Achieving Smart Water Network Management Through Semantically Driven Cognitive Systems

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Abstract. Achieving necessary resilience levels in urban water networks is a challenging proposition, with water network operators required to ensure a constant supply of treated water at pre-set pressure levels to a huge number of homes and businesses, all within strict budgetary restrictions. To achieve this, water network operators are required to overcome significant obstacles, including ageing assets within their infrastructure, the wide geographical area over which assets are spread, problematic internet connectivity in remote locations and a lack of interoperability between water network operator ICT systems. These issues act as key blockers for the deployment of smart water network management technologies such as optimisation, data driven modelling and dynamic water demand management. This paper presents how the use of a set cognitive analytic smart water components, underpinned by semantic modelling of the water network, can overcome these obstacles. The architecture and underpinning semantics of cognitive components are described along with how communication between these components is achieved. Two case studies are presented to demonstrate how the deployment of smart technologies can improve water network efficiency.

Keywords: Smart water networks · Semantics · Resilience · Cognitive systems

1 Introduction

Urban water systems are responsible for abstracting, treating and delivering clean water. They also collect, transport, treat and release waste water. These systems, are among the most critical of a nation's infrastructure and are complex systems, spread over a wide geographical area, utilising ageing assets. These systems are operated under tight financial constraints, while also operating at near capacity. This increasing demand on water resources requires more efficient water management. The ability to intelligently monitor water networks and analyze real time information is one way to enable better management of the conflict between water demand and provision [1].

To overcome these issues, the water sector is undertaking a transformation using smart systems with water networks augmented with smart technologies having been noted to promote efficacy, efficiency, and resilience in water infrastructure [2, 3]. A big

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part of these systems is the use of technology such as sensors, analytics software, and decision support tools. However, there are obstacles to deploying these smart technologies within water networks; (a) the decentralised structure of water networks where assets are managed and monitored by local technicians, with limited central monitoring/control, (b) the wide geographical area over which assets are spread, (c) problematic/expensive internet connectivity in remote locations, and (d) a lack of interoperability between water network operator ICT systems [4].

In overview, current systems to support the usage of these smart technologies are lacking in integration between sensors/actuators, analytic tools and, furthermore, lack the ability to contextualise the large amount of data collected from urban water systems in a way that promotes scalability, reliability, portability and future adaptability.

The objective of this research is to determine if the use of a cognitive systems approach overcomes the obstacles faced by water network management systems, and, secondly, if the use of semantics is an appropriate way of storing and contextualizing data within and about this system, thus improving interoperability. Thus, this paper presents a water management system augmented using cognitive software components, underpinned by a semantic model of the water network. The key novelty of this work is the application of cognitive system to large-scale water network management and, secondly, the utilization of semantics to contextualize; (a) data regarding the physical water network and (b) the structure of the cognitive system managing this network. The systems performance and novelty will be demonstrated by describing how these components can improve the performance and efficiency of water network operation.

The remainder of this paper will be structured as follows; Sect. 2 will present key background, Sect. 3 will present the overall architecture of a smart water network management system, focusing on the cognitive system components. Section 4 will provide an overview of the semantic model that underpins this management system. Section 5 will present two case studies demonstrating the functionality of this approach. Finally, Sect. 6 will conclude the paper.

2 Background

This section will provide a brief introduction to the two key topics discussed in this paper; (a) urban water systems, (b) their conceptualisation through semantic modelling and (c) the use of cognitive systems to manage physical assets in real world systems.

2.1 Urban Water Systems

Urban water systems can be defined as all processes and artifacts pertaining directly to the delivery of potable water to users and the safe removal of both foul and surface waters. The major processes of urban water systems include: (a) **water abstraction:** the extraction of water from a source, (b) **water treatment:** the purification of water, (c) **water distribution:** the process of distributing potable water from treatment plants to consumers, (d) **water usage:** utilization of water, (e) **wastewater collection:** collection and conveyance of wastewater to wastewater treatment plants and (f) **wastewater treatment and discharge:** the removal of contaminants.

2.2 Semantic Modelling

For software and humans to use data, they must derive knowledge from the data i.e. for a person to use a temperature to decide about what to wear, they must know that 'the temperature' is referring to an air temperature according to a specific unit of measurement. These semantics are typically implicit; a person can implicitly derive knowledge from a temperature with ease. In a software context, this translates to a developer evaluating the implicit semantics of data when building an application. To solve this problem of implicit semantics a semantic model can be used.

A semantic model describes the objects in a domain, and the relationships between them, in a machine interpretable manner. The use of semantic models can overcome the need for explicit integration of semantics within specific applications, reducing the time and cost necessary to develop these applications and resulting in applications that are portable and interoperable with other software components [4]. Semantic modelling has already seen significant use in the smart construction and smart cities fields [5]. However, other than recent work by the authors in [4] very little modelling widely adopted, or standardised in the water sector.

2.3 Cognitive Systems

Cognitive systems are systems of software components that exhibit cognitive ability. More specifically, these are components that can adapt their operation through their perception of the system in which they are deployed [6]. Cognitive systems are often described as being stateful, with the ability to perceive and contextualize the system in which they are deployed, and adaptable, possessing the ability to adapt their behavior to changing conditions. Cognitive systems have already seen considerable utilization in the management of the built environment. They have been utilized to manage power demand within smart grids [5] using a system of cognitive home gateways. They have also been utilized to add intelligence to the built environment, through intelligent spaces/zones/buildings and districts [7]. Finally, cognitive systems have been utilized in the smart cities context [8] to provide a cognitive management framework to show why and when objects in a smart cities system need to be connected, to enhance existing services and applications. However, despite this, the use of cognitive systems in the smart water field is rare, with their usage restricted by the slower pace of smart technology deployment currently encountered in this domain [4].

3 Smart Water Network Management

Our cognitive smart water network management system is a multi-layer event based systems featuring a series of cognitive edge services. As described previously, this system exhibits cognitive functionality to overcome issues commonly faced in the smart water field i.e. (a) the decentralised structure and wide geographical area of water networks, (b) problematic/expensive internet connectivity, and (d) lack of interoperability. The key cognitive aspects of the system are the ability of each edge service to independently manage itself, its communication and the analytical tasks it performs, based on characteristics that are specified within the semantic model. The system is broken down into two layers, core and edge. The core components operate over the entire urban water system and are generally hosted and operated centrally by water network operators. The edge components consist of a series of cognitive edge services, each of which is located at distributed locations within the water network and is responsible for managing aspects of the water network in that local area. Physically these edge services can be deployed on a variety of hardware from standard desktop computers, to custom made gateway boxes (left of Fig. 1) to small integrated controllers (right of Fig. 1).

Fig. 1. Edge service deployment methods

The detailed architecture of the system is shown in Fig. 2 and is now described in more detail:

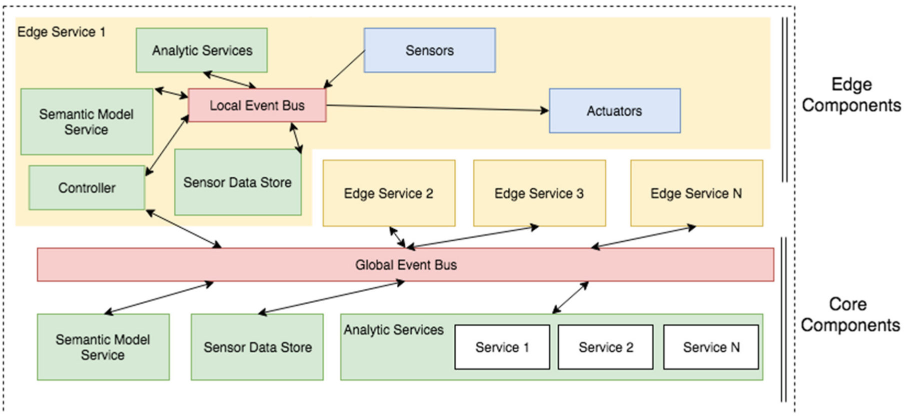

Fig. 2. Water network management architecture

Core Components: There are several core components; (a) a global event bus - responsible for distributing events to all other system components and edge services, (b) a sensor data store that archives all events from the message exchange, thus providing an historical record of all sensor readings, actuations and other event traffic, (c) a semantic model service - responsible for providing a virtualized representation of all aspects of the urban water system, through the use of the systems semantic model, and (d) a series of analytic services that perform analysis and generate new knowledge.

Edge Components: At the edge the system consists of a series of independent services that each consist of several components; (a) a local event bus - responsible for distributing events to all other components within the edge service, (b) semantic model service – that provides access to the semantic model, (c) a sensor data store that stores all data within the edge service, (d) a series of analytic services that act on the data stored within the edge service, (e) sensors/actuators within the water network that are connected to the edge service, and (f) a cognitive controller – that manages the operation of the edge service.

Communication between all components utilizes the common 'vocabulary' provided by the semantic model. This ultimately provides a common interface for software components to share data through that enriches sensed data with context and meaning. Additionally, edge services exhibit cognitive behavior through the cognitive controller's ability to intelligently manage adaptable analytic services. Each analytic service is problem specific, but the cognitive controller is a generic component that manages edge services based on characteristics specified in its semantic model. The key functionalities of the controller are to manage; (a) communication between the edge and core services, (b) the upload/download of event data between edge and core services and (c) invocation of the analytic services. Thus, the cognitive controller is the key enabler in overcoming issues of problematic/expensive internet connectivity in remote locations within water networks, by intelligently managing the use of the available internet connectivity following a set of characteristics specified in the semantic model.

4 Water Network Semantic Model

This section will describe the underpinning semantic model that is used to contextualise data originating from water network and, additionally, manage the cognitive aspects of the water network management system. The semantic model is divided into four distinct sub-models covering; (a) catchment, (b) sensors, (c) social aspects and (d) cognitive systems. Due to the scope of this paper only (a) and (d) will be discussed.

The water catchment model describes the concepts and relationships relevant to the physical infrastructure of the water value chain. This model defines a water network as a collection of nodes connected by arcs, where nodes represent assets (i.e. pumping stations, and reservoirs) and arcs represent pipes. Each node is described by its geographic coordinates, elevation, and by its arcs. The main classes and relationships of the catchment model are illustrated in Fig. 3, in this figure arrows with solid heads represent relationships, arrows with hollow heads represent sub-types.

The cognitive system semantic model describes the structure of the water network management system itself, conceptualizing the make-up of the water network management system. This model describes the edge services present and the core analytic services that are currently deployed. This includes describing what analytic services, sensors, actuators are attached to each edge service, and the connectivity that is present between edge and core services. This includes the description of connectivity rules/restrictions, and data transfer aggregators that apply. Table 1 shows the various configuration options that are currently describable by the semantic model.

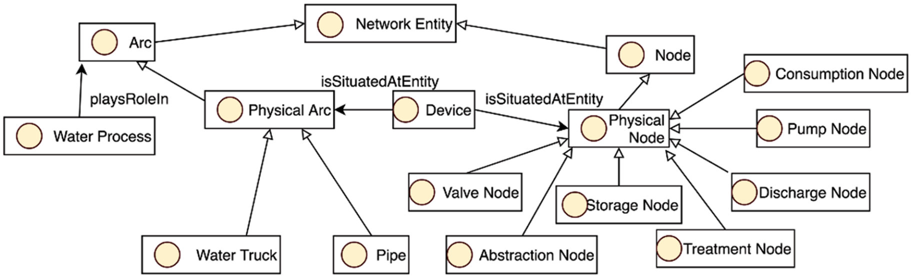

Fig. 3. Water catchment model

Table 1. Configurable properties for edge services.

Property	Description
Continuous	Service Execution - Services continually executed
Timed	Service Execution – Services executed at timed intervals
Event	Service Execution - Services executed based on received events
Connection	Service Execution - Services executed when connection to the core services exists
Availability	Connectivity Restriction - Edge service attempts to connect to core services whenever available
Timed	Connectivity Restriction - Edge service attempts to connect to core services at specified time interval
Priority	Connectivity Restriction - Edge service connects to core service to transmit high priority events whenever they are encountered. If no connection is available connection will be established as soon as available
Throttled	Connectivity Restriction - Data transmitted in each period will be limited
Connection Count	Connectivity Restriction - Number of connections in each period will be limited
All Updates	Connectivity Restriction - When connected to core services download all events received since last connection
Specified Updates	Connectivity Restriction - When connected to core services download all events matching a specified pattern received since last connection
High priority	Connectivity Restriction - When connected to core services download all high priority events received since last connection
Subsampling	Data Aggregator - Applies a specified subsampling method to the data over a given period i.e. transmit only hourly averages
Filtered	Data Aggregator - Filter out events that match a specified pattern from transmission
Presence	Data Aggregator - Transmit only the presence of specified events

5 Case Studies

This section will present early results of two case studies that have been developed to validate the applicability of this work. In both cases the development of analytic services has been eased using the semantic model to provide services with a standardized way of communicating/receiving information. However, cognitive aspects of each study differ and are reported in the following subsections.

5.1 Leakage Detection

This case study enables the detection of faults (such as leaks/pipe blockage) within a water network. The edge service in this case study is deployed at remote areas of pipeline where connectivity is either not guaranteed or costly. This edge service consists of two separate analytic services; a night flow service designed to detect smaller leaks and a burst detection service. To overcome communication issues this service will configure itself to produce and consume minimal data, reporting only detected leaks to the core and only receiving events that communicate updates to the semantic model (required to ensure it can correctly contextualize itself within the water network).

Night Flow: This is triggered on a timer when a flow reading taken near to 0200 is received. This service utilizes the water network semantic model to estimate the minimum night flow downstream of the point being monitored. If the measured night flow exceeds the estimated minimum flow by a significant amount, leakage is reported using a high priority even that is immediately communicated to the core services.

Burst Detection: The burst detection service is a simple data driven model that uses local sensor data to estimate the average flow at a given time of day. Whenever a new sensor reading is received, this service will update the data driven model with new sensor data, then, if the measured sensor data is significantly higher than the average for that time of day, a high priority leakage event is generated.

5.2 Data Driven Modelling:

This case study focuses on waste water pumping stations with combined sewer overflow tanks, many of which are in remote locations, thus data connectivity and costs are common issues. The goal of this case study is to use data driven models to predict the status of the overflow tank, and thus alert water network operators when it is expected to spill. Currently, water network operators can only detect a spill after it has occurred. This service consists of two analytic services that execute at timed intervals; a model updater and a predictor. To overcome connectivity issues this service will configure itself to connect to core services on a daily to transmit updated sensor data.

Model Update: This service updates the data driven model based on new data available from the water network. This service interrogates the existing data driven model on the edge service together with the water network catchment model to determine the data required to update the model to better reflect the current state of the water network. These data requirements are used to restrict the event updates downloaded from the core services. Once downloaded at the next timed connect the updated data is used to improve the existing data driven model.

Prediction: This service performs predictions using the data driven model at timed intervals. Should a prediction be produced that indicates the possibility of a spillage then this is communicated as a high priority event and the edge service will be immediately transmitted to the core services.

6 Conclusion

This paper has presented how the use of a set cognitive smart water software components, underpinned by a semantic model of the water network, are able to overcome obstacles to the adoption of smart technologies. These include the wide geographical area over which assets are spread causing problematic/expensive internet connectivity and the lack of interoperability between software systems.

These are underpinned by a semantic model, that provides superior interoperability between software components. This system also supports the deployment of cognitive services that can function intelligently independently of core systems components ensuring efficient and continuous operation of isolated components even when continual connectivity is not available or guaranteed. This paper has demonstrated the functionality of this approach through case studies showcasing how the water network management system can integrate analytic tools performing leakage detection and predictive modelling of the water network. In the future, more complex cognitive services must be developed to further validate the approach, current research directions include model predictive control of pumping and demand side management of domestic water usage.

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