous, static, and dynamic data. Currently, many frameworks focus on bottom interoperability layers (technical, syntactic, semantic and pragmatic) and the top interoperability layers after the pragmatic layers are defined differently in literature. In the interoperability stack (see figure 2.5), syntactic and semantic interoperability layer are the bottom-level layers that build a foundation for the top-level interoperability layers. That means pragmatic and organisational layers can not be fully interoperable if syntactic and semantic layers do not sufficiently support the current standards and ontologies of the IoT and water domain. Additionally, most of the interoperability solutions in the water are developed with the vertical application approach for smart networking and undermining the potential brought through the cross-domain integration of IoT-solutions in the water domain. In the reviewed IoT projects (e.g. SEMIoTICS and BigIoTb), the interoperability solutions are based on the transitive conversion model for data protocols, e.g. if MQTT can be converted to/from CoAP and CoAP can be converted to/from REST than MQTT can be converted to/from REST. Similar interoperability approach is adopted in the water related projects (e.g. WISDOM and WatERP), where at first a base ontology (e.g WISDOM ontology) is aligned with all possible standards and ontologies then it is used to convert from one standard/ontology to another. In all projects, semantic web technologies are utilized to build semantic models with ontologies. Achieving automation and orchestration of services with MAS is observed in some water related projects.

Research Challenges

While reviewing the current knowledge and work in IoT and water management domain, several technological and methodological advancements have been developed to address the interoperability issue among applications. Yet, there are still open questions regarding the management and sharing large amounts of heterogeneous dynamic data and information in SWNs and this is becoming more complex as new research areas emerge since technologies are being developed and integrated into SWNs. For example, the utilization of smart devices in SWN have not only brought new possibilities but also new challenges. In the following sections, some of the identified challenges are highlighted.

- Knowledge-based management and sharing of data are founded on semantic modelling approach and since an ontology of the application domain is the core of the semantic model, the intended ontology is developed with the focus on the conceptualisation of the application's domain knowledge. This is the case with most of the existing ontologies in the IoT and water domain. While developing an ontology for the water domain, there have been attempts to reusing the existing ontologies by applying Izza's approach. However, the developed ***ontology remains domain-specific and is not domain agnostic*** to be easily extended with the knowledge of other domains. So one of the challenges remains as ***currently existing semantic models lack in supporting both intra- and cross-domain interoperability for SWN and IoT domains***, instead related applications of both domains have their specific ontologies (see table 3.2). Therefore for the interoperability of these applications and management of the data from both domains, their ontologies must be extended, aligned or mapped in a semantic model that abstracts over these ontologies and become intra- and cross-domain inter-operable.

- Similar is the case in data communication protocols for IoT and SWN applications because there are too many data protocols and data representation standards for sharing data in IoT-enabled SWNs, ***therefore new tools and algorithms must be developed to support the data sharing of various data protocols and standards in IoT-enabled SWNs.*** (see tables 3.3 and 3.2). DeXMS seems to be a quite promising solution in bridging this gap, however, mediator logic must be implemented that abstracts over the considered protocols and currently this approach is only applied in IoT platforms and missing in SWNs.

- The ***Utilisation and combination of different reasoners in DSSs and semantic models*** is required to reason the integrated data and information and to advise at best to the decision-making applications. Currently, only a few DSSs and knowledge management systems support the application of multiple reasoners (see middle of section 3.1).

- ***Dynamic data and stream reasoning*** must be considered in all IoT-enabled applications, including SWN because smart sensors will be continuously and asynchronously sending the data streams. This brings many challenges, such as data changes over time, data send may be inaccurate due to faulty sensors, and data may be unavailable due to various problems, e.g. connection lost or power supply issue (see bottom of section 3.1). In addition, stream reasoners must be integrated to DSSs and semantic models to reason over huge amounts of dynamic data that is produced in IoT-enabled SWNs. For stream reasoning, a semantic model must also *consider the dynamic nature and logic behind the dynamic data, while creating ontologies.* Currently, existing ontologies are lacking this aspect.

As an outlook on the research, Early Stage Researcher (ESR) 2 will focus on developing a Data and Information Interoperability Model (DIIM) that is capable of offering syntactic and semantic interoperability of the integrated data and information to the applications in IoT-enabled SWNs. This research will aim to integrate semantic web technologies and MAS to build and manage semantic model for heterogeneous dynamic data and information that is collected by smart sensors/devices. The interoperability solution will inherit form currently existing interoperability approaches and support the ontologies of the IoT and water domains.

Conclusion

The main objective of this document is to provide readers a better understanding of the interoperability in IoT-enabled SWNs and deliver a report on reviewed literature of IoT and water domains. At first, this document introduced the importance of SWN in tackling the the water scarcity and water quality crisis, as SWNs are being build to enable remote and continuous monitoring and diagnosing of problems, manage maintenance issues and optimize the water distribution network in the entire life-cycle of water. SWNs are evolving from SCADA to next level as gradual deployment of IoT devices such as smart sensors and actuators brings an overlay of IoT offers new opportunities for intra- and cross-domain applications but it has further fuelled the interoperability issue. In an IoT-enabled SWN, the interoperability of applications can not be successful without achieving the syntactic and semantic interoperability of the data that is shared by the applications at different layers of communication. Thus, interoperability of applications remains a hot topic in industry and academia and one can still find approaches and solutions that are published recently to address interoperability.

Second part of the document presented the definitions and architecture of a SWN that are found in industry and academia. It listed the major challenges and solutions that are developed in the water domain. Since, a SWN is a result of the integration of many technologies, such as IoT for smart sensors, MAS for autonomous activity, and semantic web technologies (OWL, RDF, SPARQL, etc.) for managing and sharing data, it described the characteristics and purpose of these relevant technologies. This part also presented the fundamental concepts of a SWN, such as interoperability, interoperability levels/layers, DIKW hierarchy, knowledge-base and ontology, as they are defined in the literature.

Third part presented the report on reviewed literature. At first it listed the influential projects of EC FP7 and Horizon 2020 programme that address the interoperability challenges in the IoT and water domain. Then the relevant work on knowledge management and DSS in the water domain is presented. After this, a historical development of standards and ontologies is depicted that are being used to build semantic models and share data of observations and measurements in the IoT and water domain. Thereafter, the issue of interoperability and its approaches and solutions from IoT and SWN projects were discussed.

Finally, some of the identified challenges during the investigation are highlighted and summarized. Interoperability of applications in IoT-enabled SWN remains an issue, as current solutions do not apply on all interoperability layers and they do not build appropriate semantic models for the interoperability, management, reasoning and sharing of heterogeneous, static, and dynamic data/information.

Appendices

Acronyms

AI Artifical Intelligence. 6

AMQP Advanced Message Queuing Protocol. 8

API Application Programming Interface. 22

ASCII American Standard Code for Information Interchange. 8

BDI Believe Desire Intention. 24

BI Business Intelligence. 17

BII Business Insider Intelligence. 7

CBR Case-Based Reasoning. 17

CC Cloud Computing. 22, 23

CoAP Constrained Application Protocol. iii, 8, 22, 24, 25

CPS Cyber physical system. 3

CSV Comma-separated Values. 22

CUAHSI Consortium for the Advancement of Hydrological Sciences Inc.. 21

DCOM Distributed Component Object Model. 20

DeX Data eXchange. 22

DeXMS Data eXchange Mediator Synthesizer. v, 22, 23, 26

DIEK Data Information Evidence Knowledge. v, 13

DIIM Data and Information Interoperability Model. 27

DIKW Data Information Knowledge Wisdom. iii, iv, 12, 13, 28

DIKW/I Data Information Knowledge Wisdom/Intelligence. 13

DSL Digital Subscriber Line. 7

DSS Decision Support System. iii, v, 4, 5, 6, 16, 17, 18, 27, 28

EC FP7 European Commission Seventh Framework Programme. 16, 28

ESR Early Stage Researcher. 27

ETSI European Telecommunications Standards Institute. 19, 21

EU European Union. 23

FIPA Foundation of Intelligent Physical Agents. 15

FTTH Fiber to the Home. 7

FTTP Fiber to the Premises. 7

GIS Geographic Information System. 4, 17, 22

GML Geography Markup Language. 22

GOIoTP Generic Ontology for IoT Platforms. 20, 21

GOIoTPex Generic Ontology for IoT Platforms Extended. 20

HTTP Hypertext Transfer Protocol. 14, 22

ICT Information and Communications Technology. 6, 16

IDSS Intelligent Decision Support Systems. 17, 18

IEC International Electrotechnical Commission. 8

IEEE Institute of Electrical and Electronics Engineers. 8

IFC4 Industry Foundation Classes 4. 21, 24

INSPIRE Infrastructure for spatial information in Europe. 24

IoE Internet of Everything. 11

IoT Internet of Things. iii, v, 1, 2, 3, 6, 8, 11, 16, 17, 19, 20, 21, 22, 23, 24, 26, 27, 28

IP Internet Protocol. 7, 22

IPSM Inter Platform Semantic Mediator. 23

ISDN Integrated Services Digital Network. 7

ISO International Organization for Standardization. 7, 8, 19, 21, 22

JADE Java Agent DEvelopment Framework. 15

JSON JavaScript Object Notation (JSON). 8, 22

LCA Life Cycle Assessment. 17, 18

LD Linked Data. 14, 17, 23

LOD Linked Open Data. 14

LWM2M Lightweight Machine to Machine. 22

M2M Machine to Machine. 6

MAC Media Access Control. 22

MAS Multi-Agent System. iii, 3, 6, 15, 17, 23, 24, 25, 27, 28

MCDM Multi-Criteria Decision Making. 17, 18

MDE Model-Driven Engineering. 22, 23

MM Mathematical Models. 17, 18

MQTT Message Queuing Telemetry Transport. iii, 8, 22, 24, 25

NCOIC Network Centric Operations Industry Consortium. 10

NFC Near-field communication. 8

ODBC Open Database Connectivity. 22

OGC Open Geospatial Consortium. 17, 19, 21, 22

OLAP On-Line Analytical Processing. 17

OPC DA Open Platform Communications Data Access. 22

OPC UA Open Platform Communications Unified Architecture. 8

OSI Open Systems Interconnection. 7, 20

OWL Web Ontology Language. 6, 14, 21, 22, 28

PLC Programmable Logic Controller. 3

PRV Pressure Reducing Valves. 3

RBR Rule-Based Reasoning. 17

RDF Resource Description Framework. 6, 14, 15, 21, 22, 23, 28

RDFS Resource Description Framework Schema. 6, 14

REST Representational State Transfer. iii, 8, 14, 22, 25

RIF Rule Interchange Format. 14

SAREF Smart Appliances REFerence. 19, 21, 24

SCADA Supervisory control and data acquisition. 3, 4, 6, 22, 28

SKOS Simple Knowledge Organization System. 14

SNMP Simple Network Management Protocol. 8

SOA Service Oriented Architecture. 22, 23, 24

SOAP Simple Object Access Protocol. 8, 14, 22

SOS Sensor Observation Service. 19

SOSA Sensor, Observation, Sample, and Actuator. 19, 21

SPARQL SPARQL Protocol and RDF Query Language. 14, 28

SSN Semantic Sensor Network. 19, 21, 23

SSO Syndromic Surveillance Ontology. 21

SW Semantic Web. 16, 17

SWAN Smart Water Networks Forum. iv, 4, 16

SWEET Semantic Web for Earth and Environment Technology. 21

SWG Smart Water Grid. 4

SWIM Semantic Water Interoperability Model. 19, 21, 24

SWN Smart Water Network. iii, iv, v, 1, 2, 3, 4, 5, 6, 16, 17, 19, 20, 22, 23, 24, 26, 27, 28

SWNs Smart Water Networks. iii, 1

TCP Transmission Control Protocol. 8, 22

TCP/IP Transmission Control Protocol/Internet Protocol. 7

UDP User Datagram Protocol. 22

UPnP Universal Plug and Play. 8

W3C World Wide Web Consortium. 14, 21, 23

WatERP Water Enhanced Resource Planning. 16, 20, 21, 23, 25

WDSS Knowledge-Driven Water DSS. 17

WDTF Water Data Transfer Format. 21

WISDOM Water analytics and Intelligent Sensing for Demand Optimised Management. iii, 16, 19, 20, 21, 24, 25

WMO Water Management Ontology. 20, 21, 23, 24

WSDL Web Services Description Language. 22

WWTP Wastewater Treatment Plant. v, 18

XML Extensible Markup Language. 21, 22

XMPP Extensible Messaging and Presence Protocol. 8

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