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Integrating building and urban semantics to empower smart water solutions

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ABSTRACT

Current urban water research involves intelligent sensing, systems integration, proactive users and data-driven management through advanced analytics. The convergence of building information modeling with the smart water field provides an opportunity to transcend existing operational barriers. Such research would pave the way for demand-side management, active consumers, and demand-optimized networks, through interoperability and a system of systems approach. This paper presents a semantic knowledge management service and domain ontology which support a novel cloud-edge solution, by unifying domestic socio-technical water systems with clean and waste networks at an urban scale, to deliver value-added services for consumers and network operators. The web service integrates state of the art sensing, data analytics and middleware components. We propose an ontology for the domain which describes smart homes, smart metering, telemetry, and geographic information systems, alongside social concepts. This integrates previously isolated systems as well as supply and demand-side interventions, to improve system performance. A use case of demand-optimized management is introduced, and smart home application interoperability is demonstrated, before the performance of the semantic web service is presented and compared to alternatives. Our findings suggest that semantic web technologies and IoT can merge to bring together large data models with dynamic data streams, to support powerful applications in the operational phase of built environment systems.

1. Introduction

Building information modeling (BIM) is increasingly being researched in operational buildings, alongside technologies such as energy simulation and building automation [5,32]. Also, smart approaches such as systemic optimization [45], and load forecasting [14] are demonstrating improvements in the efficacy, longevity and efficiency of water networks [25,37]. Smart water networks are touted to deliver leakage reduction, energy savings, water quality assurance, improved customer experience and operational optimization, amongst other key performance benefits [21,22,31,43]. Research is now looking to improve water demand profiles at the building level through adaptive pricing feasibility studies, consumer feedback interfaces, gamification, and smart appliances. Hence, a new research field is emerging from the union of BIM, smart appliances, intelligent sensing, and cybernetics.

However, this complex ‘system of cyber-physical systems’ faces similar interoperability challenges to those being faced by smart grids and smart cities, where the value derived from ICT penetration is tied to the ability to share knowledge. This has been stated by authoritative bodies to occur due to i) lack of machine communication protocols, ii) lack of common data formats, and iii) lack of common meaning of exchanged content [19]. The need for common protocols and resource discoverability is being addressed by the Internet of Things (IoT), such as through the recent Hypercat standard [17]. However, this still leaves semantic aspects unresolved.

In the smart grid and smart city domains, research is actively pursuing data models which facilitate data exchange, the integration of legacy systems, and promote system security and performance [7,19]. Given the growth of smart metering in the water industry [6,33], and recent interest in smart water [22,31], it is pertinent for smart water research to learn from smart grid research. Further, many similar key ICT features are required in the water domain, so interest in a similar approach is growing [18,36].

Significant advances have been made in the field of water semantic modeling, but primarily from an earth science perspective, and primarily at the catchment scale [28,46–48]. Very little modeling

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of water consumption at the utility or building level is evident, although BIM, smart appliance and intelligent sensing models are relevant to this domain. An integrated modeling approach would be highly beneficial to promote the effective interoperation of software i) with a feedback loop at the building level, ii) which optimizes and implements demand-side management (DSM), and iii) which uses dynamic consumption data to better inform clean and waste network management decisions. This should include a detailed and consistent vocabulary and semantic model across the building and network scales. It would also be beneficial to reuse the domain independent aspects of models from the power and smart city domains, and to adopt a similar modeling approach. Applied knowledge managment work is therefore required both directly and at a meta level, to support smart water systems as well as the sharing of knowledge between smart domains.

Semantic interoperability in smart water networks is therefore a literature gap, which this paper takes a step towards addressing. The work was conducted within a European research project, which aims to integrate data and software across domestic and water utility resources. The project, 'Water analytics and Intelligent Sensing for Demand Optimised Management' (WISDOM), is utilizing semantics and web-enabled sensors to integrate business operations across the water value chain. A water value chain is defined 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. This paper proposes a smart domain water ontology, and a software platform which uses this to integrate services. This extends the state of the art of both the BIM and IoT fields towards meaningful interoperability of things and software in smart water networks.

The next section presents related work observed in the literature, Section 3 presents the use case driven methodology adopted, Section 4 then presents the main contribution; the semantic water modeling, and Section 5 presents a platform which uses the models to deliver interoperability. Ontology validation and platform experiments are presented in Section 6, and the findings are discussed along with concluding remarks in Section 7.

2. Related work

This section provides a state of the art overview of research on semantics and applications in the water domain. As such, it is structured into three sub-sections focusing on (a) the foundations of semantic modeling, (b) water modeling at the catchment and network levels, and (c) the modeling of cyber-physical systems at the building level.

2.1. Introduction to semantic modeling and ontologies

Semantic models, such as ontologies, promote interoperability as shared data formats and domain knowledge models, and play a prominent role in the World Wide Web Consortium (W3C) 'semantic web stack' [39]. They also play a role in the IoT and linked data fields, where they assist data contextualization, resource discovery, consistency and scalability [1]. Ontologies have been defined as explicit specifications of a conceptualization [49]. Therefore, an ontology describes the concepts, relationships, data properties and restrictions within a domain, in a machine-readable manner, and is often instantiated for a target system.

In use, ontologies typically support application back ends through a triple store, by capturing meaning, contextualizing data, standardizing terminology, facilitating rule application and producing new knowledge beyond that which is inputted. This assists the development of knowledge-driven applications which integrate heterogeneous resources. Critically, ontologies are vendor-neutral, which promotes extensibility, accessibility, and knowledge reuse. The following subsections describe existing semantic models in the target domains, which are summarized in Table 1.

2.2. Smart water and associated knowledge management issues

Smart water networks aim to improve the management of water and waste water systems through more intelligent approaches, such as artificial intelligence (AI) [24] and optimization [45]. Given the steeply rising number of sensors and volume of big data in the domain, comprehensive solutions must be available for these resources to be understood by machines, to support their best use in AI and advanced applications. Mounce et al. express this by stating that ontologies are a key technology for the acquisition, structuring and filtering of knowledge [23]. Further, the Smart Water Networks Forum has emphasized that as well as network interoperability, semantic understanding of data is critical to overcome the interoperability hurdle currently observed [15]. The geospatial community has produced several notable semantic models such as CityGML and its Utility network extension [28], and the INSPIRE utility network schemas [20]. This supports the fundamental

Table 1
Summary of relevant semantic models.

Acronym/name	Description	Owner	# entities	Date
SWIM	Device level IoT semantic model for the water industry.	Aquamatix	41	2016
WISDOM	Cyber-physical and social ontology of the water value chain.	Cardiff University	492	2016
SAREF	'Common denominator' of 23 smart appliance domain models.	ETSI	154	2015
WaterML2	Common format for hydrological time series data exchange.	OGC	131	2014
IFC4	Open format for building information model exchange.	buildingSMART	768	2013
Utility network schemas	Water and sewer network model; part of a large European directive for geospatial data exchange.	EC-INSPIRE	65 types	2013
WatERP	Lightweight ontology of generic concepts for water sensing and management.	EURECAT	29 classes	2013
WDTF	Format for transferring flood warning and forecasting data to the governing body. Precursor to WaterML2.	Australian Bureau of Meteorology	337	2013
CityGML UtilityADE	Domain extension for modeling utility networks in 3D city models, based on topology and component descriptions.	OGC	317	2012
SSN ontology	Describes sensors and sensor networks, for use in web applications, independent of any application domain.	W3C	80	2012
SWEET	Middle-level ontology for environmental terminology.	NASA	6000	2011
Hydrologic Ontology for Discovery	Supports the discovery of time series hydrologic data collected at a fixed point. Precursor to WaterML2.	CUAHSI	4098	2010
HydrOntology	Aims to integrate hydrographical data sources: town planning perspective, top down methodology.	Vilches-Blázquez et al.	250	2009

step of machine understanding of location metadata, but beyond this, detailed descriptions are needed of aspects such as materials, IoT device capabilities, sensor metadata, socio-technical concepts, demand-side concepts, and other cyber-physical aspects. This forms a core part of the gap being addressed by the current work. By developing a semantic web solution to these challenges, the plethora of devices and their data can be more readily discovered, accessed, and utilized by advanced applications, towards a more open and progressive ecosystem of innovation.

Typically, when utility companies contract the production or upgrade of a software solution the domain experts interact with software developers on per-project basis, resulting in ad-hoc, proprietary, and implicit extensions of data models. This has led to significant inefficiencies as the domain knowledge which is elicited during the process is lost rather than being captured in a semantic model, resulting in greater barriers to further development and lack of coherency between systems even within one company, but especially across companies. Standards act as one means of addressing this challenge by building consensus amongst stakeholders on how best to capture this domain knowledge, as this can be used as a common reference point for all further software development. However, standards face the challenge of heterogeneity amongst themselves, and of lack of adoption; without which they have little value. Specifically, standards from different communities within the sector have adopted different domain perspectives and data formats, incompatible scopes and semantics, and different levels of granularity. Also, without clear business cases or regulation to encourage the adoption of the standards, companies are unlikely to invest in the upfront task of adopting or aligning with a new data model. Building an ontology which aims to integrate these standards towards specific use cases is a viable way to mitigate the barriers mentioned between standards, as it abstracts the semantics of each standard away from their initially intended application, and allows alignment at the knowledge layer.

As ontologies are the most expressive type of data model available, they can capture the knowledge expressed in other standards, and can be converted back into many less expressive formats if required. This effort to promote the compatibility of standards also improves the business case of adoption, as utility companies are likely to experience greater return on investment from being able to interoperate a range of existing models, and the software development will be less time-consuming, and more open to competition through open standards. Therefore, integrating these fundamentally heterogeneous standards should make use of high-level conceptual mapping, abstraction, specialization, reuse, and equivalency, through an axiomization which is loose enough to allow their communities autonomy over development but strong enough to guide software developers, and ideally enable automated processes.

As an early pioneer of ontologies in the water domain, Scholten et al. defined a best practice for producing conceptual models of water systems for simulation purposes [34,35], but little work has considered the broader uses of ontologies in the domain. Whilst mathematical models serve a critical function, the role of data modeling and semantic modeling is growing as the number and heterogeneity of ICT resources in the domain accelerates [18]. This is especially pertinent considering the growth of the Internet of Things, which can leverage ontologies and Semantic Web technologies to interoperate physical devices as well as a broader range of software than just simulation packages. Despite this, the earlier stages of the process outlined by Scholten et al. (towards a conceptual model, independent of its application), are complementary to the work presented herein, which broadly followed the tasks and order prescribed by Scholten et al. Whilst the ontology of Scholten et al. aimed to achieve quality assurance for mathematical models, the current work aims to achieve deep interoperability between data schemas and domain conceptualizations.

Examples of semantic models in the smart water field are sparse. Whilst several mature ontologies were observed in the earth science field, such as the Hydrologic Ontology for Discovery [10], SWEET [27] and HydrOntology [38], these were not suitable for the application of ICT to the water value chain. The main relevant ontology observed was the WatERP "generic ontology for water supply distribution chain" [41,42]. However, the Waternomics 'linked data model' [40] contained some useful concepts, and the Infrastructure for Spatial Information in the European Community (INSPIRE) utility network model [20] standardizes basic physical water and waste water network models. The WatERP ontology is intended for relatively simple use cases, so contains only 25 classes and few details of the physical processes and components involved in water management, and it doesn't describe relationships between features of interest, or actors. The WatERP ontology is split conceptually into a 'supply and demand ontology', 'observation and measurement ontology' and an 'alerts and actions' ontology. Further, the WatERP ontology only captures high level concepts such as physical element types, and a few types of actors. Further depth is therefore required in the semantic modeling of this domain across physical, social and sensory concepts across the supply and demand parts of the value chain.

Very little relevant modeling was observed regarding water consumption at the building level. As mentioned previously, the similarity of the smart water trajectory to the smart grid trajectory implies that we should pre-empt the smart grid roadblocks manifesting in the smart water field. This will allow the delivery of intelligent demand-side management (DSM) through knowledge and software integration across the supply-demand boundary. This requires the development of semantic models for the water sector in the same vein as those observed in the energy sector, and reusing existing modeling and meta-modeling where possible. Given the importance of the domestic context and smart devices for demand-optimized management, the next section describes the modeling of these domains and their overlap with building information modeling.

2.3. Building and smart device information modeling

From a knowledge modeling perspective, BIM is the evolution of computer-aided design to also include semantic information about entities, processes and actors. The initial role of BIM was exchanging knowledge between design and construction phases, but research has increasingly applied BIM artifacts and concepts across lifecycle phases [13]. The Industry Foundation Classes (IFC) [8] have increasingly been used in operational phase cybernetics, such as in smart building energy management [44], and in optimizing building energy consumption through a knowledge-based approach [16].

The use of open data models in BIM prevents vendor tie-in; promoting software package interoperability and development by the research community. For example, they have been extended for object-based knowledge exchange [5]. Integrating building descriptions with sensor data supports semantic reasoning and artificial intelligence (AI) applications. To further this, ifcOWL is being developed [30], as the original format is not well suited for web applications. However, no work was observed using BIM in smart water cybernetics, consumption feedback, or DSM applications. IFC models only include basic water components, omitting many concepts needed for cybernetics such as; consumers, behaviors, smart appliances, sensor descriptions, sensor networks, and water billing mechanisms. Therefore, aligning ifcOWL with a water ontology would be valuable in enabling the convergence of these two fields for mutual benefit.

As well as BIM, the work of the smart appliance reference ontology (SAREF) project is highly relevant [12]. This attempts to unify 23 ontologies, by supporting alignments in systems with 3 or more smart appliance ontologies. The SAREF ontology has been adopted by

Table 2
Description of demand-optimized management scenario.

Scenario name	Demand-optimized management
Value proposition	Matching the availability of water to the demand for water should reduce energy consumption, non-revenue water (leakage and evaporation), and maintenance costs, and reduce the number of alarms by reducing the strain on the network.
Description	The integration of smart metering data, predictive models, optimization algorithms and decision support tools will allow the suggestion of set point schedules and resource management schemes for water network assets. Specifically, simulation and optimization models will be integrated with demand-side data, and GIS and telemetry data to suggest options to functional managers and information regarding the implications of control strategies. A multi-objective metaheuristic optimization will reduce the amount of pumping required and the peak pressures, hence reducing leakage and energy cost. Reducing the time water resides in reservoirs will also reduce evaporation through a just-in-time approach.
Independent variables	–Reservoir set points and schedules –Pump set points and schedules –Pressure reducing valve actuation –Control valve actuation
Input data	From water utility: –Telemetry data (flow rate, pressure, pH, stage height, temperature, chlorine residual etc.) –Valve and pump states –Sensor and observation metadata –Asset and pipe locations –Asset & pipe descriptions (material, type, size, length etc.) From consumers: –Smart metering data –Household descriptions From Environment Agency: –River levels and rainfall gauges
Pilot site	Tywyn & Aberdovey

the European Telecommunications Standards Institute (ETSI), giving significant precedence to its reuse. The semantic sensor network (SSN) ontology [9] has also been broadly adopted, and should be leveraged wherever semantics and intelligent sensing are combined. Reusing these models promotes extensibility and the reuse of the work presented herein. The next section presents the methodology followed, before the resultant semantic models and software platform are discussed further.

3. Methodology and use cases

The development of the smart water semantic model was undertaken within the broader development of a smart water interoperability and analytics platform. This allowed a clear scope, requirements elicitation, and validation to be undertaken, towards real applicability of the modeling in the smart water domain. These processes were driven by clear use cases, based on consultations with industrial stakeholders. This process is now elaborated, before two example use cases are presented.

3.1. Ontology requirements elicitation

The requirements elicitation first involved undertaking a stakeholder-oriented knowledge gathering process to understand the business, technical and regulatory contexts of the domain. This resulted in business process models and a sufficient initial understanding of the technological domain and requirements on the intended contribution. A systems analysis and design task was then undertaken to specify the functional and non-functional requirements of the semantic web service, based on a service-oriented architecture approach. These emerged from a number of use cases, sequence diagrams and scenarios, which represented the interactions and added-value mechanisms the platform intended to support: examples of this work are shown in Table 2, Figs. 1 and 2. The platform itself is discussed further in Section 5. This foundational knowledge began to clarify the breadth and depth of the required modeling, around the central concepts of smart water, demand-optimized management, and intelligent sensing. This participatory process used the expertise of water value chain stakeholders to inform the nature of an integration of large data models which would be valuable to the sector. The scope was then developed further through domain expert consultation and ontology expert refinement into a set of competency questions associated with each scenario, which marked the start of the ontology's development process.

The ontology development used an adapted version of the NeOn methodology [26], and prominently featured reuse, iteration, abstraction, and domain expertise. Firstly, candidate ontologies were identified for reuse, and these were analyzed closely against the software and knowledge modeling requirements. This found that the socio-technical system ontology of van Dam [11] and the SSN ontology [39] were ideal to produce a meta-model, to be extended with water specific knowledge from the INSPIRE and CityGML models, as

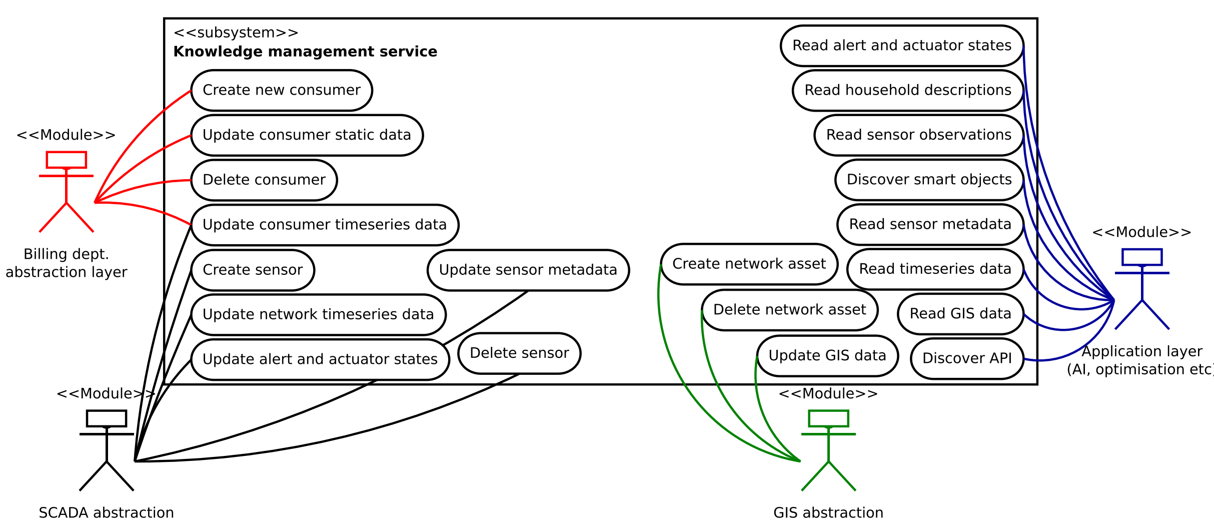

Fig. 1. Excerpt of UML use case for the knowledge management service in the demand-optimized management scenario.

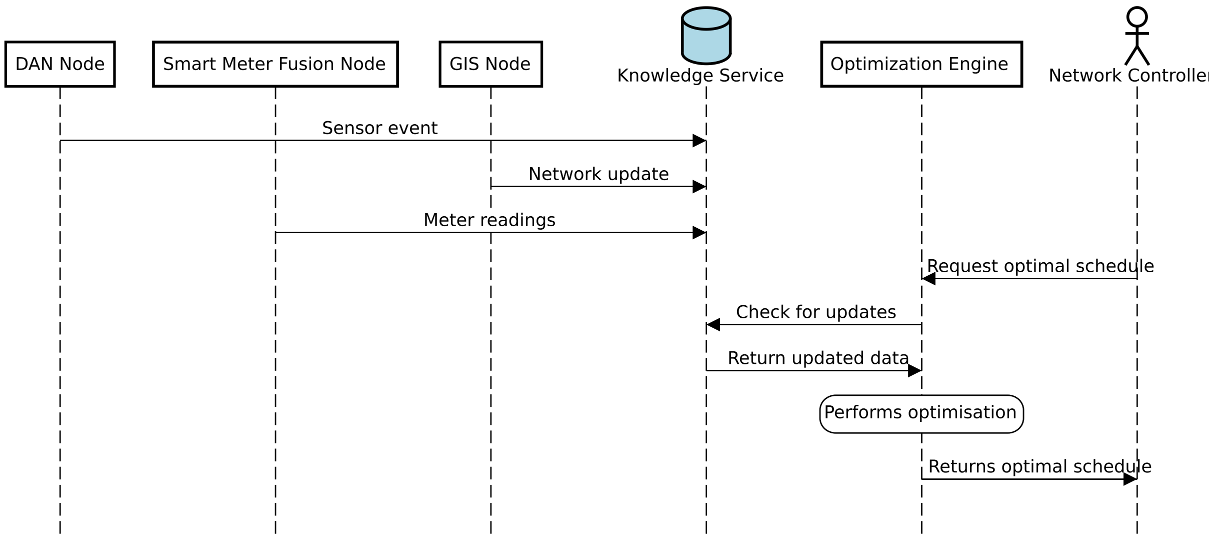

Fig. 2. Simplified sequence diagram for the demand-optimized management scenario.

well as concepts from other ontologies and new modeling where necessary. The curation of the ontology used semantic mechanisms such as abstraction, specialization, equivalency, and fragment reuse to integrate knowledge captured by existing large data models. Concepts and axioms were also elicited from the previous knowledge gathering exercise, as well as automated web crawling and semantic extraction from relevant websites, and further domain expert consultation. The ontology was then validated as a sufficient and accurate formalization of the domain vocabulary by experts from 10 companies across the European water sector, and was separately analyzed for suitability within the scopes of the platform's use cases. Two of the ontology's use cases are now discussed: demand-optimized water management, and smart home appliance interoperability.

3.2. Demand-optimized management

One of the key analytics services supported by the platform is the optimization of the operation of water networks based on contextualized smart metering of dwellings. This scenario of more dynamically matching supply to demand is presented in Table 2, and the use case model which describes the required functions of the knowledge management service to support this is shown in Fig. 1. An example, simplified, sequence diagram for delivering the scenario is illustrated in Fig. 2, where these represent excerpts of the requirements engineering process undertaken. As stated in Table 2, this scenario uses a range of optimization techniques to minimize the energy and water consumption of the network by providing online near optimal suggestions for pump, valve and reservoir setpoint control.

The optimization process includes a set of constraints such as tank and reservoir operational level ranges and minimum pressure head requirements, which are intrinsically satisfied as a result of the optimization. Upon receiving a request from the business services layer, the optimization module is initialized by requesting the current state of the water network from the ontology service. This then populates the optimization model with data such as network topology, pipe dimensions, pump descriptions and current consumption behaviors in the network. The optimization service then uses this knowledge within a hydraulic model and an artificial neural network model, and a range of candidate optimization methods.

The process outputs optimal set points for various key actuators in the network, so as to provide decision support to the staff of the water service provider based on the current and predicted demand on the network. The ontology service plays a key role in facilitating this optimization of the water network, by integrating data across domains and scales for use by the optimization module.

The use of contextualized smart meter data here allows greater reasoning and data mining over the consumption data, as correlations can be found between domestic socio-technical variables and consumption patterns. Further, the Internet of Things approach allows the home gateways to be discoverable, whilst the governance module ensures secure accessibility of the domestic data to authorized users and services.

3.3. Interoperability for smart home appliances

A use case which highlights the interoperability benefits of the semantic alignment at the building scale is shown in Fig. 3, which illustrates the hypothetical case of a consumer with both a water

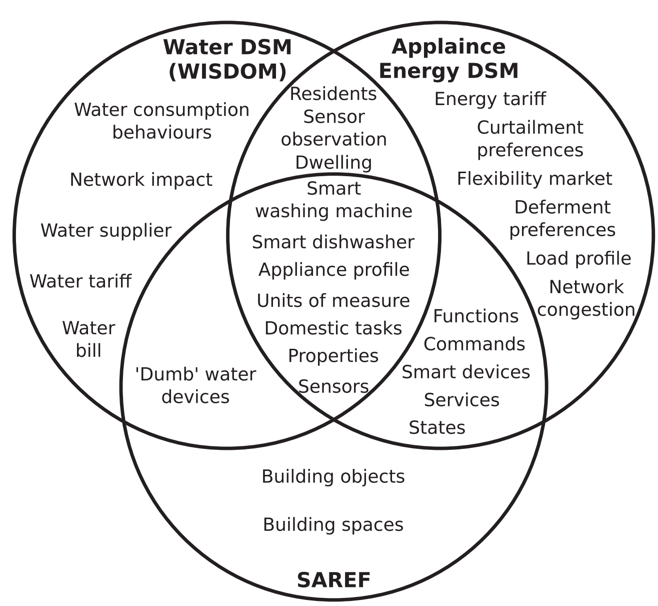

Fig. 3. Object reuse across smart home applications, through alignment with the SAREF ontology.

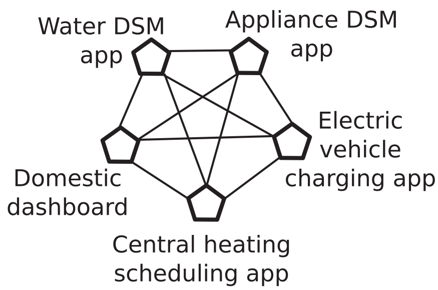

Fig. 4. Mitigation of mapping task growth with increasing entities through a common model.

feedback app and an appliance scheduling app interacting with their devices.

Fig. 3 shows the objects (physical and otherwise) which are relevant to the repositories of both applications, including those which can be reused from WISDOM by simply aligning with SAREF. If a third application is introduced, the previous mappings to SAREF have already been completed, meaning that only one mapping is required to integrate the application, as opposed to mapping to both of the other applications. This is illustrated further in Fig. 4 as a means to avoid exponential mapping tasks in the likely future case of many integrated software artifacts. Also, it is not required for one single common model to gain universal acceptance for the premise of Fig. 4 to hold; even with 2 or 3 common models (each mapped to each other) the mapping task growth is mitigated significantly.

4. Semantic water modeling

As described previously, the ontology development used an iterative process, following the recommendations of the NeOn methodology [26]. A meta-model was developed through reuse of the W3C semantic senor network (SSN) ontology [9] and the socio-technical system (STS) ontology of van Dam [11]. This meta-model was extended to model man-made water system concepts at the

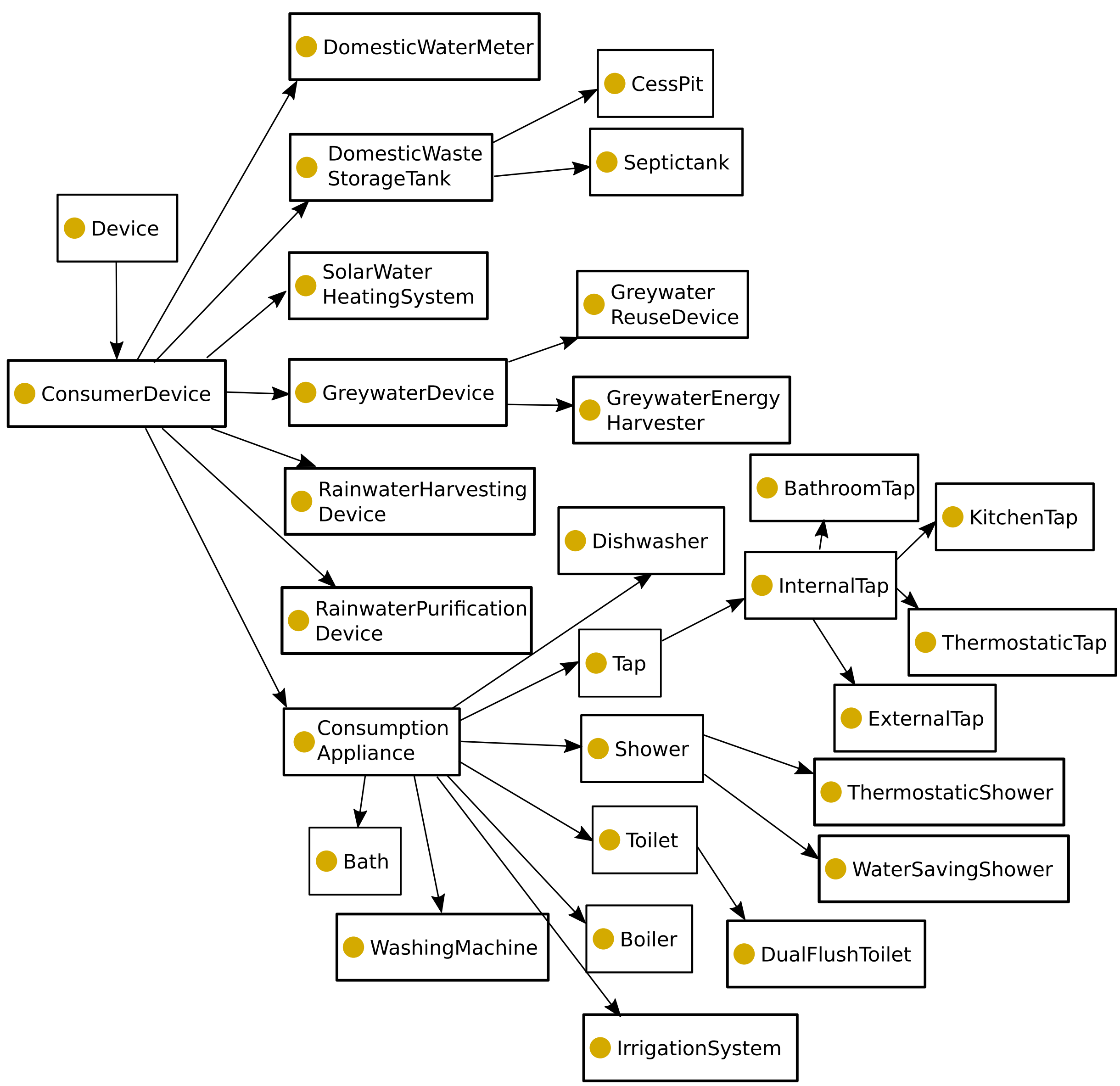

Fig. 5. Excerpt of the domestic water device taxonomy.

building and network levels of detail, as is described in the following sections.

4.1. Building scale model

The semantic model was developed using web ontology language description logic (OWL-DL), and extended the IFC, SSN, and SAREF ontologies at the building scale. This was achieved by modeling the water-consuming appliances and their usage patterns, emerging technologies such as greywater heat recovery systems, the end-users themselves, their behaviors and perspectives, water-consuming activities, and the economic aspects of water consumption.

The approach allowed a thorough contextualization of the dynamic data obtained from water and energy sensors in the dwellings. This allowed data mining for correlations, such as between consumer perspectives on water conservation and their actual actions, thereby improving the accuracy of demand predictions through profiling or machine learning algorithms. An excerpt of the device modeling is shown in Fig. 5, and the socio-technical modeling of consumption patterns is shown in Fig. 6, which are both aligned with the network-scale model described in the next section.

4.2. Building-network semantic integration

In order to integrate building and network management knowledge, each individual dwelling was modeled as a single physical node in the overall water value chain, as shown in Fig. 7, and the consumers were modeled as social nodes, in the interconnected socio-technical system of water management. This was aligned with the network level modeling, which was based on an STS meta-model, and was extended with domain concepts relevant to the social, technical, and cyber-physical aspects of the system. The main implication of cross-referencing datasets in this manner is a reduction in the complexity of building applications across varied sources, as the complexity is handled at the knowledge layer, so data is coherently unified and exposed in a rich manner.

The process resulted in an ontology of 384 classes, including detailed hierarchies of asset types, sensor types, hydraulic variables, contract types, and stakeholders in the domain. Some of the key classes involved in managing real-time data from sensors attached to the physical water network and their relationships are shown in Fig. 8. The sensory concepts shown in Fig. 8 are aligned with the W3C SSN ontology, and broad integration was achieved between the ontology and existing large data models, as discussed in the next section.

4.3. Alignment with other models

One key goal was to produce an open, vendor-neutral, and extensible common model, for reuse in other applications. This allows the semantic web to grow organically and in a modular manner, rather

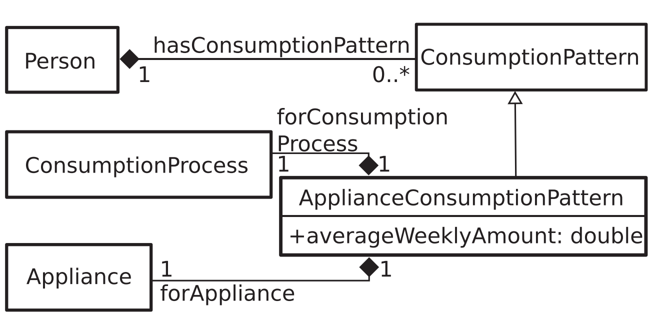

Fig. 6. Modeling pattern for domestic consumption behaviors.

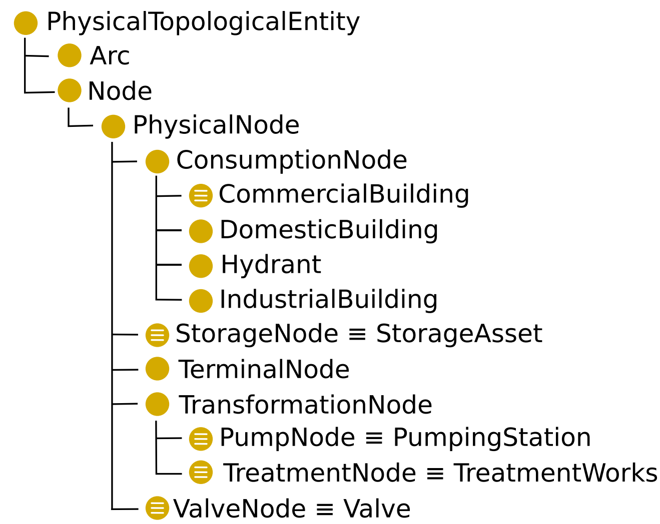

Fig. 7. Topological node class hierarchy showing domestic buildings alongside network level nodes.

than requiring a single monolithic data structure, and so the ontology was aligned with existing mature models.

The main semantic resources identified in the built environment domain were the IFCs, SAREF, and the SSN ontology, which were described briefly in Section 2.3 and Table 1.The INSPIRE Utility schema and WatERP ontology were also deemed highly relevant from the geospatial and water domain respectively. An excerpt of the alignments with these models is shown in Fig. 9, and the specific number of alignments of the ontology with various large data models is shown in Table 3. A large portion of the SSN ontology was reused, as it formed the base of the cyber-physical modeling. The SAREF ontology was aligned at a high level, where the WISDOM ontology then extended it for the water device domain. Many of the SAREF classes are example commands, properties, and states, which were mainly outside of the water domain, so little alignment could be found with these, despite the approaches being highly complementary.

The IFC concepts were aligned with the more generic physical components of the system, such as 'pipe'. The WISDOM ontology loosely constitutes an extension of the IFC water system modeling. When aligning to the IFC, the concepts of the EXPRESS version were used rather than the current version of IFC.owl. This was decided as the EXPRESS version is an international standard, whereas the OWL version is being developed to follow semantic web best practice, whilst maintaining direct compliance with the EXPRESS version [29,30]. This is illustrated in Fig. 10, and future work for the WISDOM ontology includes aligning with the final IFC.owl ontology.

The SAREF ontology models smart appliance, sensory and control concepts, which overlaps with the scope of the WISDOM domestic ontological concepts. It was considered not relevant to control most domestic water-consuming devices remotely (apart from irrigation systems, washing machines and dishwashers).

4.4. Ontology instantiation and legacy system integration

The domain ontology constitutes a vocabulary with which to describe a building's people, behaviors, and devices, as well as water and waste distribution networks, and this was utilized to create semantic model instances for deployment in the system. These also contain real-time data regarding the current state of the water network, such as the recent consumption of a district metering area (DMA). The instantiation of the domain ontology is conducted

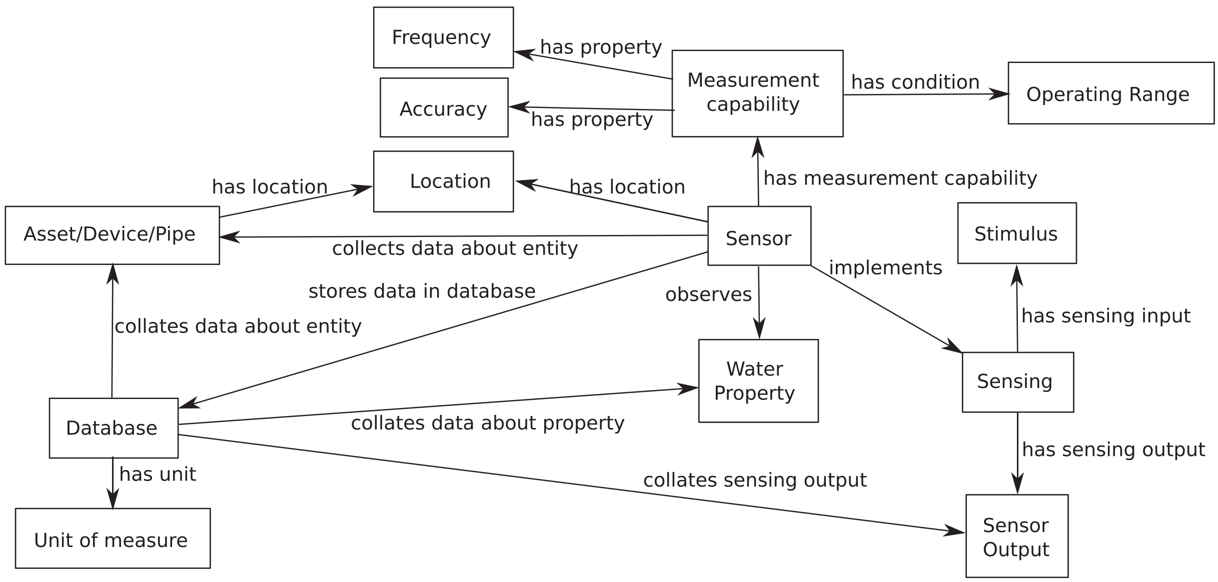

Fig. 8. Main concepts and relationships (inverses not shown) for sensory and physical knowledge integration.

through reuse of legacy data, manual processes at buildings, consumer input through a graphical user interface (GUI), and manual elicitation of expert knowledge.

The cloud platform aimed to integrate with existing ICT systems, as a step change towards smart water. The ontology therefore reuses knowledge available in geographic information systems (GIS) and sensor databases. This was achieved through a Python conversion into resource description framework (RDF) triples. Updates from real-time sensor data, domestic GUIs, and existing supervisory

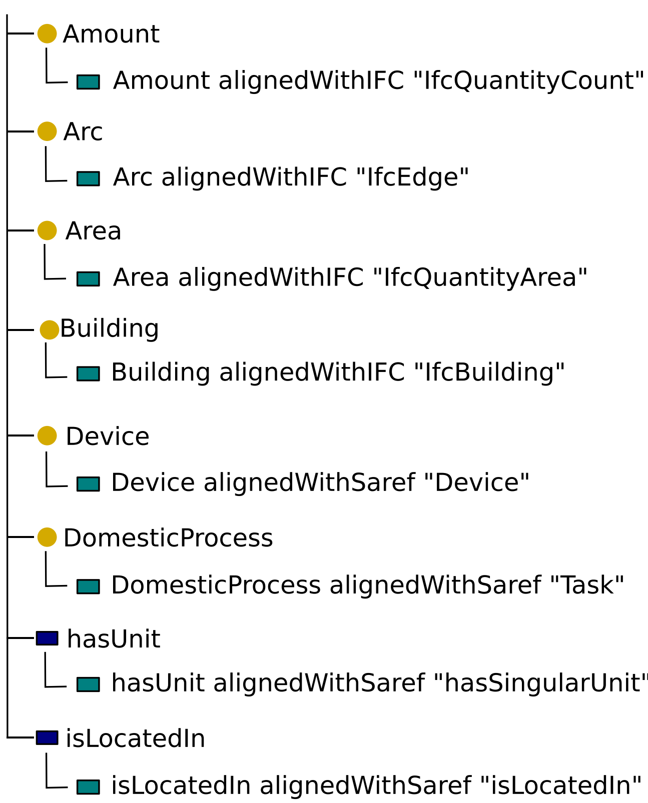

Fig. 9. Excerpt of alignments with IFC and SAREF concepts.

control and data acquisition (SCADA) systems were performed automatically after subscribing to the event bus as shown in Fig. 11. Updating the network description would require an UPDATE SPARQL query, although future work will aim to mask the SPARQL complexity.

Given the ontology's alignment with IFC and SAREF, a partial instantiation was also conducted from existing IFC.owl and SAREF data. This conversion was possible bidirectionally through a simple SPARQL CONSTRUCT query, as shown in Table 4. The resulting model needed to be completed with data outside the scope of the original models for the intended use cases. The extra required data would vary based on whether the original knowledge base fully instantiated its domain ontology, or only used a subset of it.

5. Data integration and analytics platform

5.1. Integrated demand-side management

The deployed system utilized both cloud and edge processing, based on the static domestic and network descriptions, and the dynamic data received from sensors. The hardware installed at consumers' properties was a smart flow meter, a home gateway, and a tablet which served as a graphical interface. This allowed an amount of edge processing, sufficient for consumer monitoring of water usage and comparison with previous trends and goals. The interface also allows the users to input rich semantic data regarding the social entities, consumer behaviors, and smart appliances at the property, to contextualize the dynamic data and allow greater reasoning over observations at the property. A subset of this information was then communicated to the cloud platform, which provided a full description of the building as a consumption node in the overall water

Table 3
Integration between WISDOM ontology and other large data models.

Data model	Total # entities	Semantic alignments
IFC	768	34
INSPIRE utility schema	65 types	39
SAREF	112 classes	16
WatERP	29 classes	29
SSN	80	65

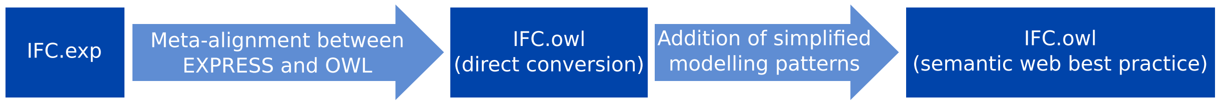

Fig. 10. Ongoing development of ifcOWL from the standardized express version.

value chain, for the purposes of utility decision support, and DSM optimization.

As well as the feedback loop closed at the building level, the work utilized the building data with network data and weather data to deliver an optimized demand-side management strategy, including the sending of targeted interactions, providing users knowledge of the current load on the network and their impact on it. This integration of data across domain perspectives and scales was achieved through the common data and meaning shared between the software entities at the edge and cloud level, such that the home gateways used the same syntax and semantics as the cloud software.

In utilizing consumer data in the cloud architecture, it was critical to preserve privacy and security, and so data sharing between consumers and the utility was carefully managed. The system therefore balanced the benefit of integrating data with the requirement for data security and privacy by distinguishing between private and shared objects. This approach is illustrated in Fig. 12. Critically, this approach of sharing partial world views between agents is well suited for the application of ontologies, which are regarded as ideal for storing and inferring over incomplete knowledge sets due to their use of the open world assumption. The building level conceptual modeling of the water value chain ontology was completely aligned with the broader network and sector-scale model, by modeling both alongside each other. This enabled semantic clarity when using the ontology at either scale and when sharing messages across scales.

5.2. Semantic web service implementation

Building level knowledge was mainly exchanged as RDF data, but also used JavaScript Object Notation (JSON), whilst maintaining homogeneity with the OWL model. This was fed into the data fusion and filtering service before updating the knowledge base through the ontology web service. This allowed the demand management optimization and other intensive services to occur in the cloud, whilst respecting each consumer's own desires and agency.

The ontology service consisted of a water value chain domain ontology common across pilot sites, and instantiations of this ontology, to create a separate knowledge base for each pilot site. The types of classes instantiated included various types of pipe, pump, reservoir, valve, domicile, sensor, people, organizations, natural water bodies, smart meters, appliances, and usage patterns. The domain ontology was instantiated at each site so as to describe the systems at the site sufficiently for the use cases, which didn't require fully

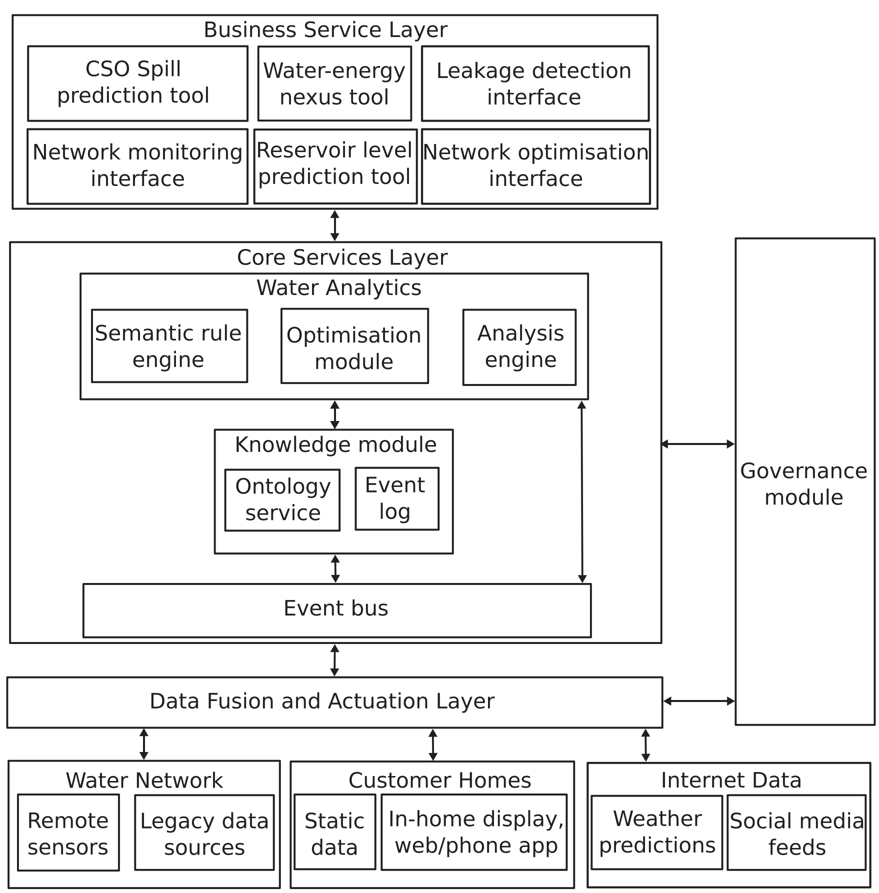

Fig. 11. Functional architecture of the proposed ICT solution.

Table 4
Example schema conversion (prefix statements omitted).

```
Source data:
wisdom:washingMachine rdf:type wisdom:ElectricAppliance, owl:NamedIndividual
wisdom:meter_01 rdf:type wisdom:DomesticWaterMeter, owl:NamedIndividual
wisdom:meter_02 rdf:type wisdom:DomesticWaterMeter, owl:NamedIndividual
wisdom:building_01 rdf:type wisdom:DomesticBuilding, owl:NamedIndividual

SPARQL query:
CONSTRUCT { ?individual rdf:type owl:NamedIndividual, ?NewClass}
WHERE{{ ?individual rdf:type owl:NamedIndividual.
?individual rdf:type ?WisdomClass.
?WisdomClass wisdom:alignedWithSaref ?NewClass }
UNION {
?individual rdf:type owl:NamedIndividual.
?individual rdf:type ?WisdomClass.
?WisdomClass wisdom:alignedWithIfc ?NewClass }}

Output data:
wisdom:washingMachine rdf:type saref:Device, owl:NamedIndividual
wisdom:meter_01 rdf:type Saref:Meter, owl:NamedIndividual
wisdom:meter_02 rdf:typeSaref:Meter, owl:NamedIndividual
wisdom:meter_01 rdf:type Ifc:IfcFlowMeter, owl:NamedIndividual
wisdom:meter_02 rdf:type Ifc:IfcFlowMeter, owl:NamedIndividual
wisdom:building_01 rdf:type Ifc:IfcBuilding, owl:NamedIndividual
```

instantiating the ontology at any one site. The resulting knowledge bases (instances) were stored as persistent RDF triples on dedicated virtual machines within a cloud computing framework, using the Jena TDB triple store within a custom wrapper. The knowledge bases were queried via a RESTful web service, which offered convenience GET functions for most common tasks, as well as a SPARQL endpoint, based on the ARQ package [2].

Apache Jena [3] was used to store and interact with the graph database, which mandated an RDF-centric approach, written in Java. The Jena ontology application programming interface (API) and transactional database (TDB) API allowed rapid deployment of a persistent OWL-DL ontology. Jena stores ontologies using the ontology model class (OntModel), (an extension of the RDF model class), and hence views ontologies as more descriptive versions of RDF models. The built-in Jena reasoner was used to infer new knowledge from existing knowledge, and hence created RDF triples. Persistence of the ontology was provided by the Jena TDB layer, meaning that data isn't lost if the service is terminated or crashes.A custom web service was built instead of using Fuseki, which was found to be time consuming to extend and integrate with the other components. The knowledge management service is illustrated in Fig. 13. A custom API was developed which provided a SPARQL endpoint and a number of convenience functions for common tasks, such as retrieving the latest sensor reading by passing its ID. As the knowledge management component is primarily a back-end web service, it had no GUI and relied on command-line administration. However, given the use of Jena, which has wide community support and several open source user interfaces, a GUI could be developed for managing the server with relatively little effort. A front-end interface was developed to showcase the system integration function of the approach, which is discussed in the following section.

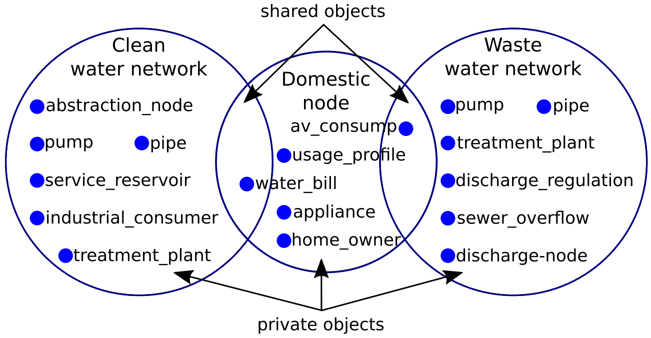

Fig. 12. Integration of object knowledge across the water value chain to highlight the capability for data privacy.

The main use cases of the ontology service are requests for information from other WISDOM system components, and updates to the knowledge bases following sensor events or when consumers change static knowledge about their dwelling, such as registering new appliances or behaviors. The RESTful GET method which executes a SPARQL SELECT query accepts a URL-encoded SPARQL request and executes this using the Jena ARQ package. The result of the semantic web service software is knowledge about the water network, formatted in either CSV, standard SPARQL JSON response [50], a simpler but proprietary JSON format, or an RDF graph. As well as integrating data from sensors and static data, the ontology can also integrate results from analytics services and other application layer software by storing their outputted knowledge and providing discovery capabilities.

The deployment of the ontology as a web service supports the benefits of a service-oriented architecture [19] and hence allows plug-and-play capability with other software components of the WISDOM architecture, and potentially beyond. After development, the software was deployed in a secure cloud environment.

5.3. Integrated supply-side management

As well as using the building scale data with network-scale data to deliver DSM functions, the contextualized consumption data was used to better inform upstream demand-optimized management decisions. This primarily involved the optimization of pumps and reservoir levels to minimize energy consumption and water losses, based on the current and predicted demand profiles, and network knowledge such as pipe leakages, and weather predictions. Also, in the waste water network, the consumption data helped to infer the volumes of waste water entering the network, which was used alongside weather data to predict combined sewer overflow events. These applications were delivered through self-contained business services, which utilized the analytics, storage, and governance, of the core services of the system.

The system was conceptually arranged into 4 architectural layers: sensing infrastructure, data acquisition and actuation, core services and business services, as shown in Fig. 11 previously. The core services layer contains the system's semantic integration service, optimization and analytics services, event bus and governance module. These core components utilize data communicated from the sensing infrastructure to the event bus via the data acquisition layer, and are delivered to users through the GUIs and edge analytics which form the business service layer. The key innovation is the use of the core services to integrate analytics across heterogeneous data sources by standardizing data syntax and meaning, which is tested in the following section.

6. Validation and experiments

The validation of the process adopted and the interoperability artifacts produced was conducted through 2 stages: firstly the validation of the domain model as an accurate, sufficient and shared conceptualization of the domain. Secondly, the validation of the ontology instantiation and deployment as a web service, through software testing, was conducted. This was then reinforced through experimentation in the scenario of smart home software interoperability.

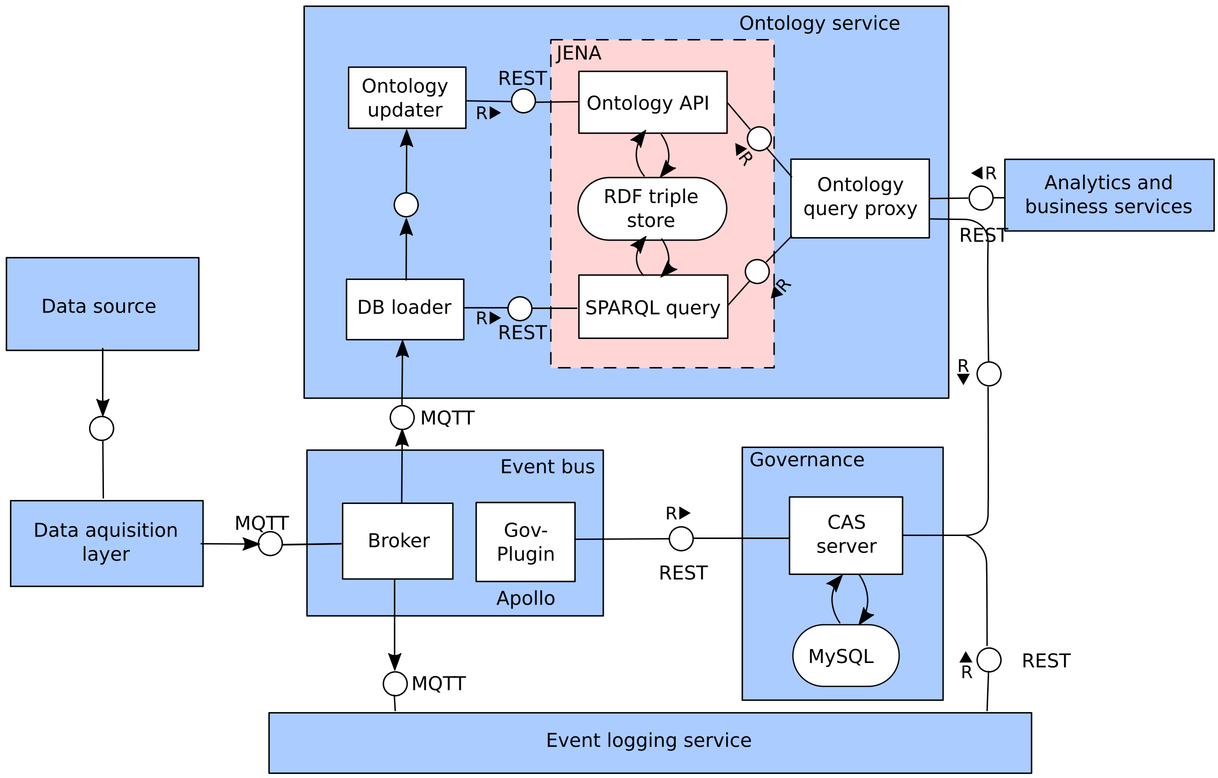

Fig. 13. System components of the proposed middleware, showing its role between data sources and analytics.

6.1. Ontology verification and validation

The validity of the domain ontology was checked in an iterative manner, starting with verification through simple automated consistency checking to ensure correct syntax usage, followed by competency question 'litmus testing', and the validation of the ontology by domain experts within the project. Finally, the ontology was validated by a range of experts from across the domain, independent to the project. The results of this process are now briefly outlined.

Preliminary consistency checks were successfully conducted on the ontology within the Protégé ontology development application. This shows that the ontology is a valid use of OWL syntax, serialized in extensible markup language (XML) notation; that the process had in fact produced a semantic model. The second validation stage was to test whether the semantic model produced met the criteria it was intended to meet; the competency questions prescribed in the initial scoping stages. These covered the breadth and depth of the domain deemed necessary to be modeled, resulting in 40 questions which the ontology needed to answer, such as:

- "What devices are present in property X?"
- "What is the consumption profile of device X?"
- "What are the water consumption views of person X?"
- "What is the current water pressure in pipe X?"
- "How much water is currently in reservoir X?"

These questions could all be answered when formalized as SPARQL queries, such as shown in Table 5, where the queries were answered in circa 15 ms. Specifically, the location of nodes, assets, and sensors in the network were stored (including elevation), as well as the lengths of utility network pipes, and the network's topology. Modeling pipes in buildings was not necessary for the use cases, although this could be achieved with little difficulty through the ontology's alignment with IFC.owl.

The ontology was then tested to determine if it is an accurate, sufficient and shared conceptualization of the domain. This was conducted initially within the project, through the industrial partners in Wales and Italy. The high level approach adopted was agreed as suitable, and the majority of the detailed modeling was also agreed. Some changes were made based on the feedback received, including the addition of actuator concepts in parallel to the existing sensor concepts. The revised ontology was then fully agreed on by these partners, and the same process was conducted with representatives from 8 external companies from across the European water industry. Again, the model was broadly validated and a handful of minor additions were suggested and incorporated. Some of the comments from the expert validation session were:

- "The ontology addresses the problem of interacting between tools, such as GIS, Systems Applications Products (SAP), and customer data"
- "Include alarms as well as sensors"
- "Governing body is also called 'regulator'"
- "Include water testing company"

The 2nd comment was addressed by aligning with and extending the alarm ontology of the WatERP project. The 3rd comment has been addressed by adding a comment to the class, and the 4th comment was addressed by including a 'waterTestingCompany' class. The majority of the comments were advisory or generic, such as:

- "The work could be considered as a type of enterprise service bus"
- "An ontology is also called a taxonomy"
- "Sensors could also be 'social sensors', which report numbers of tweets etc. "
- "Collaboration relationships exist between utilities which share a water resource"

Table 5
Example competency questions (prefix statements omitted).

Natural language question:
What is sensor E2000's current reading?

SPARQL query:
SELECT ?reading
WHERE {
wis:E2000 rdf:type wis:LevelSensor.
wis:E2000 wis:hasLatestOutput ?output.
?output dul:hasDataValue ?reading }

Output (CSV format):
reading
2 .00

Natural language question:
What is Pipe_01's material?

SPARQL query:
SELECT ?material
WHERE {
wis:Pipe_01 rdf:type wis:Main.
wis:Pipe_01 wis:hasMaterial ?material }

Output (CSV format):
material
wis:PVC

Natural language question:
What is the length of Pipe_01?

SPARQL query:
SELECT ?length ?unit
WHERE {
wis:Pipe_01 rdf:type wis:Main.
wis:Pipe_01 wis:hasLength ?length
wis:Pipe_01 wis:hasLengthUnit ?unit}

Output (CSV format):
length, unit
3, meters

6.2. Software testing

Following the validation of the domain ontology, this was instantiated for a real Welsh pilot site by using survey data from residents as well reusing GIS data and data from sensor, social and asset databases, as well as heuristic knowledge, operating manuals and product specification sheets. This pilot site knowledge base was then deployed in the cloud based system described previously; with live data updating the instantiation every 15 min. Testing was conducted as to the performance of the ontology service within the cloud platform for both retrieval and updating of data, through the RESTful GET and PUT methods. These utilized the SPARQL SELECT and UPDATE functions respectively.

The service was deployed on a personal laptop (i5-3317U CPU @ 1.7 GHz, 8 GB memory, Windows 7 64-bit) so as to test the service's performance, rather than including latency by testing the service in a cloud environment. The semantic model tested was an instantiation of the water value chain and domestic model, consisting of 1722 named individuals and circa 15k triples. 11 identical GET requests were issued to the service to retrieve the current sensor reading at an arbitrary sensor in the network, and this test was repeated 5 times, with the service restarted between each test to reset any caching which had occurred. A similar testing protocol was conducted for PUT requests to update the sensor reading, and more realistic testing was conducted by varying the GET request issued, varying the PUT request issued, and finally alternating between GET and PUT requests. The results of the GET request testing are shown in Fig. 14 below, which clearly shows caching, and that the typical response time which could be expected would be circa 550 ms. The PUT testing indicated a very similar trend, but with approximately an additional 100 ms response time across the requests. Changing the request between subsequent requests didn't result in any significant difference in the response time to these results.

The ontology service consumed circa 113MB of memory on start-up, and following caching, peaked at circa 800MB after 20 requests. Following start-up, a request consumed on average 81% of the available processing power, but after 5 requests this reduced and stabilized at circa 11%. Further work will investigate the platform's scalability and compare implementation choices, such as alternatives to Apache Jena.

6.3. Data model integration and schema conversion

One intended benefit of the approach was to integrate existing data models, which are formalized in different data formats, and often using heterogeneous domain perspectives. This was achieved in two ways. Firstly, at the intersection of existing models, equivalency and alignment between them and the WISDOM ontology meant that the shared data could be interoperated across the models, an example of which is illustrated in Fig. 15. Note that mappings were made between the existing models and the developed ontology, rather than between the existing models directly, hence promoting interoperability through a common model. Secondly, where the models described similar or related concepts, semantic methods such as graph modeling techniques, abstraction, and mereological relationships were used to express a 'path' relating the concepts. This provided a coherent web of concepts and relationships which integrates the models that exist or relate to the water domain. One outcome of this was ease of integrating GIS data with telemetry data, where the development of a GUI which retrieves data from these traditionally isolated sources was significantly simplified. This GUI is shown in Fig. 16.

The benefit of using the semantic web approach to promote interoperability across software with different domain perspectives was tested by performing a schema conversion from a knowledge base of devices instantiated within the WISDOM ontology into a set of SAREF individuals. This RDF data could then be used within an UPDATE

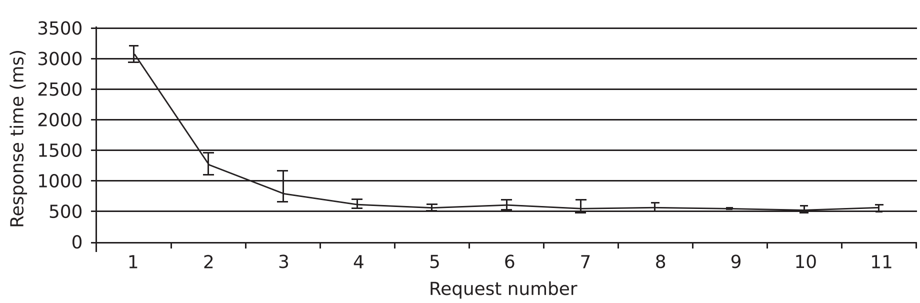

Fig. 14. Average response time of the ontology web service across several SELECT queries.

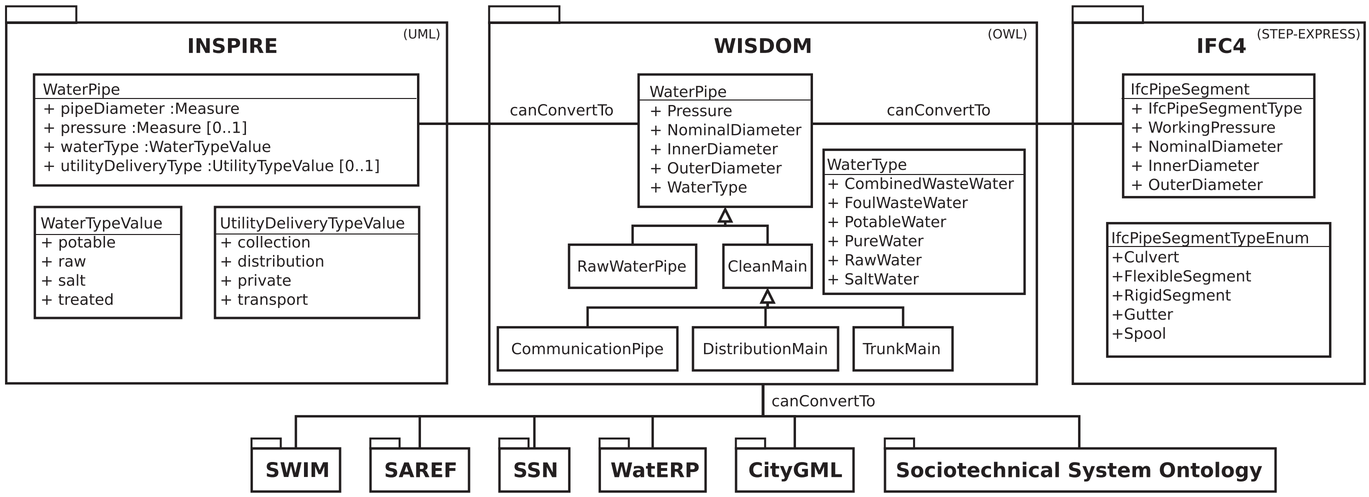

Fig. 15. Illustration of data integration between existing data models.

SPARQL query to add the individuals to a SAREF knowledge base. A similar approach could be used in the more likely case of converting to an application specific ontology which is also mapped to the SAREF ontology, by loading both ontologies and the SAREF ontology into memory. This could also convert object and data properties between knowledge bases if appropriate mappings were formalized. The conversion was conducted through a simple SPARQL CONSTRUCT query. Excerpts of the source data, SPARQL query and output data were shown in Table 4. Careful federation of the shared objects would be required to manage access rights and update priority, for example whether the application using the target knowledge base could update properties regarding individuals in the source knowledge base. The implication of this is that software developers could utilize data from across these domains far more easily, more powerfully, and with more confidence that the data was being correctly understood and contextualized.

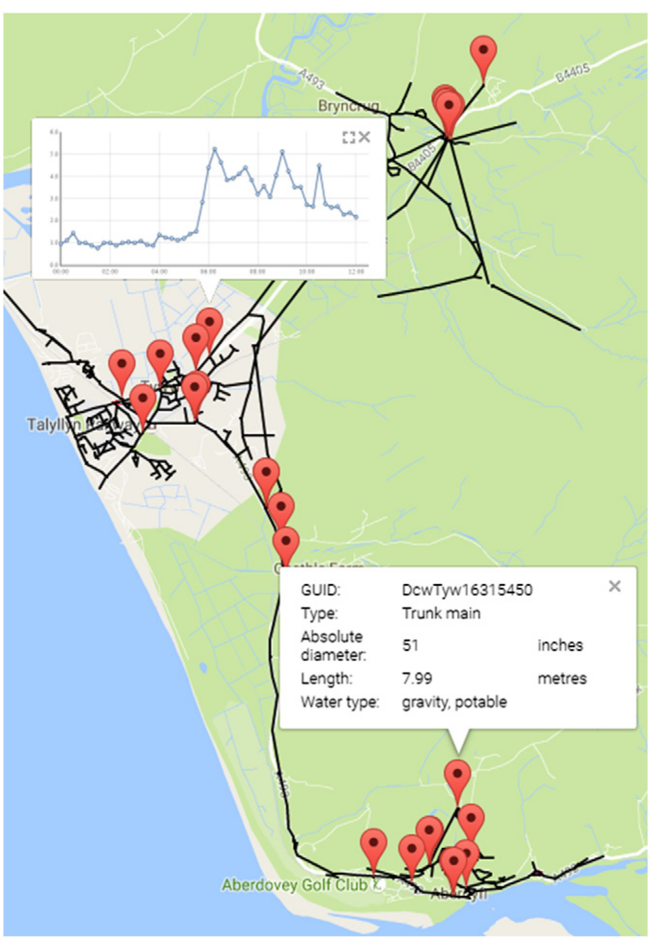

Fig. 16. GUI which illustrates the integration of GIS and telemetry data.

7. Discussion

The proposed system aims to support intelligent water sensing, analytics, services and interfaces, towards optimization of the water network at the utility level, as well as in homes, through interoperability and demand-side management. A key innovation of the proposed solution, and the focus of this paper, is the integration of heterogeneous data sources and varied analytics and visualization components, through a domain ontology, which has been instantiated and deployed within a dedicated web service. The successful scoping, creation, alignment, validation, and software testing of the ontology and web service are the main achievements presented. The utility of such an approach has been highlighted within the network optimization service, as the ontology web service allows this to utilize data from across the water value chain at runtime.

It has been discussed that delivering demand-side management strategies requires the integration of building and network-scale data. This has been achieved through semantic alignment of the concepts across the demand and supply sides and the development of software to expose this to applications. Specifically, a coherent data schema for demand-side appliances, socio-technical concepts, and smart metering data, as well as supply-side GIS, telemetry, and socio-technical data, has been produced. The results presented show that the ontology and its software deployment are sufficient as a conceptualization of the water domain for use within a near real-time decision support system. The validation of the domain ontology displays that it is agreeable amongst a wide range of stakeholders within the industry, and that it could contribute significantly to the international standards identified by ICT4Water [18] as critical towards the penetration of ICT within the water domain. Further, the benefit of the approach of interoperating programs which have heterogeneous internal data structures and domain perspectives through semantic alignment has been demonstrated and use cases for this presented. The software testing conducted indicates that the performance of the ontology service and SPARQL endpoint, which represents an extension of the Apache Jena APIs, was sufficient for the velocity and volume of requests and updates deemed typical within the target software platform's use cases.

The key novelty presented lies in the semantic representation of the water value chain as a detailed manifestation of a socio-technical-sensory system, at the network and building scales. By describing the system of systems in terms of its geospatial components and its features from other domain perspectives, this goes beyond the ontological modeling conducted elsewhere to offer greater depth and breadth. Specifically, the 'observation and measurement ontology' of the WatERP ontology is similar to the WISDOM sensor ontology, due to their shared roots in the W3C SSN ontology [9], although the WatERP ontology's alignment with the SSN ontology is shallow; only reusing a few high level concepts. However, the WISDOM sensor ontology thoroughly reuses the SSN ontology, and extends it directly in order to be relevant to the water domain. The WatERP 'supply and demand ontology' contains concepts from across the rest of the WISDOM ontology, but again only captures high level concepts such as physical element types (storage, transfer, etc.) and a few types of actors (bulk water suppliers, consumers, regulators and water utilities). Hence, the WISDOM ontology is suited to a different purpose to the WatERP ontology. Further, the WISDOM ontology captures domestic knowledge, so as to allow the integration of consumers within the water value data chain and hence contextualize smart meter and behavioral data.

As well as a contribution towards the water industry, the presented alignments with the IFC as well as the use cases and architecture shown, contribute towards the field of building information modeling, by allowing the application of the paradigm in the operational phase of buildings. This was achieved by extending the IFC with operational concepts in a domain ontology, and by integrating static data and near-real-time data in a knowledge base, with historical data in an aligned 'noSQL' database.

Smart water systems are emerging as a method of leveraging ICT and artificial intelligence to improve the key performance indicators of water networks by utilizing existing sensor networks where available, deploying new sensors, integrating data silos within and across organizations, and applying artificial intelligence techniques matured in other domains. This aims to improve the efficiency and longevity of water networks as well as reducing energy consumption, water losses and costs whilst improving consumption profiles through demand-side management strategies. Whilst smart water networks are still an emerging trend, their benefits appear promising, and despite most water networks not utilizing sensor networks sufficiently to currently be considered 'smart', early adopters of the approach are paving the way, and the likely future scenario of water networks enriched with may smart devices will require a robust, flexible and scalable interoperability solution. Further, with the BIM paradigm gaining global momentum, utilizing design and construction data alongside operational data, IoT solutions and sensor descriptions holds the potential to unlock vast cost, resource, and CO_2 emission savings through intelligent management.

Ongoing work includes the development of a custom semantic inference engine to allow the ontology service to directly contribute to the analytics functionality of the system through semantic web rule language (SWRL) rules. Also, to mitigate the scalability challenges which ontologies represent regarding processing power, the application of distributed RDF stores is being investigated, to further mimic and benefit from the highly distributed nature of the existing web. It is also important to note that whilst interoperability benefits are observed without the existence of a single standardized semantic model for the domain, a model which represents a standardized domain consensus ontology would be highly valuable to further reduce the number of semantic alignments required to widely interoperate perspectives and software in the domain.

8. Conclusion

Applying ICT and artificial intelligence to water management holds similar potential benefits to those in smart grids and smart cities, especially with the recent growth of BIM. However, semantic interoperability is a critical obstacle [15,18], and existing ontologies leave significant gaps in the smart water domain. This paper has proposed a detailed and expressive ontology, and a semantic web service, which aim to integrate GIS and topological network descriptions, telemetry data, BIM, smart metering, and smart appliances, which takes a step towards filling this gap. The ontology was described and then tested, before example use cases and a software deployment were discussed. The findings suggest that semantic web and IoT technologies can merge to bring together large models, such as in BIM, with dynamic data streams, to support powerful applications in the operational phase of built environment systems.

Acknowledgments

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