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Enabling IoT-enhanced Data Models for Context-aware Hydropower Plants

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Abstract

Hydroelectric power, or hydropower, harnesses the potential energy of water descending from higher to lower elevations to generate electricity. As a well-established and cost-effective renewable energy technology, it not only produces power but also supports significant water management services. The integration of Internet of Things (IoT) technologies in hydropower plants has shown significant potential in enhancing monitoring, efficiency, and control capabilities. However, current implementations often lack a holistic and standardized approach to contextual modeling. To address this gap, this paper presents a comprehensive approach to modeling the structural and operational components of hydropower plants (HPPs) using NGS-LD data models. We propose detailed NGS-LD data models that incorporate both static properties (e.g., location, structural attributes), relationships (e.g., component interactions, hierarchical dependencies) and dynamic properties (e.g., real-time sensor data, operational status). These models are designed to facilitate efficient data integration, support decision-making processes, and enable the development of interoperable and replicable IoT applications for smart hydropower plants. We validate our approach through deployment and testing on a federated context broker architecture using real-world data from HPPs.

CCS Concepts

• **Computing methodologies** → **Modeling methodologies**; • **Information systems** → **World Wide Web**; • **Computer systems organization** → *Embedded and cyber-physical systems*.

Keywords

Renewable Energy, Data Models, Internet of Things (IoT), NGS-LD, Smart Energy, Interoperability, Context-Aware Systems

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1 Introduction

Energy is one of the major factors driving the world economy. Renewable energy sources have seen particular traction recently due to their low environmental impact, with hydropower often regarded as particularly advantageous [18]. Hydroelectric power or simply hydropower, is a renewable energy source where electrical energy is derived from the potential energy of water moving from higher to lower elevations. It is a proven, mature, predictable, and price-competitive technology. Beyond energy production, hydropower infrastructure features significant water management services, and supports other variable renewable energy sources, such as wind and solar, by providing essential storage and load balancing services [25].

In recent years, the integration of IoT technologies in hydropower plants has showcased that it might revolutionise the industry, enhancing monitoring, efficiency, and control capabilities [8, 19]. IoT-enabled systems enable real-time data collection and analysis, facilitating more efficient and responsive management of hydropower operations. Various studies have demonstrated the potential of IoT in optimizing different aspects of hydropower management, from micro-hydropower plants to large-scale installations [3, 23] These innovations underscore the transformative impact of IoT on the hydropower sector.

Despite these advancements, current IoT implementations in hydropower often focus narrowly on specific plants or applications, lacking a comprehensive approach to modeling contextual information. This gap highlights the need for standardized data models that can capture the diverse structural and operational components of hydropower plants in a holistic manner. Building Information Modelling (BIM) ontology-based and other linked data approaches have been explored in the smart energy industry [5, 11, 17, 21, 24]. However, there remains a need for a standard's based, domain-specific information model, with sufficient substance to capture the intricacies of hydropower infrastructure, to support interoperable and replicable smart solutions in the hydropower sector.

This work contributes to the state-of-the-art by defining and providing a novel set of data models for smart hydropower plants based on the NGS-LD standard [2]. These models offer a detailed and semantically enriched representation of hydropower plant components, incorporating both static properties and dynamic observations. The proposed models are designed to enhance data integration, support decision-making processes, and facilitate the deployment of IoT applications in hydropower plants. By adopting a comprehensive and standardized approach to data modeling, this work aims to contribute to the development of more efficient, reliable, and sustainable hydropower systems.

The remainder of this paper is organized as follows: Section 2 reviews related work on IoT technologies in hydropower plants, highlighting current implementations and existing data models, and identifying their limitations. Section 3 outlines the motivation for developing new data models, emphasizing the need for comprehensive and standardized approaches, and provides an overview of the key components of hydropower plants. Section 4 presents the proposed NGS-LD data models, detailing their structure, relationships, and properties, and explaining the reasoning behind the design choices. Section 5 describes the deployment and testing of these models in a real-world context, showcasing the practical application and validation of the models in enhancing data integration and decision-making. Finally, Section 6 concludes the paper by summarizing the findings, discussing the implications of the proposed models, and outlining future research directions.

2 Related Work

The integration of IoT technologies in hydropower plants is transforming the industry by enhancing monitoring, efficiency, and control capabilities. Numerous studies have explored this potential, demonstrating significant advancements in various aspects of hydropower management.

Ginting et al. [8] developed an IoT-based monitoring system for micro-hydropower plants (micro-HPPs) that records real-time data on voltage, current, and water volume. This system has shown considerable promise for future applications in monitoring micro-hydro output power. Similarly, Sumarna et al. [19] implemented an IoT-based monitoring system for a micro-HPP utilizing an Archimedes screw turbine, providing valuable insights into voltage, current, and power generation. The floating structured hydropower plant designed by Afridi et al. [3] integrates IoT for real-time monitoring and visualization of electrical parameters via mobile apps, demonstrating its effectiveness in remote areas. Vandana et al. [23] introduced a hybrid pump hydro-photovoltaic system utilizing IoT for agricultural applications, combining solar energy and hydropower for efficient water pumping and electricity generation. Despite these advancements, current IoT implementations often focus narrowly on specific hydropower plants or applications without considering the broader context. They lack a standardized approach to modeling contextual information comprehensively.

To address the structural characteristics of hydropower plants, BIM has emerged as a transformative tool in the construction industry and is gaining traction within the hydropower sector [24]. BIM has been applied to various aspects of hydropower, including design, collaboration, monitoring, scheduling, cost analysis, sustainability assessment, and geotechnical investigation. However, even for the structural components of hydropower plants, there is a clear lack of specific standards and guidelines that allow for IoT capabilities. The availability of widely adopted (de-facto standard) information models is key for creating a global digital single market of interoperable and replicable (portable) IoT-enabled smart solutions in multiple domains, not only for smart hydropower plants but also for smart cities, smart agrifood, smart utilities, and smart industry. Data models play a crucial role because they define the harmonized representation formats and semantics that will be used by applications to both consume and publish data.

There have been efforts to try to model and use hydropower plants semantics beyond simple BIM applications. With the focus on enhancing cyber-security in power plants, Tabak et al. [21] emphasize the importance of coupling data from diverse sources within a hydropower plant with a data model that retains the original semantic information, facilitating structured data interpretation without compromising system performance. For a similar cyber-security oriented focus, Guo et al. [9] present a novel fault diagnosis method for hydropower systems that employs a knowledge graph to store structured and unstructured data, allowing for intelligent fault diagnosis through a Bi-LSTM model with an attention scheme.

As regards standard data models for representing the whole scale of HPP operations and their components in detail, a clear vision is currently lacking. The IEC 61968/61970 CIM Common Information Model [17] is a series of standards under development that aims to standardize the information exchange between electrical distribution systems. Ontology-based approaches have also been explored for modeling relevant information. Booshehri et al. [5] propose the Open Energy Ontology (OEO), a collaborative effort to represent the context of energy system analysis based on standard terminologies used by human experts in this field. It is designed to improve transparency and facilitate comparability and transferability of energy system modeling and scenario analysis. In Kofler et al. [11], the authors discuss a system that must be aware of various energy parameters and facilities, as well as providers, to make energy-efficient decisions for the eco-friendly operation of smart homes. They create a smart home knowledge base following the Web Ontology Language (OWL) standard and model an example energy provider generating electricity through hydropower. However, all these ontologies are designed to represent a broader variety of energy providers and consumers and lack detailed components present in hydropower plants. On a penstock [12] of an HPP for example, there is no way to represent an IoT device placed on a specific part of this component

The FIWARE Foundation has introduced SmartDataModels¹ as a means to enable data portability in applications for Smart Cities, Smart Environment, Smart Energy, among others. These models focus on providing data models following the NGS-LD standard. This is an ongoing project, providing data models related to the Energy Domain, including models for Batteries, Energy Metering, and Green Energy. The adaptation of IEC standards (CIM) is one of the goals of this effort.

Most of the discussed work include comprehensive data models dealing with the most common functionalities performed by energy management systems. Nevertheless, there are concepts of particular applications and components (such as in our case with the hydropower plants) that are not included in the standard data models. For this reason, it is necessary to extend the existing data models into something more domain-specific, targeting the smart Hydro Power Plant domain rather than the broader energy domain.

3 Motivation

Before delving into the need for modeling the context of the components of a smart hydroPower plant, we discuss its basic structure. Hydropower plants and their classification can vary widely [10,

¹www.smartdatamodels.com

22]. Hydropower facilities are mainly categorized based on type and capacity². Facility types include storage or reservoir, Run-of-River (RoR), pumped storage hydropower plants, and in-stream hydropower schemes. Capacity types range from Pico, Micro, Mini, Small, Medium, to Large. Despite variations in components across different types of HPPs, the main components remain largely consistent [20]. For instance, storage and pumped-storage HPPs differ mainly in their dam structures to ensure storage capacity, with pumped storage plants having additional mechanisms for pumping water back to the top reservoir.

Typically, the components of an HPP include a dam, intake with trash rack and gates, pipeline or tunnel (Penstock), main valve, turbine and generator, transformer, tailrace pipe, and grid connector, as illustrated in Fig. 1. Additionally, a comprehensive description of an HPP must include the surrounding environment, such as properties of the water, reservoirs, or rivers that the plant interacts with.

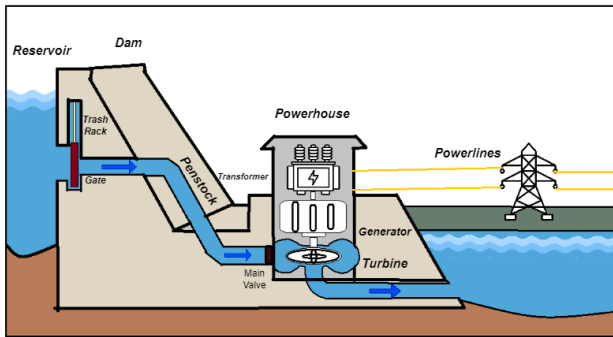


Figure 1: Diagram of a typical "reservoir" hydropower plant, illustrating key components

We next explore the significance of context awareness in optimizing IoT applications for HPPs. Indeed, context awareness is crucial for the optimal operation of any IoT application as it involves understanding the situation in which an IoT system operates to provide relevant information and services [15]. Sanchez et al. [16] differentiate between raw data and context information. Raw (sensor) data is unprocessed data retrieved directly from sources such as sensors, while context information is data processed from raw sensor data, checked for consistency, and enriched with metadata. For example, GPS sensor readings are raw data, which, when organized to represent geographical locations, become context information.

In the context of smart IoT-enhanced HPPs, context awareness plays a pivotal role. It determines what information and services should be presented to the user. For example, when an operator accesses the control system, they need real-time data on water flow, turbine performance, and energy output. Context-aware IoT applications connect to various sensors—measuring water levels, weather conditions, and equipment status—to retrieve and present this data to the operator. This context includes location, time, environmental conditions, and the specific operator’s access rights.

Automatic execution of services is another critical feature in the IoT paradigm. In a smart HPP, if sensors detect increased water

flow due to heavy rainfall upstream, the IoT application should automatically adjust turbine settings to optimize energy production and prevent overflow. These actions should be taken automatically based on the context. Numerous sensors attached to various parts of the hydropower plant—such as water inflow rates, turbine efficiency metrics, and environmental conditions—produce large volumes of data that must be collected, analyzed, fused, and interpreted. This process requires collecting and tagging context with sensor data for accurate processing and understanding.

Context is especially important when different organizations collaborate. Consider a visualization dashboard application for HPPs spanning two organizations. An application depends heavily on the exact context of each provider’s data. For instance, querying the dashboard for “all water flow measurements of small capacity hydropower plants from the last month” sounds straightforward but is highly context-dependent. There is no global agreement on classifying hydro systems by installed power, leading to wide variations in the definition of “small-scale hydro”, see Table 1. For example, ‘small hydro’ is defined as below 1.5 MW in Sweden but below 50 MW in China.

Table 1: Small-scale hydropower by installed capacity (MW) as defined by different countries [7]

Country	"Small-scale hydro" hydropower plant capacity (MW)
Brazil	≤ 30
Canada	< 50
China	≤ 50
European Union	≤ 20
India	≤ 25
Norway	≤ 10
Sweden	≤ 1.5
United States	5-100

Understanding these nuances is critical for developing effective IoT applications for HPPs. Thus, we find that to enable IoT-enhanced HPP operations, it is essential to model both the dynamic and static properties of these spaces. This involves understanding not only the components of the power plant but also the devices, observations, and actuations. By comprehensively modeling these aspects, we can ensure optimal performance, efficient data integration, and effective decision-making processes.

4 Data Models for Smart HydroPower Plants

This section presents our approach to creating comprehensive data models for smart hydropower plants using the NGSI-LD standard. We start by discussing existing NGSI-LD data models and their limitations. Next, we introduce our proposed novel NGSI-LD data models tailored for the hydropower domain. We provide detailed descriptions of these models, including their structure, relationships, and properties, while also providing the reasoning behind our design choices.

²<https://www.hydropower.org/ifa/discover-types-of-hydropower>

4.1 Existing NGS-LD Data Models

To create our models, we have chosen to use the NGS-LD standard [2]. The NGS-LD specification has been proposed by the ETSI Industry Specification Group for Cross-Cutting Context Information Management (ISG CIM). It comprises an information model with semantic characteristics connected to Linked Data and ontologies. In short, it is an API and data model for publishing, querying, and subscribing to context data, aiming to facilitate the open exchange and sharing of structured data among various parties.

As mentioned in the related work, there has already been an effort to create an NGS-LD CIM-based data model for the energy sector. However, the existing models fall short in several areas. To illustrate the current limitations and the necessity for more domain-specific extensions, we examine the existing models for the smart hydropower plant domain.

For hydropower plants, four different kinds of entities have already been defined, as shown in Fig. 2. These include the "HydroPowerPlant" entity, the "HydroPump" entity, the "HydroGeneratingUnit" entity, and various *governors* for different kinds of turbines. A governor [1] in a hydropower plant is a feedback control system designed to regulate the speed and power output of a hydroelectric turbine. According to the descriptions adapted from CIM data models³, a "HydroPowerPlant" entity is a hydro power station that can generate power or pump water. When generating power, the generator turbines receive water from an upper reservoir. When pumping water, the pumps receive their water from a lower reservoir. The "HydroGeneratingUnit" is a generating unit whose prime mover is a hydraulic turbine (e.g., Francis, Pelton, Kaplan), essentially the generator component. A "HydroPump" entity is considered a synchronous motor-driven pump, typically associated with a pumped storage plant.

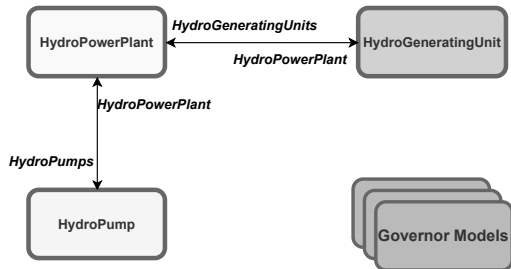


Figure 2: Relationships among hydropower plant related entities in the Fiware "SmartEnergy" data models.

Most of the effort in existing modeling appears to be focused on the NGS-LD entity types related to different governors. The governor maintains stable turbine operation by adjusting the flow of water to the turbine based on a setpoint signal and feedback from the turbine's speed and other relevant parameters. Essentially, a governor ensures the turbine operates at a desired speed and power output, using feedback mechanisms to continuously adjust the water flow to maintain stability and efficiency in power generation. Governors can be either electrohydraulic, using electronic

³github.com/smart-data-models/dataModel.EnergyCIM/tree/master/HydroPowerPlant

signals and hydraulic mechanisms, or mechanical-hydraulic, using mechanical components for speed regulation.

In the github repository where the various "Energy CIM" models have been published⁴, we can see that there are many entities defined for different governors, such as 'GovHydro1-4', 'GovHydroDD', 'GovHydroFrancis', 'GovHydroIEEE0', 'GovHydroIEEE2', 'GovHydroPID', 'GovHydroPID2', 'GovHydroPelton', 'GovHydroR', 'GovHydroWEH', and 'GovHydroWPID'. However, there are no relationships connecting the governors to the other entities. There is no way to determine, for example, which specific governor entity via ID is used at which hydropower plant, which turbine it specifically controls, and which generator is connected to that turbine. All these relationships, which are context information useful for IoT hydropower plant applications, do not currently exist.

4.2 Di-Hydro NGS-LD Data Models

Considering all the above, there are numerous additions we can make to the existing entity types. Firstly, it is important to model all the structural and operational components of an HPP, as described in Section 3. This requires adding specific attributes and properties to describe the contextual information of these structural components. For example, as illustrated in the snippet in Listing 1 (in Key Values Format), a dam component can have various static properties such as its type (Earthfill, Rockfill, Concrete Gravity, etc.), the dam volume/height/length, and others. Since we leverage NGS-LD, the specific semantics behind these properties, such as "Measurement unit for length is in meters," can be traced by checking the context. With linked data, any changes to the context will be reflected across the entire model.

```

1  "id": "urn:ngsi-ld:Dam:001",
2  "type": "Dam",
3  "name": "Main Dam",
4  "damType": "Earthfill",
5  "damVolume": {
6    "value": 8,
7    "unitCode": "MCM"
8  },
9  "damHeight": {
10   "value": 130,
11   "unitCode": "MTR"
12  },
13  "damLength": {
14   "value": 540,
15   "unitCode": "MTR"
16  },
17  "context": "https://raw.githubusercontent.com/satrai-lab/di-
    hydro-data-models/main/context.jsonld"

```

Listing 1: Snippet of a dam entity with only some static properties.

Similarly, a turbine component can have various static properties such as its supplier, type, rated power, rotation speed, maximum head, and minimum head. An example is shown in Listing 2.

```

1  "id": "urn:ngsi-ld:Turbine:001",
2  "type": "Turbine",
3  "name": "Turbine T2",
4  "supplier": "Andino",
5  "turbineType": "Kaplan",
6  "ratedPower": {
7    "value": 3.4,
8    "unitCode": "MW"
9  },

```

⁴<https://github.com/smart-data-models/dataModel.EnergyCIM>

```

10 "rotationSpeed": {
11   "value": 375,
12   "unitCode": "RPM"
13 },
14 "maxHead": {
15   "value": 21.6,
16   "unitCode": "MTR"
17 },
18 "minHead": {
19   "value": 20.5,
20   "unitCode": "MTR"
21 },
22 "context": "https://raw.githubusercontent.com/satrai-lab/di-
hydro-data-models/main/context.jsonld",

```

Listing 2: Snippet of a turbine entity with only some static properties.

Likewise, a generator component can have various static properties such as its supplier, type, rated power, active power, power factor, voltage regulation range, and winding insulation class. An example is shown in listing 3.

```

1 "id": "urn:ngsi-ld:Generator:001",
2 "type": "Generator",
3 "name": "IM Generator",
4 "supplier": "ATB Sever",
5 "generatorType": "IM 8421",
6 "ratedPower": {
7   "value": 4.0,
8   "unitCode": "MVA"
9 },
10 "activePower": {
11   "value": 3.4,
12   "unitCode": "MW"
13 },
14 "ratedPowerFactor": 0.862,
15 "voltageRegulationRange": {
16   "value": "+-5",
17   "unitCode": "%"
18 },
19 "windingInsulationClass": "F",
20 "context": "https://raw.githubusercontent.com/satrai-lab/di-
hydro-data-models/main/context.jsonld"

```

Listing 3: Snippet of a generator entity with only some static properties.

Beyond the specific properties of various entities, we include a "RelativePosition" property, inspired by the Transportation model described by Bouloukakis et al. [6], which detailed a bus vehicle model with spatial properties in 2D and 3D space. This is essential for visualizing the exact placement of devices within plant components and enhancing context for applications. For example, knowing the exact placement of water flow sensors in the penstock can help identify potential blockages within the penstock, as showcased in the example of Fig. 3.

However, having only static properties to represent the entities is insufficient. The digital depiction of hydropower plant components in our data model needs to contain various logical relationships between different entities. These relationships should facilitate querying of important and distinct information. For example, consider entities such as "HydroPowerPlant" and "Dam." If only the relationship "HydroPowerPlant has Dams" exists, searching for which hydropower plant a dam belongs to, would require searching all the hydropower plants present in a data management system and checking the "HydroPowerPlant has Dams" relationship. By establishing bidirectional relationships wherever logical and possible, such as "Dam is part of HydroPowerPlant," we can avoid unnecessary processing. This enhances the efficiency of our data

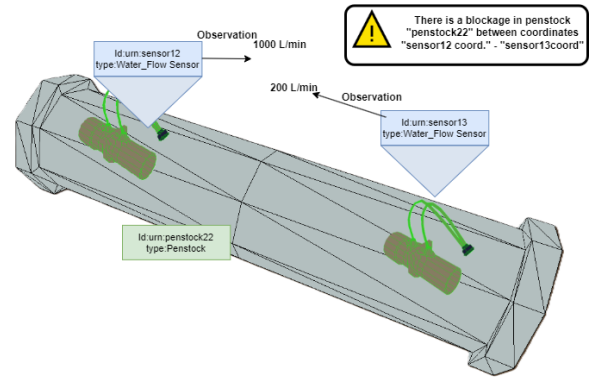


Figure 3: Illustration of water flow sensors inside a penstock. The spatial information provided by the relative position attribute is crucial for identifying potential blockages and enhancing the contextual understanding of sensor data within the HPP components.

model, facilitating straightforward and efficient querying of the HPP components.

In Fig. 4, we illustrate a small subset of the relationships in the NGSI-LD property graph of our data model for the static components of a smart hydropower plant. This figure showcases key bidirectional relationships, such as "HydroPowerPlant has Dams" and "Dam is part of HydroPowerPlant," "HydroPowerPlant contains Turbines" and "Turbine is part of HydroPowerPlant." These relationships allow for efficient navigation and querying within the data model, ensuring that each component can be easily located and its connections to other components clearly understood.

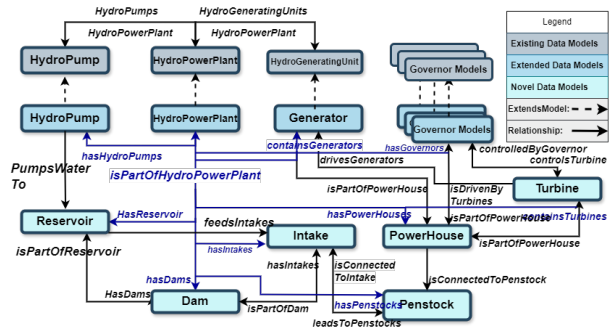


Figure 4: Subset of the relationships in the NGSI-LD property graph of our data model, static components of a smart HPP

In the context of IoT-enhanced HPPs, it is crucial to consider another aspect of context information: the dynamic properties of the system, including various IoT devices, their observations, and actuations. For this, we adopt a modeling approach similar to Papadakis et al. [13], inspired by existing ontologies. This approach recognizes the need to separate physical devices from the entities they measure or control in NGSI-LD-based models. By treating an observation of a device as an independent object, developers can create portable applications utilizing high-level observations rather

than specific device properties. This model allows multiple observations to be associated with current or future IoT devices, separating physical device properties from their observations or actuations. Consequently, the observation/actuation attribute is promoted to a full-blown entity, establishing appropriate relationships with the device it originates from and the smart space it belongs to.

We also highlight that no generic device model can cover every device; instead, a refined model is needed for each type of device. For example, having a water flow rate attribute might be relevant for a turbine sensor in an HPP, but redundant for a temperature sensor. Additionally, not every device functions solely as a sensor; some can be used as actuators. As an example of actuation in a smart HPP, a control panel might adjust the flow of water based on sensor readings. The observations made by the device and any applications utilizing these measurements will remain unaffected by changes to the physical device, which may lead to new device attributes. An example of a water flow device for an HPP is shown below. This device has various static properties and relationships, as well as an associated observation entity, which holds the actual value that is 'observed' (water flow rate):

```

1  { "id": "urn:ngsi-ld:WaterFlowSensor:001",
2    "type": "WaterFlowSensor",
3    "name": "Main Penstock Water Flow Sensor",
4    "relativePosition": {
5      "type": "Point",
6      "measurementUnit": "m",
7      "Dimensions": "3D",
8      "coordinates": [45.0,9.0,3.0]
9    },
10   "OnObject": "urn:ngsi-ld:Penstock:001",
11   "observations": "urn:ngsi-ld:Observation:WaterFlow:001",
12   "context": "https://raw.githubusercontent.com/satrai-lab/di-
13     hydro-data-models/main/context.jsonld"
14 },
15 { "id": "urn:ngsi-ld:Observation:WaterFlow:001",
16   "type": "Observation",
17   "name": "Water flow rate measurement in Penstock Section 1",
18   "category": "PhysicalObservation",
19   "dateModified": "2024-07-17T13:20:30Z",
20   "measurement": {
21     "waterFlowRate": {
22       "value": 120,
23       "measurementUnit": "m^3/s"
24     }
25   },
26   "measurementType": "waterFlow",
27   "context": "https://raw.githubusercontent.com/satrai-lab/di-
28     hydro-data-models/main/context.jsonld"

```

Listing 4: Example of a water flow device and its observation entity for a HydropowerPlant.

In summary, in our data model, each hydropower plant component can reference both the specific device responsible for measurements (to clarify the underlying hardware) and the corresponding high-level observation or actuation data. A simplified relationship diagram illustrating this is shown in Fig. 5.

Thus, using this separation of device properties from their observations or actuations ensures flexibility and scalability in smart HPP operations, facilitating efficient data management and application development. All our data-models presented in this section are available as open source at: <https://github.com/satrai-lab/di-hydro-data-models>

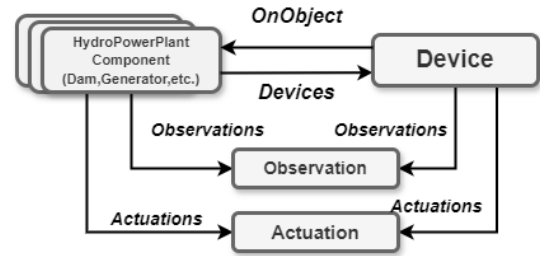


Figure 5: Simplified diagram of dynamic device data relationships in hydropower plant components

5 Deployment and Use Case Scenario

In the scope of the "Di-Hydro" project (<https://dihydro-project.eu>), we tested our NGSi-LD data models on a federated context broker architecture using data from real HPPs distributed across different countries. One of the primary goals of this project was to create comprehensive NGSi-LD data models that accurately represent the physical spaces of HPPs and their properties, both static (such as location) and dynamic (such as temperature, water conditions, warnings etc.).

With this deployment we wanted to make sure that with our data models we can match the following key objectives of the project:

- **Supporting Decision-Making Processes:** Ensuring that the data models support decision-making processes by allowing software components to generate semantically enriched entities. These enriched entities help in interpreting and contextualizing data, leading to more informed and timely decisions. The models were designed to facilitate the integration of real-time data with historical data, enabling predictive analytics and proactive maintenance strategies.
- **Designing Relationships for Easy Querying:** Designing relationships within the HPP data model to facilitate easy querying of important information. This includes establishing bidirectional relationships carefully crafted to reflect the hierarchical and functional dependencies among the various components of the HPPs, enhancing the efficiency of data retrieval and ensuring that critical information is readily accessible with intuitive and efficient queries.
- **Establishing Instances and Integration:** Establishing instances of HPPs following the NGSi-LD data model and integrating them into a federated system. This federated system supports data exchange within and across HPP clusters, which refer to groups of hydropower plants that are geographically or operationally related. This enables a collaborative data environment, allowing data from multiple HPPs to be aggregated, analyzed, and utilized effectively. The integration process ensures data integrity and privacy via the setup of secure and reliable communication channels between the context brokers.

We deployed the NGSi-LD data models on a federated context broker architecture, as depicted in Fig. 6. This architecture facilitates the integration of data from various HPPs, enabling seamless data exchange and interoperability. The design allows HPP entities

to share context entities across different operational layers, supporting data exchange within and across the "Di-Hydro" project's HPPs using a fully federated layered model. This model orchestrates the interaction between physical and digital components, spanning from the bottom layer, with tangible assets such as sensors, actuators, and associated machinery, to the higher operational "managerial" digital layers.

The federated data exchange design offers several benefits. By dividing brokers into administrative, network, geographic, contextual, or load-based domains [4], it reduces administrative and communication overheads as context providers and context consumers can communicate with the nearest and most relevant brokers. It also enhances data security by keeping sensitive information within the original data sources, minimizing the risk of exposure during data transfers. Additionally, this decentralized approach supports scalability, allowing the system to grow and adapt to increasing data volumes and complexity without significant reconfiguration.

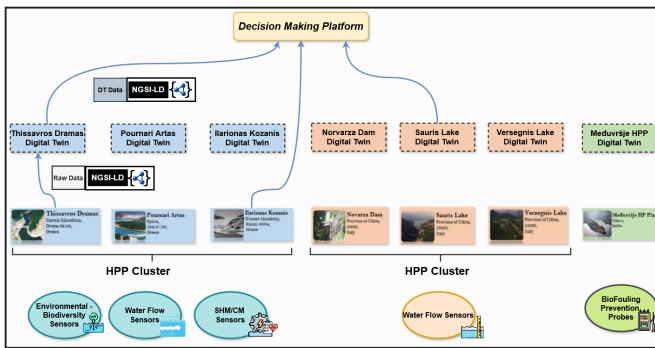


Figure 6: Federated Architecture used in Testing Di-Hydro Data Models.

Each of the HPPs has at least one federated node. For testing purposes, we chose to use the Scorpio NGSI-LD context broker⁵. According to the official NGSI-LD Excel file⁶ detailing the current compatibility of the development version of the main under development context brokers Orion-LD⁷, Stellio⁸, and Scorpio⁵ against the features (up to v1.8.1) of the NGSI-LD API specification, only Scorpio supports fully a federated deployment. It achieves this by implementing the NGSI-LD context registry component. The NGSI-LD context registry is a software functional element where NGSI-LD context source (sources of context information that implement NGSI-LD consumption and subscription) register the information they can provide. Scorpio brokers use this registry to find the appropriate NGSI-LD context sources capable of supplying the information required to serve an NGSI-LD request. The presented federated architecture is thus implemented using Scorpio nodes combined with appropriate NGSI-LD context source registrations. There have been efforts to develop federated NGSI-LD solutions, such as ComDeX [14], but these are still in a more nascent stage

⁵<https://github.com/ScorpioBroker/ScorpioBroker>

⁶https://docs.google.com/spreadsheets/d/18tq0_PZF15WCfYUElcdI6M3Vlin4hP-M

⁷<https://github.com/FIWARE/context.Orion-LD>

⁸<https://github.com/stellio-hub/stellio-context-broker>

and do not yet provide the full capabilities required for large-scale federated operations.

We use a unified architectural deployment for each federated node, as shown in Fig. 7.

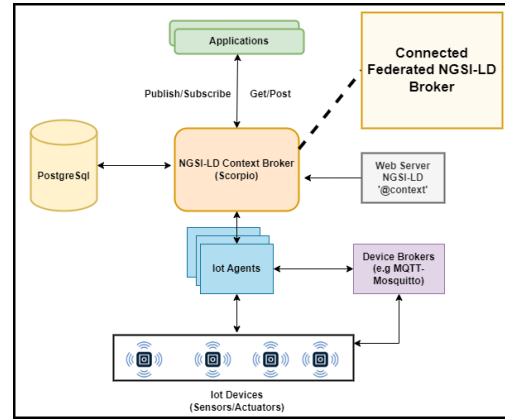


Figure 7: Unified Architectural Implementation Details for Each Federated Node.

Table 2: An example of the technical description for hydropower plants.

	HPP A	HPP B	HPP C
Installed Capacity	160MW	380MW	310MW
Turbine type	Francis	Kaplan	Pelton
Num. of Turbines	2x80MW	4x95MW	3x103MW
Yearly production	340GWh	460GWh	250GWh
Net Head	105m	152m	85m
Dam Type	Rockfill	Rockfill	Arch Dam
Dam Volume	8.3m.c.m.	13.1m.c.m.	8.8m.c.m.
Dam Height	128m	168m	92m
Dam Length	550m	490m	570m
Reservoir Volume	408m.c.m.	683m.c.m.	712m.c.m.
Reservoir Useful Volume	315m.c.m.	570m.c.m.	299m.c.m.
Avg Yearly Water Intake	1027m.c.m	962m.c.m	1467m.c.m
Reservoir Min Op Lvl	367m	322m	101m
Reservoir Max Op Lvl	397.5m	378m	122m
Reservoir Max lvl	401m	384.8m	127m

At the center of each federated node is our selected context broker, which is a middleware software component that manages context information, providing NGSI-LD endpoints for both consumption and provision. The context broker stores, retrieves, and updates context data, ensuring that it is accessible and up-to-date for various applications and services. For the storage component, a PostgreSQL database is deployed alongside the Scorpio broker. The '@context' of our NGSI-LD models are hosted on a webserver accessible by all brokers (a change in the context is reflected across all brokers). All NGSI-LD-based context brokers such as Scorpio, Stellio, and Orion exclusively use the well-defined NGSI-LD interface; this interface is also used when receiving instructions from third-parties and again when communicating with NGSI-LD aware components around the context broker itself. It is unrealistic to expect devices, both existing and newly deployed, to use the NGSI-LD

API directly. Thus, for the deployed devices in the HPP to be able to publish to the context broker, we need to use IoT Agents, based on each device. An IoT Agent is a component that lets a group of devices send their data to and be managed from a Context Broker using their own native protocols. This brings a standard interface to all IoT interactions at the context information management level.

Having this deployment, we can start testing our data models. First, we provision information about the static properties of hydropower plants, provided mostly in paper format converted to digitized tables. A snippet of example of how static information provided looks like can be seen in Table 2. After, information is converted to NGSI-LD (JSON-LD) files and uploaded via POST to each relevant context broker. To test the dynamic properties aspects, we create virtual sensors that generate dummy information about measurements (biodiversity measurements, water flow) based on the actual sensors that are created for the "Di-Hydro" project requirements. After adding this information to the brokers and connecting the virtual sensors, we test various NGSI-LD queries using dummy applications.

To demonstrate the capabilities of our data models, we develop an application that allows users to query and visualize the data. This application provides a user-friendly interface for making complex NGSI-LD queries and retrieving relevant information. The proposed data models enable these queries by providing a structured and semantically rich representation of HPP components. Below are some examples of the queries used to test the data models.

The following query retrieves all dam entities and their associated properties within a specific hydropower plant. By using our data model, each dam's static attributes, such as type, volume, height, and length, can be efficiently queried and retrieved. This capability, for example, is crucial for infrastructure management and planning, as it allows for a detailed overview of dam characteristics within the plant.

Query: Retrieve all dams and their properties within a specific hydropower plant:

```
curl -X GET 'serveraddr/ngsi-ld/v1/entities/?type=Dam&q=isPartOfHydroPowerPlant==urn:ngsi-ld:HPP:001'
```

In the next example, we first retrieve the observation IDs associated with a specific penstock. Using these IDs, we then query for real-time and historical water flow rate measurements, filtering by a specified date range. This showcases how dynamic properties and historical data can be accessed and analyzed using our data models, which, in this example, is essential for monitoring and optimizing water flow management over time.

Query: Get Real-Time and Historical Water Flow Rate Measurements for a Specific Penstock. Filtering by Date Range:

```
curl -X GET 'serveraddr/ngsi-ld/v1/entities/urn:ngsi-ld:Penstock:001?attrs=observations'
curl -X GET 'serveraddr/ngsi-ld/v1/entities/?type=Observation&id=urn:ngsi-ld:Observation:WaterFlow:001,urn:ngsi-ld:Observation:WaterFlow:002&attrs=measurement.waterFlowRate&options=temporalValues&timerel=between&time=2024-07-01T00:00:00Z&endTime=2024-07-31T23:59:59Z'
```

The following query retrieves all turbines within a specific powerhouse along with their efficiency metrics and the governors controlling them. By establishing multiple context relationships, such as the ones between turbines and governors, our data models enable detailed queries that support operational insights.

Query: Find all turbines and their efficiency metrics within a specific powerhouse, showing which governors control them:

```
curl -X GET 'serveraddr/ngsi-ld/v1/entities/?type=Turbine&q=isPartOfPowerHouse==urn:ngsi-ld:PowerHouse:001&attrs=efficiency,controlledByGovernor'
```

By deploying these data models in a real-world environment, we confirmed the practicality and applicability of our NGSI-LD data models. The federated context broker architecture proved to be a robust platform for integrating and managing diverse datasets, ultimately contributing to the overall goal of creating a comprehensive and interoperable data environment for hydropower plants.

6 Conclusions and future work

This paper presents a comprehensive approach to modeling the structural and operational components of hydropower plants using NGSI-LD data models. Our work focused on creating detailed and semantically enriched entities that represent both static properties (e.g., location, structural attributes) and dynamic properties (e.g., real-time sensor data, operational status). The deployment and testing of these data models on a federated context broker architecture, using real-world data from hydropower plants, demonstrated their effectiveness in enhancing data management and decision-making processes. The models allowed for more accurate data integration, improved contextual understanding, and enabled timely responses to operational changes. This is achieved through the ability to query, visualize, and analyze integrated data from multiple hydropower plants in a coherent and interoperable manner. The results indicate a promising direction for future developments in smart energy management systems, paving the way for more efficient, reliable, and sustainable hydropower plant operations.

Future work will focus on refining our data models based on feedback from hydropower plant operators and further testing. We aim to explore the integration of additional data sources, such as weather forecasts, market data, and environmental monitoring systems, to further enrich the data environment and enhance decision-making capabilities. Promoting the broader adoption of our NGSI-LD data models within the energy sector and collaborating with industry stakeholders to drive standardization efforts is another important area of focus. Additionally, developing user-friendly interfaces and visualization tools will help operators and decision-makers interact with the data models more effectively and intuitively.

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