DigiEV: A digital twin for electric vehicle charging infrastructure in the E4C ecosystem

Report of End of Studies Internship (IS.3001)

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Je, soussignée Daphne Tuncer, maître de stage de l'élève Isep, ZHAO Chao, atteste avoir pris connaissance du cahier des charges du rapport de stage Isep, avoir lu et évalué le présent rapport au regard du cahier des charges et des pratiques de mon employeur, et autorisée sa transmission à l'Isep.

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I would also like to express my gratitude to ISEP, where I am pursuing my Master's degree, for its academic support and for providing me with the opportunity to pursue my aspirations.

Lastly, I gratefully acknowledge E4C for providing the resources and support that made this internship possible.

Abstract

The success of electric mobility requires not only advanced electric vehicles but also an integrated infrastructure that combines electricity provision, information distribution, and intelligent system control. Digital twin technology has emerged as a powerful approach to manage complex infrastructure operations and evaluate deployment strategies for electric vehicle charging networks [1].

This report describes the work conducted during my six-month internship at Laboratoire Ville Mobilité Transport (LVMT) - École nationale des ponts et chaussées (ENPC), focusing on the design and development of a digital twin system to simulate the energy impact of electric vehicle charging infrastructure. The project employed FIWARE technology as the core framework, utilizing Python for system development and data processing to model the complex interactions between energy consumption and user behavior in charging station.

The developed digital twin system successfully established a comprehensive platform for simulating charging station operations, built upon NGSI-LD standard compliance to ensure semantic interoperability. The system utilizes MongoDB and CrateDB as backend databases for efficient data storage and time-series analysis, while providing RESTful API interfaces for seamless system integration and external interactions. This platform enables real-time monitoring and analysis of charging infrastructure performance, providing valuable insights for optimizing charging station deployment, predicting energy demand patterns, and improving overall system efficiency. The work contributes to enhanced decision-making capabilities for electric vehicle charging infrastructure planning and management through standardized data models and accessible programming interfaces.

This internship significantly enhanced my technical expertise. Additionally, I strengthened my research skills through extensive literature review and analysis of current challenges in sustainable transportation infrastructure. This experience has profoundly sparked my interest in academic research and opened new perspectives for my future career.

Keywords Digital Twin, Simulator, Semantic Model, Electric Vehicle, Charging Infrastructure, FIWARE, NGSI-LD

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Introduction

The global transition toward electric mobility is regarded as a cornerstone of efforts to decarbonize the transport sector and meet international climate targets. According to the International Energy Agency, electric car sales reached nearly 14 million in 2023, and are projected to exceed 17 million in 2024, representing more than one-fifth of global car sales [2]. However, this rapid diffusion of electric vehicles (EVs) poses systemic challenges that extend beyond vehicle manufacturing. The widespread adoption of EVs crucially depends on the development of robust charging infrastructure and the integration of energy systems capable of supporting increasing loads while ensuring reliability and user acceptance [3].

Charging infrastructure represents both a key enabler and a potential bottleneck in the electrification of mobility. Without adequate charging coverage, prospective EV users may face range anxiety, undermining confidence in the technology and slowing adoption [3]. At the same time, deploying charging networks entails high capital costs and introduces technical challenges related to grid integration, station placement, and operational optimization. France, for instance, has set ambitious goals of 400,000 publicly accessible charging points by 2030, yet as of 2023 fewer than 100,000 had been deployed, revealing the scale of investment and coordination required [4]. This "chicken-and-egg" problem—insufficient infrastructure limiting EV adoption, while weak demand discourages infrastructure investment—highlights the importance of strategically planned deployment [5].

To address these challenges, advanced modeling and simulation tools have been proposed to guide infrastructure planning and management. Digital twin technology, in particular, offers a powerful approach to replicate complex physical systems in a virtual environment, enabling real-time monitoring, scenario evaluation, and predictive analytics. Recent studies highlight the potential of digital twins to support the integration of charging infrastructure with smart grids, optimize location and capacity decisions, and enhance decision-making under uncertainty [6, 3].

This report builds upon this context by presenting the work conducted during a six-month internship at the Laboratoire Ville Mobilité Transport (LVMT), École nationale des ponts et chaussées (ENPC). The project focused on the design and development of a digital twin system for simulating the energy impact of EV charging infrastructure, employing the FIWARE framework and NGSI-LD standards to ensure interoperability. By coupling backend databases (MongoDB, CrateDB) with real-time APIs, the system provides a scalable platform for monitoring charging operations and assessing deployment strategies. The work contributes to ongoing research in sustainable mobility by demonstrating how digital twins can support the optimization of EV charging infrastructure within smart city ecosystems.

This report is organized into seven main chapters, each addressing specific aspects of the internship work and its broader context:

Chapter 2 **Context** first introduces the institutional framework, including ENPC, LVMT and E4C. It then describes the supervision and project framework. Finally, it outlines the research background, covering energy and environmental challenges in transport, electric vehicles and charging infrastructure, digital twin and simulation, as well as data models and interoperability.

Chapter 3 **Related work** examines existing technologies, including FIWARE, BRICK, Web of Things (WoT). This chapter also identifies current challenges and positions our contribution within the existing body of knowledge.

Chapter 4 **Methodology** details the system architecture, semantic data modeling approach using NGSI-LD, backend database implementation, API subscription mechanism, and visualization components. It concludes with an analysis of difficulties encountered, and deviations from initial specifications.

Chapter 5 **Case studies and experiment** presents the definition and initialization of three experimental scenarios, results obtained using both real and synthetic data, and validation of the digital twin system performance.

Chapter 6 **Analysis management** addresses social and environmental responsibility aspects of the project and discusses innovation management and digital tools for decision-making in research.

Chapter 7 **Conclusion** summarizes the main outcomes of the internship and reflects the future work.At the same time, this chapter connects the technical achievements with personal growth and career prospects.

Context

1 Institutional Framework

This six-month internship was conducted at the **Laboratoire Ville Mobilité Transport (LVMT)**, a research unit affiliated with **École nationale des ponts et chaussées (ENPC)**, with funding provided by the **Energy4Climate interdisciplinary center (E4C)**. This institutional arrangement reflects the collaborative nature of contemporary energy and mobility research to address complex challenges in sustainable transportation infrastructure. The following sections detail the structure, missions, and research orientations of these three interconnected organizations that provided the framework for this research project.

ENPC represents one of France's most prestigious engineering institutions. Founded in 1747 by Daniel-Charles Trudaine, ENPC is among the oldest French Grandes Écoles, historically focused on training engineering officials and civil engineers. The school has evolved to offer wide-ranging education including computer science, applied mathematics, civil engineering, mechanics, finance, economics, innovation, urban studies, environment and transport engineering. In July 2024, ENPC became the sixth member school of Institut Polytechnique de Paris (IP Paris), joining École polytechnique, ENSTA Paris, ENSAE Paris, Télécom Paris and Télécom SudParis. Located on the Champs-sur-Marne campus, ENPC maintains a strong international presence with 43% of its students obtaining double degrees abroad and 30% of the engineering cohort being international students. The institution's research excellence is supported by 12 research laboratories, covering domains crucial to ecological, digital, and energy transitions, positioning it as a key player in addressing contemporary sustainability challenges.

LVMT serves as the direct host institution for this research project. Created in 2003, this multidisciplinary research laboratory operates as a joint research unit between Université Gustave Eiffel and École nationale des ponts et chaussées. Celebrating its 20th anniversary in 2023, LVMT brings together nearly 90 researchers in social sciences and engineering sciences, with expertise spanning economics, anthropology, sociology, geography, urban planning, technical economics, mathematical modeling, and computer science. The laboratory's scientific objective centers on understanding and modeling interactions between mobility practices, transport infrastructure, and spatial organization and development. Research activities are organized around four thematic axes: mobility practices and urban access; territorial dynamics and public action; city-transport interactions; and economic analysis and transport modeling.

E4C provides the funding framework and broader research context for this internship. Launched in June 2019 by IP Paris and ENPC, E4C addresses energy transition through research, training, and innovation. The center gathers 21 laboratories from Institut Polytechnique de Paris and 5 associated laboratories from ENPC, creating a unique interdisciplinary platform for energy and climate research. Nearly 30 laboratories work within E4C on four cross-cutting themes designed to reduce greenhouse gas emissions, improve energy efficiency, deploy renewable energy, and propose relevant energy policies. The center combines diverse scientific disciplines including social and economic sciences, materials sciences and engineering, applied mathematics, computer science, and geophysics.

2 Research Supervision and Project Continuity

2.1 Research Supervision Team

This internship project was conducted under the joint supervision of two tutors, reflecting the interdisciplinary nature of digital twin technologies and their application to energy mobility systems.

Dr. Daphné Tuncer is my supervisor from ENPC, specializing in digitalisation in the energy and mobility sectors. Prior to joining ENPC, She spent many years in the UK Higher Education. Her research keywords include electric mobility, cyberphysical systems, data management, and applied data science.

Dr. Georgios Bouloukakis from Télécom SudParis, provides co-supervision with expertise in IoT/Edge-driven middleware and distributed software systems. He is an experienced researcher and educator with over one decade of teaching and mentoring of students, having supervised 2 postdoctoral researchers, 4 Ph.D. thesis, 4 R&D developers and 48 bachelor/master theses.

2.2 Research Project Integration and Continuity

This internship project represents a direct continuation of research within the E4C framework, following the work of **Niemat Khoder**. Niemat's internship focused on the static modeling of buildings, where she developed detailed 3D representations of demonstrators such as DrahiX (office building in E4C campus). Her work contributed to establishing semantic representations of building components and visualizing their spatial and structural organization.

On this foundation, this project expands the application area from smart buildings to electric vehicle charging infrastructure, while maintaining the core concept of semantic interoperability. Unlike Niemat's research, which focuses on static structures and visualization, this project introduces dynamic data modeling, incorporating data such as the session duration, energy consumption, and user behavior into the system model, thus providing a more comprehensive description of the system's operation.

The two projects share technical continuity in that they both use NGSI-LD as the semantic modeling standard and FIWARE as the IoT platform, thus ensuring consistency in the overall methodology of the E4C research activities. However, shifting the focus to electric vehicle charging research also requires some adjustments, such as using a time-series database like CrateDB to process energy consumption data, and developing API interfaces to support simulation and prediction functionalities.

In this way, the project extends Niemat's static modeling approach toward more dynamic mobility energy systems, maintaining interoperability principles while addressing the specific challenges of charging infrastructure.

3 Research Background

The rapid transition towards sustainable mobility and low-carbon energy systems presents both opportunities and challenges for researchers and practitioners. This section reviews the key research background relevant to the internship, focusing on energy and environmental challenges in transportation, the development of electric vehicle charging infrastructure, the role of digital twin and simulation methods, and the importance of data models for semantic interoperability.

3.1 Energy and Environment Challenges in Transport

Transport is a central contributor to both energy use and environmental pressures. In France, it represented about 32% of final energy consumption in 2023 [7], and around 66% of total final consumption of oil products is attributable to transport [8]. It is also the largest national source of greenhouse-gas (GHG) emissions, accounting for approximately 32% of territorial emissions in 2022, with road transport—cars and heavy vehicles—being the dominant contributors [9].Beyond climate impacts, transport significantly contributes to local air pollution. The European Environment Agency notes persistent exposure to NO_2, $PM_{2.5}$, and ozone in urban areas with substantial health impacts [10].

Meeting these challenges requires a rapid shift toward low-carbon energy in transport. Electricity demand in France is projected to rise to 580-640 TWh by 2035, driven partly by electromobility; according to RTE, this scenario is feasible only with accelerated renewable deployment and smart charging strategies [11]. Therefore, electrifying mobility must be accompanied by a decarbonized electricity supply and effective demand-side management to deliver benefits for climate, air quality, and energy security.

3.2 Electric Vehicles and Charging Infrastructure

The rapid growth of electric vehicles (EVs) is transforming the transport and energy sectors. Global EV sales neared 14 million in 2023, accounting for 18% of all new cars, with projections of around 17 million in 2024, or more than one-fifth of global car sales [2]. Yet the acceleration of EV adoption depends critically on the availability of suitable charging infrastructure.

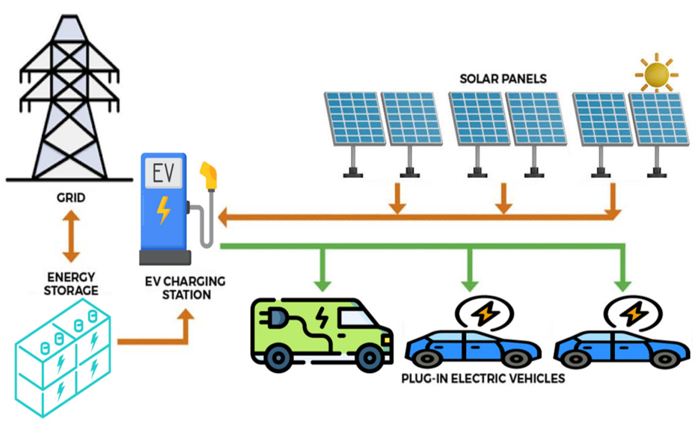

Fig. 2.1 A typical EV charging infrastructure [12]
Including electricity grid, renewable generation (solar panels), energy storage systems, charging stations, and plug-in electric vehicles.

A typical EV charging infrastructure (EVCI) shown in Figure 2.1 highlights the importance of coordinating generation, storage, and charging to ensure reliable and sustainable operation. EVCI is both an enabler and a potential bottleneck of EV transition. Research highlights a persistent "chicken-and-egg" problem: users hesitate to purchase EVs without adequate charging coverage, while investors are reluctant to finance charging stations without a critical mass of EV users. Studies show that strategic deployment of charging points is more cost-effective than merely enlarging battery capacity, as infrastructure provision directly reduces range anxiety and supports large-scale diffusion [3].

From a planning perspective, charging infrastructure must address three dimensions: technical, economic, and user acceptance. Technical issues involve compatibility of charging standards, grid integration, and power demand management. Economically, the high costs of fast-charging stations require careful location and sizing strategies. User acceptance hinges on convenience, accessibility, and charging time, which significantly influence EV adoption [13]. In summary, while EV adoption continues to expand rapidly, the success of the transition is inseparable from charging infrastructure. Planning, optimization, and digitalisation of charging networks will determine whether electrified transport can scale sustainably and equitably.

3.3 Digital Twin and Simulation

The increasing complexity of electric vehicle (EV) charging networks, their tight coupling with the power grid, and the variability of user behaviour make planning and operation challenging. Digital twin technology is increasingly viewed as a powerful tool to manage the complexity of charging networks, enabling real-time monitoring, scenario analysis, and integration with renewable power and storage systems [1]. A digital twin is defined as a "live digital coupling of the state of a physical asset or process with a virtual representation that produces functional output" [14].Figure 2.2 shows a typical EVCI. Unlike conventional models or static simulations, digital twins establish a continuous bi-directional link between the physical system and its digital replica, enabling real-time monitoring, predictive analytics, and feedback control [15, 16].

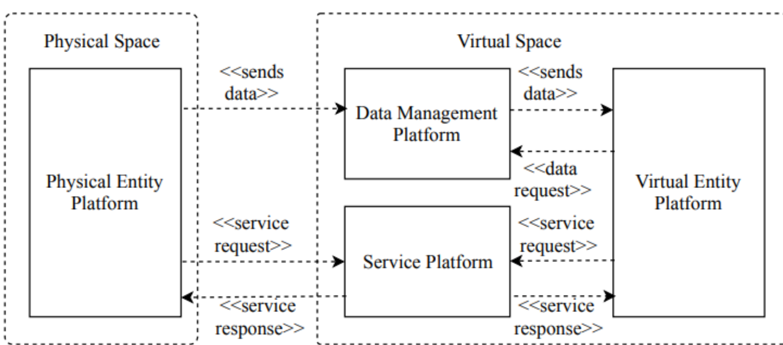

Fig. 2.2 **A Typical Digital Twin Framework** [17]
A digital twin includes both physical and virtual space,with four components: Physical Entity Platform, Data Management Platform, Service Platform and Virtual Entity Platform.

In the context of EV charging infrastructure, digital twins offer several advantages. First, they enable multi-scale simulation of charging demand and grid interaction, supporting optimal siting and sizing of charging stations. Second, they allow scenario analysis under uncertainty, including stochastic EV arrivals and variable renewable generation, thereby enhancing grid stability and resilience [18]. Third, digital twins provide a platform for testing cyber-physical interactions, including cybersecurity assessment, without disrupting operational systems [19]. These capabilities make digital twin frameworks particularly suitable for managing charging networks within smart cities and integrating them into future vehicle-to-grid (V2G) and vehicle-to-building (V2B) systems.

Simulation remains at the core of digital twin applications. Studies classify applications into *simulation*, *monitoring*, and *control* purposes [16]. For EV charging, simulation provides the foundation to evaluate control strategies, optimize energy flows, and quantify environmental impacts. Discrete-event simulation platforms, such as OPTIMUS, extend these capabilities by integrating building energy use, grid events, and charging policies, allowing benchmarking of control algorithms under realistic conditions [18].

3.4 Data Models and Interoperability

Digital twins function as high-fidelity virtual counterparts of physical systems, supporting real-time monitoring, simulation, and control. However, realizing their full potential hinges on seamless data interoperability—the ability of multiple systems to exchange, interpret, and act upon shared information. Without standardized representations, digital twin implementations often remain siloed, each relying on proprietary formats that limit aggregation and coordinated analysis across domains [20]. Addressing this fragmentation requires robust standards and transformation mechanisms to align heterogeneous digital twin models [21].

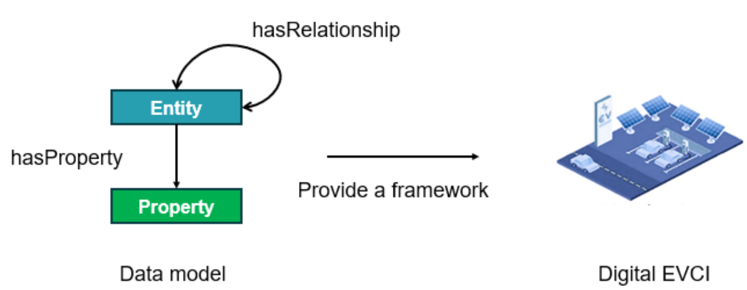

Fig. 2.3 From Data Model to Digital Twin
Data model is an abstract model that organizes and standardizes the relationships and properties of real-world entities.

Data models and ontologies play a crucial role in enabling interoperability. They provide a shared vocabulary and structure that allow systems to interpret information consistently across semantics, constraints, and behaviors [22]. Semantic technologies, knowledge graphs, and ontology-based integration frameworks are increasingly used to bridge modeling languages and domains, facilitating automated data fusion and richer collaboration between digital twins [23]. In addition, conceptual interoperability frameworks, such as those proposed by the Digital Twin Consortium, define atomic data entities and standardized messaging patterns to support modular composition of digital twins across system boundaries [24].

For infrastructures such as electric vehicle (EV) charging networks, interoperable data models are indispensable. They enable cross-system coordination between charging stations, grid services, and building energy systems; support automated integration of sensor data, user behavior, and energy flows; and provide a foundation for composable architectures where charging, storage, and renewable generation twins can interact within a unified ecosystem. Ensuring accurate, semantic-level interoperability is thus a prerequisite for building comprehensive, reliable, and scalable digital twin systems that can address the challenges of sustainable and intelligent mobility.

Related work

1 Brick

Brick is a uniform metadata schema designed to represent building entities—such as equipment, sensors, and spatial locations—and the relationships between them using an ontology-based framework [25]. The project was initiated by a consortium of U.S. and European universities and research institutes, including UC Berkeley, UCLA, Carnegie Mellon University, UC San Diego, University of Virginia, University of Southern Denmark, and IBM Research Ireland. The work was first presented at ACM BuildSys 2016 and continues to evolve under the open-source Brick Schema community (`https://brickschema.org`).

It addresses the interoperability challenges of heterogeneous Building Management Systems (BMS), where vendor-specific naming and label inconsistencies hinder the portability of applications. Brick defines a normalized vocabulary (tags and tag sets) along with fundamental relationships like *hasPoint*, *isPartOf*, *feeds*, and *controls*, enabling semantic queries over RDF-based knowledge graphs via SPARQL.

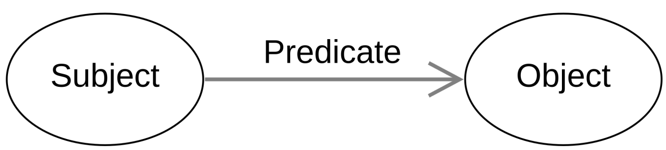

Fig. 3.1 An RDF graph with triple connecting

A key design choice of Brick is its reliance on the Resource Description Framework (RDF). RDF is a W3C standard data model for representing information as a graph of triples, each consisting of a *subject*, *predicate*, and *object*. For example, a triple may state that "Room 101 *hasPoint* Temperature Sensor". This graph-based representation allows entities and their relationships to be linked in a uniform, machine-readable way, and queried with the SPARQL language. By adopting RDF, Brick benefits from decades of semantic web research, existing toolchains for reasoning, and the ability to interoperate with other ontologies.

Brick's key strengths include its clarity, expressiveness, and demonstrated portability. In a validation involving six heterogeneous buildings totaling approximately 630,000 ft^2 and about 17,700 BMS data points, Brick achieved mapping coverage of around 98% of the metadata and supported eight representative applications— such as occupancy analytics, fault detection, demand response, and energy apportionment—without modification [25]. These results highlight how a compact, orthogonal schema can significantly reduce integration costs and enable cross-site reuse of analytics and control logic.

However, Brick also has limitations when considered in the context of transportation systems. Its focus on static subsystems within buildings means it lacks native constructs

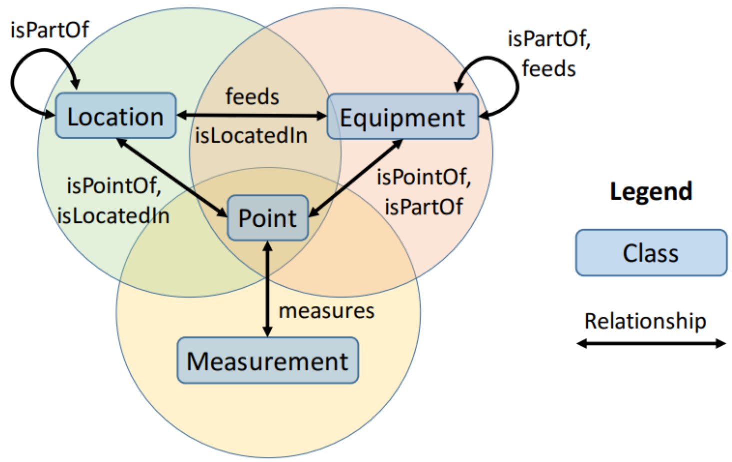

Fig. 3.2 Information concepts in Brick and their relationship to a data point [25]

to represent *temporal events* (e.g., EV charging sessions), *mobile entities* (e.g., vehicles), or domain-specific regulatory and forecasting aspects. For example, a recent evaluation of semantic technologies in building energy flexibility found that Brick could represent only about 16% of EV charging–related concepts, and entirely failed to capture regulatory constraints or environmental forecast information. Therefore, while Brick is effective in building-scale modeling, it must be complemented with dynamic, context-aware frameworks such as NGSI-LD for applications in EV charging infrastructure and smart mobility systems.

In summary, Brick combined with RDF provides a powerful and well-structured way to model static building metadata, making equipment, sensors, and spaces machine-readable and portable across sites. The use of RDF triples and SPARQL enables interoperability and semantic reasoning that are essential for digital twin applications at the building scale. Nevertheless, Brick is less suited to domains that require continuous handling of dynamic, time-varying data and mobile entities, such as transportation systems and EV charging infrastructures. These scenarios demand data models capable of representing temporal events, context updates, and cross-domain interactions in real time.

2 Web of Things (WoT)

The WoT initiative began around 2014 within the World Wide Web Consortium (W3C) Interest Group and was formalized in the WoT Working Group, with the first recommendations—covering the WoT Architecture and the Thing Description—published in 2020 [26].W3C is an international standards organization founded in the United States in 1994 but with a globally distributed membership and governance.

At its core is the *Thing Description* (TD), a machine-readable document based on JSON-LD that specifies the metadata, properties, actions, and events of a device [26]. A TD serves as a semantic contract between a device (the "Thing") and applications, allowing developers to interact with devices through uniform APIs regardless of vendor-specific protocols.

The strengths of WoT lie in its ability to provide a lightweight, technology-agnostic abstraction for devices. By describing functionalities in JSON-LD, WoT enables semantic in-

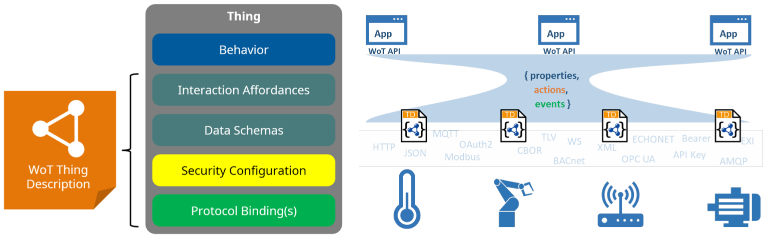

Fig. 3.3 IoT Metadata in TD (left) and WoT mappings (right)
In general, WoT is a protocol agnostic approach and provides a common mechanism to define how specific protocols such as MQTT, HTTP, CoAP or Modbus can be mapped to the WoT's interaction properties-action-event abstraction. [26]

teroperability between devices that expose different protocols (e.g., HTTP, CoAP, MQTT). This abstraction facilitates integration of IoT devices into larger ecosystems, allowing web applications, gateways, and digital twin platforms to discover and use device capabilities in a consistent way. The WoT standard is also modular, supporting security, binding templates, and scripting APIs, which together ease the deployment of scalable IoT systems.

Despite these advantages, WoT also has limitations when applied to transportation and EV charging infrastructure. WoT focuses on the device level—standardizing access to sensors and actuators—but it does not by itself provide higher-level semantics for systems such as charging networks, mobility services, or energy markets. As a result, WoT alone cannot capture domain-specific relationships (e.g., vehicle arrival events linked to charging tariffs, or the coordination between multiple charging stations). In practice, WoT is most effective when used in combination with higher-level frameworks which can forming a layered approach to interoperability in smart transport systems.

3 FIWARE and NGSI-LD

FIWARE is an open-source platform initiative launched in 2011 under the European Union's Seventh Framework Programme (FP7), initially supported by the European Commission and a consortium of European companies and research organizations. It is now managed by the FIWARE Foundation, a non-profit association based in Berlin, Germany, which coordinates global adoption of FIWARE technologies across smart cities, energy, industry, and mobility. At the heart of FIWARE is the *Context Broker*, the core component that manages context information about entities in the physical and digital world. The most widely used implementation is the Orion Context Broker and its NGSI-LD compliant extension Orion-LD.

The FIWARE Next Generation Service Interfaces (NGSI) define the standard API for context management. NGSI-LD, standardized by ETSI (European Telecommunications Standards Institute) in 2019, extends earlier NGSI versions by adopting linked-data principles and JSON-LD serialization [27]. It provides an entity–property– relationship model that is semantically interoperable and aligned with semantic web technologies. Each NGSI-LD entity can represent a real-world object (e.g., an EV charging station), its properties (e.g., capacity, current load), and its relationships (e.g., connected to a power grid or located in a district). The Context Broker exposes these entities via a publish–subscribe API, allowing real-time updates and notifications.

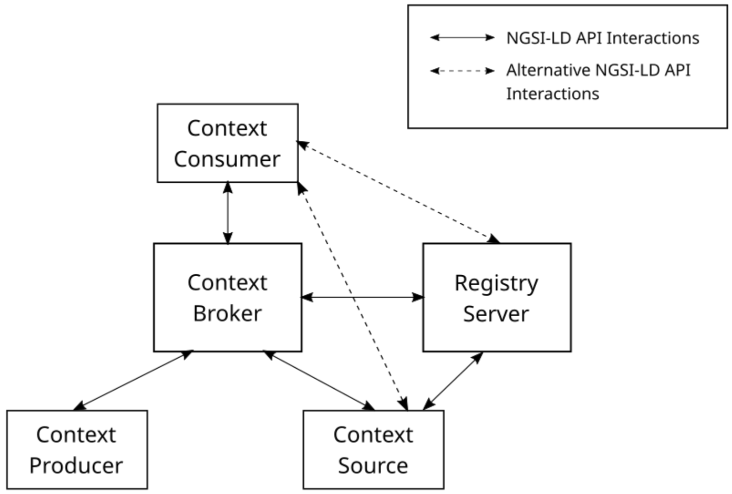

Fig. 3.4 NGSI-LD Architecture Interactions
Context Consumer retrieves information through queries or subscriptions, Context Producer creates, updates, and deletes entity data, Context Broker serves as the primary access point that aggregates and returns data, Context Source stores data and announces available data types to the Registry Server, and Registry Server records data types from each Source to help the Broker discover required information.

The strengths of FIWARE and NGSI-LD lie in their ability to handle *dynamic context* at scale. Through the Context Broker, applications can subscribe to changes (e.g., a vehicle starting or ending a charging session) and react immediately. This dynamic and event-driven model is particularly advantageous in domains such as transport and energy, where continuous synchronization with rapidly changing environments is required. FIWARE also provides a broad ecosystem of enablers—such as IoT agents, data processing components, and dashboards—that simplify integration with IoT devices and data platforms, facilitating large-scale deployments in smart cities worldwide [28].

Nevertheless, FIWARE and NGSI-LD also present challenges when applied to transportation and EV charging infrastructure. While NGSI-LD defines a generic model, it does not provide detailed domain semantics for vehicles, tariffs, or multimodal transport flows. Developers often rely on the *Smart Data Models* initiative, jointly maintained by the FIWARE Foundation, ETSI, and the Open & Agile Smart Cities (OASC) network, to obtain domain-specific schemas. Furthermore, heterogeneous modeling practices across projects can hinder semantic consistency, and complex cross-domain interactions (e.g., integrating mobility services with energy markets) often require additional semantic integration layers.

4 Internship Challenges and Contribution

The analysis of related frameworks highlights that Brick, WoT, and FIWARE each address different layers of interoperability. Brick provides a static ontology for building metadata, WoT enables device-level interoperability via standard Web interfaces, and FIWARE offers a scalable framework for dynamic context management in smart environments. Table 3.1 summarizes their origins, strengths, and limitations.

Tab. 3.1 Comparison of FIWARE, Brick, and WoT

Aspect	**FIWARE**	**Brick**	**WoT**
Main focus	Dynamic context management through Context Broker and NGSI-LD API	Semantic ontology framework for building metadata and relationships	Device interoperability via Web standards and protocols
Modeling method	NGSI-LD (Linked Data with JSON-LD serialization)	RDF + OWL ontology with SPARQL queries	Thing Description using JSON-LD and Web APIs
Pros	• Real-time context updates • Subscription mechanisms • Cross-domain interoperability • Scalable REST APIs	• Unified building semantics • Strong reasoning capabilities • Rich relationship modeling • Standardized vocabulary	• Protocol-agnostic access • Standardized APIs • Web integration • Device abstraction
Cons	• Limited domain ontologies • Depends on Smart Data Models • Device-level control constraints	• Weak dynamic data handling • Limited temporal modeling • Mainly static metadata focus	• Weak semantic reasoning • Limited complex system modeling • Primarily device-layer focus
Organization	FIWARE Foundation and ETSI	Brick Schema community	W3C

From this comparison, it becomes evident that while Brick and WoT provide valuable capabilities, they are not sufficient for the specific challenges of modeling and managing electric vehicle (EV) charging infrastructure. Brick is too static to capture real-time charging events, and WoT does not extend beyond device-level descriptions. In contrast, FIWARE and its NGSI-LD standard are designed for real-time, cross-domain interoperability and have already been adopted in numerous European smart city and energy projects.

Given that this research is funded within the European context, FIWARE is a natural choice as it is an EU initiative, standardized by ETSI, and actively supported by the FIWARE Foundation. Beyond alignment with funding priorities, FIWARE is also technically best suited for the EV charging scenario, as it provides the necessary dynamic context management, integration of IoT data, and publish–subscribe mechanisms required for real-time infrastructure simulation.

Although FIWARE has proven effective for smart city applications, some **challenges** remain. Its modeling focus is typically on the city-wide or district scale (e.g., mobility services, energy demand). As such, the standard provides limited support for station-level modeling that captures the detailed behavior of individual EV charging station. This gap is critical, since station operations involve specific characteristics such as connector types, charging session dynamics, user behavior, and local grid interactions that cannot be fully expressed through generic NGSI-LD entities. Bridging this gap requires extending FIWARE-based models with domain-specific concepts that can describe charging stations with sufficient granularity. Without such refinements, digital twins built on FIWARE risk losing fidelity at the level most relevant to operational optimization.

This internship **contributes** to addressing the above challenges by:

- Extending FIWARE from its traditional smart city scope to the *charging station level*, enriching the model with entities and attributes that capture the operational details of EVSEs (Electric Vehicle Supply Equipment).
- Developing NGSI-LD compliant data models based on *real data* collected from the E4C campus, ensuring that the digital twin framework reflects actual charging patterns, station utilization, and grid impacts.
- Implementing these models within the FIWARE ecosystem, centered on the Orion-LD Context Broker, and integrating them with supporting components for storage, monitoring, and simulation.
- Demonstrating how the refined FIWARE-based digital twin can provide actionable insights at the station level, supporting deployment strategies, demand forecasting, and operational optimization.
- Showing that the proposed approach is *scalable and generalizable*, as the methodology applied to the E4C campus can be transferred to other campuses, districts, or urban areas to enable more detailed and interoperable EV charging infrastructure modeling.

Methodology

1 High-Level View: System Architecture

Figure 4.1 presents a high-level view of the proposed system architecture, which is fully based on the FIWARE framework and NGSI-LD standard. The architecture follows a modular design to enable real-time context management, historical data storage, and visualization of electric vehicle (EV) charging infrastructure.

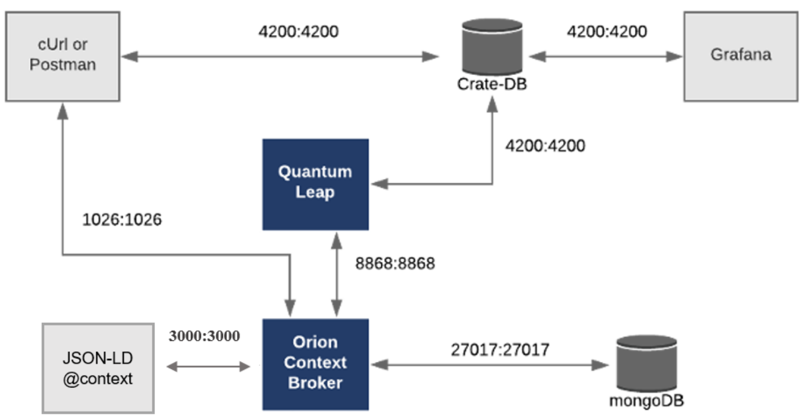

Fig. 4.1 **DigiEV System Architecture**

At the core of the architecture lies the **Orion-LD Context Broker** (port `1026`), which manages all NGSI-LD entities, properties, and relationships. Incoming context data, described in JSON-LD, is ingested into Orion through RESTful APIs (typically tested with cURL or Postman). Orion ensures semantic interoperability by linking each entity with its external `@context` definition, served by a JSON-LD context server (port `3000`).

Two databases support the broker. **MongoDB** (port `27017`) stores the latest state of entities and metadata, while **CrateDB** (port `4200`) stores historical time-series data. To bridge between Orion and CrateDB, the system employs **Quantum Leap (QL)** (port `8868`), which subscribes to Orion and translates every entity update into time-series entries stored in CrateDB. In this way, QL decouples context management from historical data persistence.

For visualization and monitoring, **Grafana** (also connected via port `4200`) queries CrateDB directly, enabling the creation of dashboards to analyze charging patterns, station utilization, and grid impacts. This modular setup therefore provides both:

- *Real-time monitoring* of current states via Orion-LD and MongoDB.
- *Historical analysis* via Quantum Leap, CrateDB, and Grafana.

Data Flow Description

The workflow of the system can be summarized in the following steps:

1. **Data ingestion:** Context information describing EV charging infrastructure (e.g., charging sessions, station status) is formatted in NGSI-LD (JSON-LD) and sent to the Orion-LD Context Broker (port `1026`) using REST APIs (via cURL or Postman).
2. **Semantic enrichment:** Orion-LD validates the data against the JSON-LD `@context` (served on port `3000`), ensuring semantic consistency across entities, properties, and relationships.
3. **Context storage:** Orion-LD stores the latest state of each entity in **MongoDB** (port `27017`), which acts as a short-term persistence layer for current context information.
4. **Time-series processing:** The **QL** service (port `8868`) subscribes to Orion-LD. Every time Orion emits an update, QL converts it into a time-series entry and persists it in **CrateDB** (port `4200`).
5. **Visualization and analytics:** **Grafana** connects to CrateDB (via port `4200`) to generate dashboards for both historical and real-time analysis of charging infrastructure, enabling insights into charging demand, station utilization, and grid impacts.

This pipeline ensures that both the *current state* of EV charging infrastructure (via Orion-LD and MongoDB) and its *historical evolution* (via Quantum Leap and CrateDB) are available for analysis, providing a comprehensive digital twin representation.

All services in the proposed architecture are containerized and deployed using **Docker** and **Docker Compose**. Each component (Orion-LD, MongoDB, Quantum Leap, CrateDB, Grafana, JSON-LD context server) runs as an isolated container, exposing its standard ports as shown in Figure 4.1. The use of Docker provides several advantages:

- *Portability:* the whole architecture can be reproduced on different machines with minimal configuration.
- *Isolation:* each service is encapsulated in its own container, avoiding dependency conflicts.
- *Scalability:* containers can be scaled (e.g., multiple instances of Orion-LD or CrateDB) to handle higher workloads.
- *Maintainability:* the configuration of all services, including port mappings and volumes, is defined in a single `docker-compose.yml` file, making the setup reproducible and easy to extend.

This containerized setup ensures that the FIWARE-based digital twin system can be rapidly deployed, tested, and extended in practical scenarios such as the E4C campus testbed.

2 Design Data Model

`@context` File

Within the NGSI-LD standard, the `@context` file represents the cornerstone of semantic data modeling. Its main purpose is to provide globally unique and machine-readable identifiers (URIs) for entities, properties, and relationships. In this way, when different systems exchange data, they can not only understand the structure but also interpret the meaning of the information consistently.

In this project, to describe the digital twin of the charging infrastructure, I designed a dedicated `@context` file. The beginning of this file is shown below:

```
"@context": {
    "type": "@type",
    "id": "@id",
    "ngsi-ld": "https://uri.etsi.org/ngsi-ld/",
    "fiware": "https://uri.fiware.org/ns/data-models#",
    "schema": "https://schema.org/",
    "ChargingPoint": "fiware:ChargingPoint",
    "ChargingPointStatus": "fiware:ChargingPointStatus",
    "ChargingSession": "fiware:ChargingSession",
    "ChargingStation": "fiware:ChargingStation"}
```

- `"type"` and `"id"` define the fundamental structure of NGSI-LD entities (their type and identifier).
- `"ngsi-ld"`, `"fiware"` and `"schema"` point to the NGSI-LD standard, the FIWARE data model repository, and the `schema.org` vocabulary, respectively. These ensure reusability and standard compliance of the model.
- `"ChargingPoint"` is defined as `fiware:ChargingPoint`, representing an individual charging connector.
- `"ChargingPointStatus"` describes the operational status of a connector (e.g., available, occupied, reserved).
- `"ChargingSession"` corresponds to a charging event triggered by a user interacting with the infrastructure.
- `"ChargingStation"` represents a physical charging facility that may host multiple charging points.

After defining the `@context` file, the next step was to design the entities and their interconnections. Figure 4.2 illustrates the main components of the data model used in the digital twin of the charging infrastructure.

Static and Dynamic Entities

The model is structured around a clear distinction between:

- **Static entities:** These describe relatively stable infrastructure components such as `ChargingStation`, `ChargingPoint`, and `EV`. Their properties change rarely (e.g., location, maximum power).
- **Dynamic entities:** These represent operational states that evolve over time, such as `StationStatus`, `PointStatus`, `EVStatus`, and particularly the `ChargingSession`. Dynamic entities are the key carriers of time-series data.

Bidirectional Relationships

The model also supports bidirectional relationships to ensure semantic consistency across the system. For example:

- A `ChargingPoint` is linked to its parent `ChargingStation` through `refChargingPoint`, while the reverse relation `refChargingStation` allows navigation back from the station to its connectors.
- A `ChargingSession` is associated with both the `ChargingPoint` and the `EV`, reflecting the real-world interaction between the vehicle and the infrastructure. The reverse relations (`refChargingSession`) enable tracing sessions from either perspective.

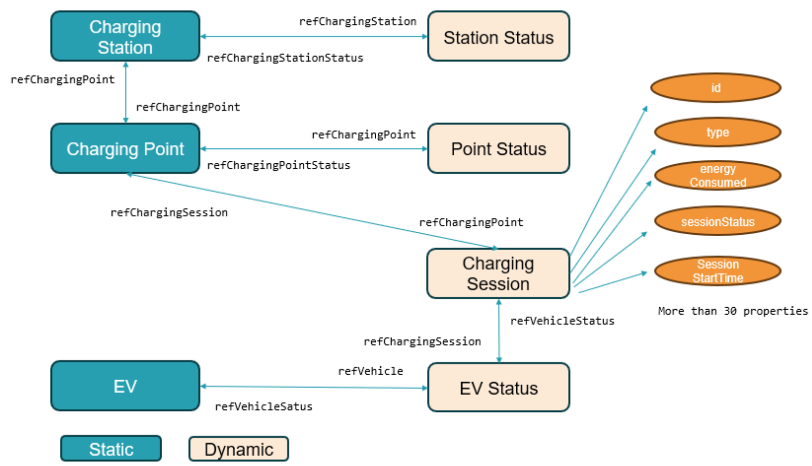

Fig. 4.2 Entity and relationship structure (Property Graph)

Entity Properties

Each entity contains a set of attributes. For example, a `ChargingSession` may include more than 30 properties, such as:

- `id`, `type`: core NGSI-LD attributes.
- `sessionStartTime`: the timestamp when the session begins.
- `energyConsumed`: the amount of electricity delivered during the session.
- `sessionStatus`: operational status of the session (authorized, charging, completed etc.).

By structuring the model in this way, the digital twin can accurately represent both the static infrastructure and the dynamic operational data, while maintaining semantic interoperability in compliance with the NGSI-LD standard.

Validation of the Model with Swagger

To ensure that the designed entities comply with the NGSI-LD standard, I validated the model using **Swagger** (OpenAPI). Swagger provides a formal way to describe RESTful APIs and entity schemas, offering both human-readable documentation and machine-readable validation.

In practice, the `ChargingSession` entity was transcribed into an OpenAPI specification, including its properties, enumerations, and relationships. For example, the attribute `sessionStatus` was defined with a controlled vocabulary (`initiated`, `authorized`, `charging`, `suspended`, `completed`, `failed`, `cancelled`). Using the Swagger Editor, the specification was checked for syntax correctness, type consistency, and completeness. Swagger UI was then used to visualize the schema, explore example payloads, and confirm that enumerations and relationships were properly represented.

This validation step ensured:

- **Correctness:** detection of missing or mis-typed fields,
- **Clarity:** clear documentation of attributes and allowed values,
- **Interoperability:** alignment with NGSI-LD semantics, enabling integration across FIWARE components.

By incorporating Swagger validation, the digital twin data model gained robustness and transparency, bridging conceptual design with implementation and guaranteeing semantic compliance with the NGSI-LD standard.

3 Backend: MongoDB and CrateDB

The backend of the digital twin system relies on two complementary database systems: **MongoDB** and **CrateDB**. Both were essential to guarantee that the entities created from real-world data could be stored, queried, and analyzed efficiently.

MongoDB is a widely adopted NoSQL database designed to store data in a flexible, document-oriented format. Instead of relying on rigid schemas, MongoDB organizes information in JSON-like documents, making it highly compatible with NGSI-LD entities.

In the context of this project, MongoDB served as the persistence layer for the **Orion Context Broker**, and was responsible for:

- Storing the **current state** of all NGSI-LD entities, such as `ChargingStation`, `ChargingPoint`, and `ChargingSession`,
- Allowing fast read/write operations for context queries,
- Supporting heterogeneous structures, which is important since different entities may have different attributes and relationships.

The strength of MongoDB lies in its **flexibility** and **real-time responsiveness**, which made it the ideal choice for managing the operational state of the charging infrastructure.

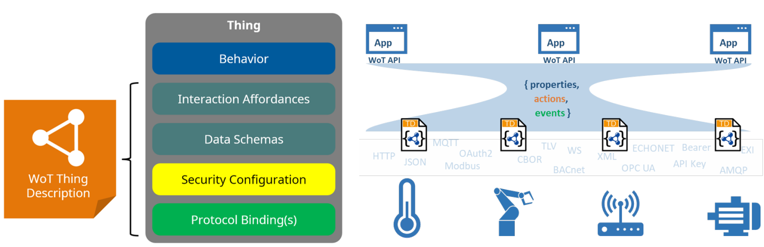

Fig. 4.3 Table structure and entities
In general, WoT is a protocol agnostic approach and provides a common mechanism to define how specific protocols such as MQTT, HTTP, CoAP or Modbus can be mapped to the WoT's interaction properties-action-event abstraction. [26]

CrateDB is a distributed SQL database that combines the familiarity of relational queries with the scalability of NoSQL systems. It is particularly optimized for handling large volumes of **time-series data**.

In this project, CrateDB was used to:

- Store the **historical evolution** of dynamic entities, such as charging sessions and status changes,
- Enable efficient querying of attributes that evolve over time (e.g., `sessionStartTime`, `energyConsumed`, `sessionStatus`),
- Support analytical tasks and visualizations, since CrateDB integrates seamlessly with tools like Grafana.

Unlike MongoDB, which only keeps the latest state, CrateDB provided the **temporal dimension**, making it possible to analyze long-term patterns in charging behavior and infrastructure usage.

Complementarity

Together, MongoDB and CrateDB formed a robust backend:

- **MongoDB** ensured that the most up-to-date context was always available in real time,
- **CrateDB** provided scalability and analytical power for studying historical data.

This dual-database architecture guaranteed that the digital twin could support both **operational monitoring** and **strategic analysis**, which are equally important for the management of charging infrastructure.

Tab. 4.1 Comparison of MongoDB and CrateDB in the backend architecture

Aspect	**MongoDB**	**CrateDB**
Data model	Document-oriented (JSON-like)	Distributed SQL, optimized for time-series
Main role	Stores the **latest state** of NGSI-LD entities	Stores the **historical evolution** of dynamic entities
Strengths	Flexibility, schema-less design, fast context queries	Scalability, efficient time-series queries, integration with analytics tools
Typical usage	Querying current charging point or session status	Analyzing long-term charging behavior and energy consumption trends

4 QuantumLeap and the Subscription Mechanism

While MongoDB and CrateDB provide the persistence layer, the link between them is managed by **QuantumLeap (QL)**. QuantumLeap is a FIWARE component specifically designed for time-series management, enabling the storage and retrieval of temporal data associated with NGSI-LD entities.

Role of QuantumLeap

QuantumLeap acts as middleware between the Orion Context Broker and CrateDB. Its main responsibilities include:

- Receiving entity updates from Orion via the subscription mechanism,
- Transforming NGSI-LD payloads into a time-series format,
- Inserting temporal records into CrateDB for further analysis and visualization.

This ensures that the **current state** of entities is always maintained in MongoDB, while their **historical evolution** is stored in CrateDB.

The Subscription Mechanism

At the core of QuantumLeap's operation lies the **NGSI-LD subscription mechanism**. A subscription defines the conditions under which Orion notifies another component (in this case, QuantumLeap) about changes in entities.

A typical subscription includes:

- **Target entity type:** e.g., `ChargingSession`,
- **Attributes of interest:** e.g., `sessionStartTime`, `energyConsumed`, `sessionStatus`,
- **Notification endpoint:** the URL of the QuantumLeap service,
- **Notification format:** NGSI-LD compliant JSON.

When an entity matching the subscription is created or updated, Orion automatically triggers a notification. QuantumLeap receives this message, processes it, and writes the corresponding time-series entry into CrateDB.

Practical Example

In my project, I defined subscriptions for the `ChargingSession` entity. For each update (such as session initiation, charging progress, or completion), Orion sent a notification to QuantumLeap. As a result:

- The current state of the session was updated in MongoDB,
- The full temporal history of the session was accumulated in CrateDB.

This mechanism ensured that the digital twin could support both **real-time monitoring** and **historical analysis** without additional manual intervention.

Summary

By introducing QuantumLeap and the subscription mechanism, the backend architecture gained the ability to automatically capture time-series data. This allowed the digital twin to provide not only an instantaneous view of the charging infrastructure but also long-term insights into its operation, essential for analytics such as demand forecasting, anomaly detection, and infrastructure optimization.

5 Data Visualization with Grafana

To complete the backend pipeline, the digital twin framework integrates **Grafana** as the visualization layer. Grafana is an open-source analytics and monitoring platform that connects to CrateDB and provides interactive dashboards for exploring time-series data.

Role in the System

While MongoDB and Orion Context Broker provide access to the current state of entities, and CrateDB stores their historical evolution, Grafana enables users to:

- Visualize charging patterns over time (e.g., session durations, energy consumption curves),
- Compare usage between different charging stations or points,
- Monitor real-time infrastructure status alongside historical trends,
- Detect anomalies and inefficiencies through dashboards and alerts.

Practical Implementation

In my project, I configured Grafana to connect directly to CrateDB as a data source. Using SQL queries, I extracted attributes from `ChargingSession` entities such as:

- `sessionStartTime` and `sessionEndTime` for calculating durations,
- `energyConsumed` for analyzing charging demand,
- `sessionStatus` for monitoring operational states.

These values were then visualized through line charts, bar graphs, and time-series panels, providing an intuitive understanding of both short-term and long-term charging behavior.

Added Value

Grafana dashboards not only improved the interpretability of the data but also:

- Supported **decision-making**, by highlighting peak usage periods and energy demand fluctuations,
- Enhanced **operational monitoring**, by offering near real-time visualization of the infrastructure,
- Facilitated **communication**, as dashboards could be shared with stakeholders for reporting and strategic planning.

Summary

By integrating Grafana with CrateDB, the digital twin achieved a complete data lifecycle: from **real-world collection** (E4C charging stations), to **standardized modeling** (NGSI-LD entities), to **backend persistence** (MongoDB + CrateDB), and finally to **human-centered visualization**. This closed the loop of the architecture, transforming raw data into actionable insights.

6 Difficulties Encountered and Lessons Learned

During the development of the digital twin system, several difficulties arose that influenced both the implementation process and the final design. These challenges can be grouped into three main areas: domain knowledge, technical resources, and deviations from the initial specifications.

Domain Knowledge and Data Modeling

At the start of the project, my understanding of electric vehicle (EV) charging infrastructure was limited. This created challenges in defining appropriate entities and attributes for the NGSI-LD model. To overcome this, I conducted a thorough literature review and studied existing semantic models such as the **Brick ontology**. By combining insights from academic papers with standardized data models, I was able to enrich my understanding and build a more consistent representation of charging infrastructure.

Limited Documentation on FIWARE

Another challenge was the lack of up-to-date resources for FIWARE components. Many official tutorials had not been maintained for several years, which made it difficult to find reliable references. For example:

- Initially, I planned to use **WireCloud** as the front-end visualization tool, but discovered that it had not been actively maintained for nearly eight years. This forced me to abandon the idea and search for more sustainable alternatives such as Grafana.
- For time-series data persistence, I first experimented with **Mintaka**, but found that its capabilities were limited compared to QuantumLeap. Consequently, I decided to replace Mintaka with QuantumLeap.

Integration Challenges with NGSI-LD

QuantumLeap was originally designed with native support for NGSI-v2 rather than NGSI-LD, which introduced compatibility issues. Through detailed analysis of the official documentation and extensive testing, I was able to configure and adapt QuantumLeap for NGSI-LD entities. This process required additional research and debugging but ultimately strengthened my understanding of the FIWARE ecosystem and its evolution.

Differences from Initial Specifications

Compared to the initial plan, several significant changes were made:

- WireCloud was excluded due to lack of maintenance, and Grafana was adopted instead for visualization.
- Mintaka was replaced by QuantumLeap for improved time-series persistence.
- Adjustments were necessary to ensure full NGSI-LD compliance, particularly when integrating QuantumLeap.

Summary

Although these difficulties introduced delays and required adaptations, they also offered valuable learning opportunities. I gained deeper knowledge of EV charging infrastructures, developed skills in semantic data modeling, and built resilience in navigating incomplete or outdated documentation. Ultimately, the adjustments strengthened the robustness and sustainability of the final system design.

Case studies and experiment

1 Field Study at E4C Charging Stations

To ground the digital twin in real-world conditions, I conducted a field study at the **E4C campus charging stations**. During this visit, I collected operational datasets covering the period **2023–2025**. The dataset contained detailed records of charging activities, including session start times, durations, energy consumption, and connector usage. This empirical foundation ensured that the system was not only tested with synthetic data but validated against actual infrastructure behavior.

2 Data Cleaning and Preprocessing

The raw dataset required significant preparation before being used to create NGSI-LD entities. Using **Python**, I performed the following steps:

- Removed incomplete or corrupted records,
- Standardized time formats and attribute naming conventions,
- Corrected missing or inconsistent values,
- Structured the dataset into NGSI-LD compliant JSON payloads.

This preprocessing ensured semantic consistency and made the data suitable for integration with the FIWARE ecosystem.

3 Entity Creation

Based on the cleaned dataset, I instantiated the NGSI-LD data model by creating entities and publishing them to the Orion Context Broker. The final set of entities included:

- **1 `ChargingStation`** entity, representing the physical E4C charging facility,
- **1 `ChargingPoint`** entity, corresponding to the charging connector in use,
- **1 `EV`** entity, representing the electric vehicle interacting with the infrastructure,
- **2,200 `ChargingSession`** entities, each capturing the temporal and operational details of individual charging events.

These entities were distributed across MongoDB (for the latest state) and CrateDB (for historical time-series records), ensuring both real-time context management and analytical capabilities.

4 Summary

By combining on-site observations, real data collection, rigorous preprocessing, and automated entity creation, the experimen

Define and Initialize the 3 scenarios result of real data (cite some Kristian's work) result of fake data

5 Simulation Scenarios

In addition to the real dataset collected from the E4C charging stations, I also designed synthetic experiments to evaluate the flexibility of the digital twin system under different user behavior assumptions. Three charging start-time scenarios were simulated, as illustrated in Figure 5.1.

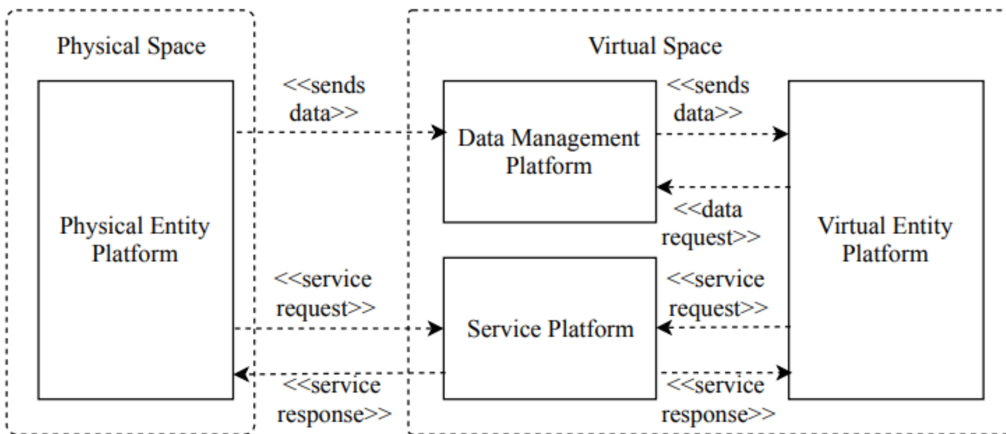

Fig. 5.1 Three charging scenarios simulated within the digital twin

Scenario 1: Random Time

In this scenario, charging sessions were generated at completely random moments within the year:

- Days $\in [0, 364]$,
- Hours $\in [0, 23]$,
- Minutes $\in [0, 59]$,
- Seconds $\in [0, 59]$.

Rationale: This represents uncontrolled charging behavior, where users connect their vehicles without considering price signals, grid conditions, or time of day. It serves as a *baseline scenario* to evaluate the system under maximum randomness.

Scenario 2: Slot Time

In this scenario, charging sessions follow a probability distribution across four time slots:

- Morning (7:00–11:00): 20%,

- Daytime (11:00–18:00): 30%,
- Evening (18:00–22:00): 20%,
- Night (22:00–7:00): 30%.

Rationale: This reflects typical mobility and charging patterns observed in practice: drivers often charge after commuting in the morning or evening, or leave vehicles plugged in overnight. It provides a more realistic scenario compared to purely random charging.

Scenario 3: Informed Time

In this scenario, user decisions are influenced by external factors such as dynamic electricity prices or demand-response programs:

- 60% of sessions occur during **off-peak hours** (10:00–16:00), modeled with a normal distribution,
- 40% of sessions are distributed randomly across all other times.

Rationale: This simulates *smart charging strategies*, where users or automated systems shift demand to off-peak hours. It illustrates how incentives and grid-awareness can reduce stress on the electricity network and improve overall efficiency.

Summary

The three scenarios—**random**, **slot-based**, and **informed**—were designed to capture a spectrum of charging behaviors: from uncontrolled, to realistic, to optimized. By testing the digital twin under these conditions, I could assess whether the backend and visualization pipeline remained consistent and scalable across different user behavior models.

6 Analysis of Real Data and Generation of Synthetic Sessions

To ensure that the digital twin was both grounded in reality and capable of supporting simulation, I worked with two complementary datasets: the **real charging sessions** collected from the E4C stations and the **synthetic sessions** generated under controlled scenarios.

Analysis of Real Historic Data

The real dataset contained approximately **4,400 charging session records** from 2023–2025. A statistical analysis was conducted to extract key characteristics:

- The **mean session duration** was approximately **225.9 minutes**.
- The **mean energy consumption** was approximately **15.9 kWh**.
- Boxplot analysis revealed that successful sessions (`ended`) had diverse durations and consumption levels, whereas failed sessions (`failed`) were typically very short with negligible energy use.

A linear regression confirmed the strong correlation between duration and energy consumption:

$$\text{consumption} = 0.0557 \times \text{duration} + 3.3513$$

This model indicated that longer sessions consume proportionally more energy, with a baseline offset due to fixed overhead.

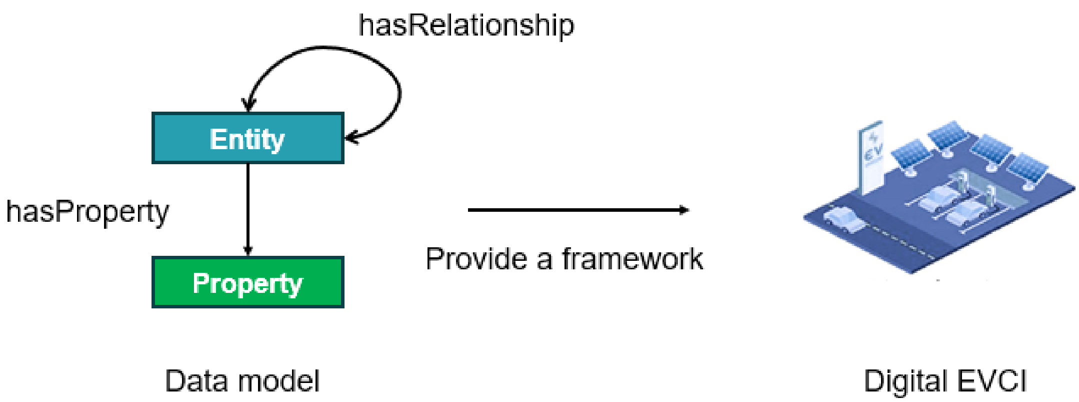

Fig. 5.2 Analysis of real charging session data: duration distribution, consumption distribution, and duration–consumption correlation.

Generation of Synthetic Charging Sessions

Based on the insights from the real dataset, I generated synthetic `ChargingSession` entities for the three charging scenarios (random, slot-based, informed). When creating these entities, the following measures were taken to preserve realism:

- **Temporal distribution:** Session start times followed the probability rules defined by the three scenarios.
- **Durations:** Session lengths were sampled from distributions calibrated against the real data.
- **Energy consumption:** For each synthetic session, the value was derived using the regression model, ensuring consistency between duration and consumption.

This process resulted in thousands of synthetic sessions that shared the same statistical properties as the real dataset, while allowing controlled experiments under different charging behavior assumptions. The combination of empirical grounding and simulated flexibility validated the robustness of the digital twin architecture.

7 Performance Evaluation

To evaluate the responsiveness of the system, I tested the performance of three basic NGSI-LD operations: **create**, **update**, and **delete**. Each test was executed 20 times, and the response times were recorded. The results are summarized in Table 5.1.

Tab. 5.1 Performance evaluation of NGSI-LD operations (20 iterations each)

Operation	**Success rate**	**Min (ms)**	**Max (ms)**	**Average (ms)**	**Median (ms)**
Create	100% (20/20)	10.3	27.5	17.5	18.4
Update	100% (20/20)	10.6	20.1	16.4	18.3
Delete	100% (20/20)	10.6	20.3	13.7	13.0

Analysis

The results show that all three operations achieved a **100% success rate** with no failures. Response times were consistently low across all operations:

- **Create** operations averaged 17.5 ms,
- **Update** operations averaged 16.4 ms,
- **Delete** operations averaged 13.7 ms.

These results demonstrate that the backend architecture provides fast and reliable entity management, even when handling multiple iterations of create, update, and delete requests.

8 Frontend Visualization with Grafana

To provide an intuitive interface for exploring the data stored in CrateDB, I integrated **Grafana** as the visualization layer of the digital twin. Grafana allowed me to design interactive dashboards that display the temporal evolution of charging activities and energy consumption.

Bar Chart Visualization

One of the main visualizations I implemented was a series of **bar charts** showing the variation of energy consumption over time. These charts provided a clear overview of charging demand across different periods and allowed comparisons between usage patterns.

Interactive Features

The Grafana dashboards were designed to be fully interactive:

- **Time selection:** Users can choose any custom time window (daily, weekly, monthly) to observe energy consumption trends.
- **Charging point selection:** The dashboard includes filters that allow users to focus on a specific charging point or aggregate multiple points for comparison.
- **Dynamic queries:** All charts are powered by SQL queries to CrateDB, ensuring that data is updated in real time as new sessions are ingested.

Added Value

By combining these features, the Grafana dashboards enabled:

- Quick identification of peak demand hours,
- Analysis of charging point utilization levels,
- Better understanding of long-term energy consumption patterns.

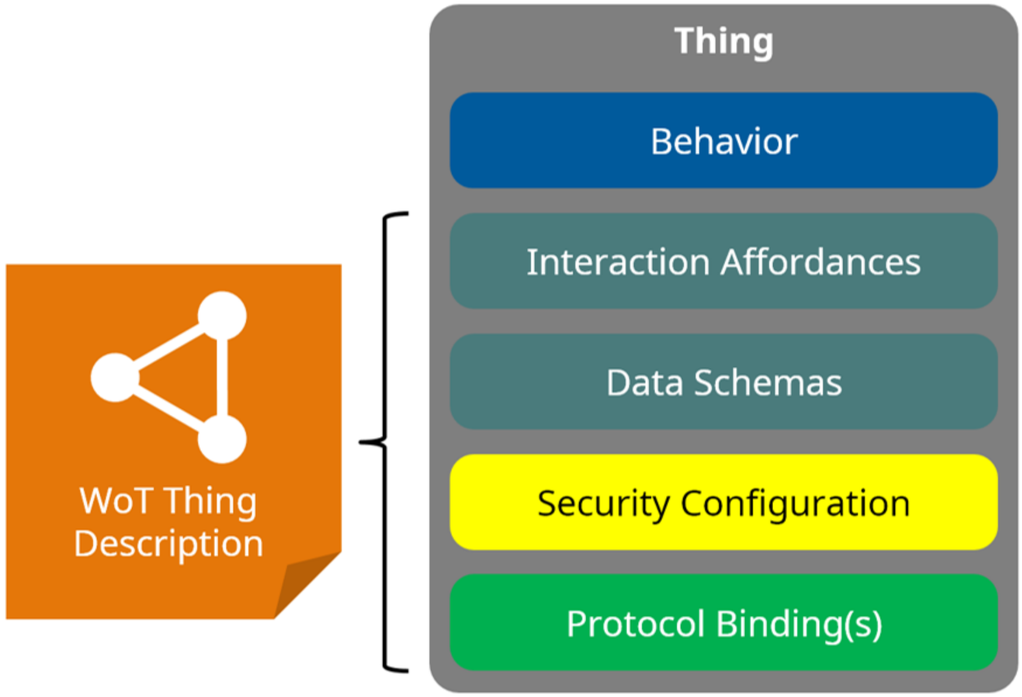

Fig. 5.3 Example Grafana dashboard: energy consumption variation over time, with interactive selection of time windows and charging points.

Summary

The integration of Grafana completed the digital twin pipeline by turning raw and historical data into actionable insights. Through interactive dashboards, stakeholders can now monitor charging activity, analyze energy demand, and explore infrastructure usage patterns in real time.

Analysis management

1 Social and Environmental Responsibility (RSE)

Concepts and Keywords

Corporate Social and Environmental Responsibility (RSE) refers to the responsibility of organizations for the impacts of their activities on society and the environment. Key concepts associated with RSE include: *sustainability, climate action, social equity, human rights, community development, and ethical governance.* In the context of electric vehicle (EV) infrastructure, the most relevant priorities are:

- **Environmental sustainability:** reducing greenhouse gas emissions and improving energy efficiency through electrification,
- **Communities and local development:** ensuring accessibility of charging infrastructure for both urban and rural areas,
- **Social equity:** guaranteeing equal opportunities for all users to benefit from the EV transition without discrimination.

RSE and Economic Development

Far from being a constraint, RSE is a driver of sustainable economic growth. Integrating RSE strategies contributes to:

- Reducing long-term costs (environmental damage, public health issues),
- Opening new markets, especially in clean technologies and green mobility,
- Strengthening competitiveness through alignment with European regulations such as the **EU Green Deal** and **Fit for 55** package [?].

For France, RSE is embedded in industrial and environmental policies. The *Stratégie Nationale Bas-Carbone* emphasizes the electrification of transport and the development of circular economy practices, including battery recycling and second-life applications.

Relevance to the Internship Context

During my internship, RSE principles directly influenced the development of the EV charging digital twin:

- **Energy efficiency:** by modeling charging sessions, it was possible to evaluate energy demand and propose optimizations for reducing peak loads,
- **Integration with renewable energy:** simulation scenarios considered alignment of charging times with solar and off-peak availability,

- **Social impact:** data modeling highlighted the importance of equitable distribution of charging points across regions, preventing disparities in mobility access.

Thus, the project not only had a technological dimension but also addressed social and environmental challenges aligned with RSE objectives.

Conclusion and Recommendations

RSE and economic development are complementary: sustainability concerns set the direction, while innovation provides the tools to achieve these goals. For companies and research laboratories, adopting RSE strategies in EV infrastructure implies:

- Supporting fair access to charging infrastructure,
- Integrating renewable energy into charging networks,
- Enhancing transparency and stakeholder engagement through digital twins.

In the long term, this alignment strengthens both competitiveness and societal value creation.

Conclusion

1 Conclusion of the Internship

This internship provided me with the opportunity to design and implement a digital twin for electric vehicle (EV) charging infrastructure using the FIWARE framework. Starting from data modeling with NGSI-LD, I developed an interoperable representation of charging stations, charging points, electric vehicles, and sessions. I integrated real datasets collected from the E4C charging stations (2023–2025) and complemented them with synthetic scenarios to test scalability and flexibility. The backend architecture, based on MongoDB and CrateDB, successfully supported both real-time context management and historical analysis, while QuantumLeap ensured temporal data persistence. Finally, Grafana dashboards provided stakeholders with interactive visualization tools for monitoring energy consumption and infrastructure usage.

Overall, the project demonstrated the feasibility of combining standardized semantic models with real-world data to create a robust and scalable digital twin. This experience also gave me hands-on expertise in both data engineering and IoT system integration, bridging theory and practice.

2 Future Work

Although the system is functional, several improvements can be considered for future development:

- **Scalability testing:** Extend performance tests to larger datasets (tens of thousands of sessions) and multiple charging stations to validate system robustness.
- **Advanced analytics:** Incorporate predictive models (e.g., demand forecasting, anomaly detection, and optimal load balancing) to enhance decision-making.
- **Integration with external data and IoT devices:** Extend the system by combining charging data with external data streams such as renewable energy production, weather forecasts, and dynamic electricity pricing. In parallel, integrate IoT devices (e.g., smart meters, charging sensors, and on-site monitoring equipment) to capture real-time operational parameters. This would enable advanced demand-response strategies and provide a more holistic view of the interaction between vehicles, infrastructure, and the energy grid.
- **Enhanced front-end:** Develop a more user-friendly web interface, potentially with dynamic maps and real-time alerts, to complement Grafana dashboards.
- **Standardization efforts:** Contribute to ongoing FIWARE/NGSI-LD data model standardization, especially for EV infrastructure.

3 Career Impact and Personal Development

This internship significantly contributed to my personal and professional development. By aligning with competencies identified in the RNCP framework for the role of **iot / IoT Architect (Architecte IoT)**, I was able to develop key skills across several domains :contentReference[oaicite:0]index=0.

Developed Competencies

- **Architectural Design and Analysis:** I refined my ability to analyze user requirements and design scalable, secure IoT architectures—from sensor interfaces to data persistence layers—according to RNCP expectations :contentReference[oaicite:1]index=1.
- **System Integration and Data Flow Management:** The integration of NGSI-LD data models, Orion Context Broker, MongoDB, CrateDB, QuantumLeap, and Grafana reflects the end-to-end data flow design capabilities expected of an IoT architect :contentReference[oaicite:2]index=2.
- **Technical Leadership and Project Execution:** Managing the entire pipeline—data collection, modeling, backend implementation, scripting, simulation experiments—strengthened my ability to coordinate multidisciplinary technical tasks and deliver functioning systems :contentReference[oaicite:3]index=3.
- **Innovation and Continuous Learning:** Addressing undocumented FIWARE components, adapting NGSI-v2 tools to NGSI-LD, and refining simulation strategies demonstrated a proactive approach to technological innovation and ongoing knowledge updating :contentReference[oaicite:4]index=4.
- **Communication and Documentation:** Producing structured documentation of the system architecture, experimental design, and performance results enhanced my capability to clearly communicate technical concepts to a diverse audience :contentReference[oaicite:5]index=5.

Impact on My Career Trajectory

This internship reinforced my interest in research at the crossroads of digital twins, IoT platforms, and sustainable mobility systems. Given this deepened motivation and strengthened expertise, I intend to pursue a **PhD**, focusing on advanced topics such as :

- Semantic modeling and standardization for EV infrastructure,
- Predictive and optimization methods for smart charging under variable grid conditions,
- Scalable architecting of IoT systems in energy-aware ecosystems.

In summary, this experience not only consolidated critical technical and methodological competencies aligned with RNCP expectations for IoT professionals, but also clarified and propelled my long-term academic and professional ambitions.

Annexe

Annexe 1 - List of Interviewees (Chapter 6)

- **Dr.Daphne Tuncer:** Chercheure ENPC
- **Dr.Georgios Bouloukakis:** Assistant Professor at University of Patras

Annexe 2 - Internship Advertisement

DigiEV: Design and integration of a digital twin for electric vehicle charging infrastructure in the E4C ecosystem

Supervision team: Dr Daphne Tuncer (ENPC) and Dr Georgios Bouloukakis (TSP)

Context

The success of electric mobility is not only based on state-of-the-art electric vehicles such as rapidly charging passenger electric cars, light-weight electric bicycles, or long-distance electric trucks. It also necessitates the deployment, management and maintenance of an integrated infrastructure that couples electricity provision, information distribution, and software-based system control.

Digital twin approaches have been emerging as leverages to manage the operations and performance of complex system infrastructures, as well as to evaluate their deployment plans. A digital twin is a physical or virtual representation of a physical environment (*e.g.*, network of charging stations). It mimics the characteristics of the system (IoT infrastructure, smart grid) and helps analyse and predict the behaviour of a system under multiple, possible operating conditions. Creating realistic digital twins is a challenging task. Real world systems involve a vast array of heterogeneous interconnected objects; build upon a large set of functions; involve human activities that are hard to model, observe and track. In the case of a charging infrastructure for electric mobility, this necessitates to take account of the energy supply—which can be mixed- the information and communication systems, the software components that control the charging activities, as well the behaviour of human agents (*i.e.*, the demand).

Objectives

The objective of the placement is to implement a digital twin of the charging infrastructure of E4C on the campus of Institut Polytechnique de Paris. The proposed digital twin will provide a tool for the technical team of the demonstrators of E4C to evaluate the performance of the existing charging infrastructure, as well as to assess and compare the deployment plans of new stations on the campus. More specifically, the project will involve three main tasks.

Task 1 – To develop a digital twin of the charging infrastructure of E4C, including modelling static data (charging station specifications) and dynamic data (energy supply and charging demand).

Task 2 – To integrate the digital twin of the charging infrastructure with the federation of digital twins of the DRAHI-X, SIRTA and Building 103, developed as part of a 2024 E4C-supported internship project[1], co-supervised by Dr Bouloukakis and Dr Tuncer.

Task 3 – To design and implement a set of realistic scenarios in order to demonstrate how the digital twin tool can be used to control, manage and extend the current infrastructure, including illustrating the functionality of a scheduling mechanism to control the energy supply, showing the process of monitoring the infrastructure, or applying an optimisation method to deploy a new station.

The student undertaking the project will be responsible to showcase the results of the project to the technical team of E4C at the end of the placement.

1 A Federation of Digital Twins for Sustainability in the E4C Ecosystem

About the placement

- 6 months – starting March or April 2025
- Located at Ecole des nationale des ponts et chaussees, Institut Polytechnique de Paris, France
- Joint supervision between Ecole nationale des ponts et chaussees et Telecom SudParis
- Part of the Energy4Climate (https://www.e4c.ip-paris.fr/#/fr/) multidisciplinary research center of Institut Polytechnique de Paris
- Open to final year engineering school / master (MEng / MSc) student

Skills and competence

- Fluent in English
- Good knowledge of programming (preferably Python and Java) and data structures.
- Good knowledge of standard data format (JSON, CSV, XML)
- Good knowledge of the REST architectural style and RESTful APIs
- Knowledge of Semantic Web Standards (RDF, OWL) is an asset but is not required.

Contact

To apply, contact
- Daphne Tuncer, Ecole des nationale des ponts et chaussees, daphne.tuncer AT enpc.fr
- Georgios Bouloukakis, Telecom SudParis, georgios.bouloukakis AT telecom-sudparis.eu

by providing the following documents:
1. CV
2. Motivation letter
3. Transcripts of the last 3 years
4. A course report or article written in English (if any)

Relevant references

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Annexe 3 - CV

ZHAO Chao

Skilled and interested in Data Science, AI and Cloud
A combined background in engineering and computer science
Open-mind, results-oriented, humble person

English: Fluent & C1 | **French**: Intermediate & B2 | **Chinese**: Native speaker & C2

Contact +33 6 79 86 14 98 | chao.zhao@enpc.fr | Boulogne-Billancourt,92100,Ile-de-France

Tech Stack

Databases : MySQL, PostgreSQL, MongoDB | **BI** : Power BI, Office Pack | **Big Data/Cloud** : Airflow, Elasticsearch, Spark, AWS, Azure | **Data Science** : NumPy, Pandas, Matplotlib, R | **ML/DL** : Scikit-learn, Pytorch, Tensorflow, Keras | **Semantic Web** : Ontological, Protégé, NGSI-LD | **Programming** : Python, Linux, GitHub, HTML, CSS, PHP, JavaScript

Education

Engineer Diploma of Data Intelligence
ISEP - Institut supérieur d'électronique de Paris — *Sept 2023 - Oct 2025*
Bachelor of Building electrical and intelligence
Shenyang Jianzhu University (China) — *Sept 2014 - Jun 2018*

Professional Experience

Intern Full Stack R&D – Optimization by Digital Twin (DT) for EV Infrastructure (EVI)
Institut Polytechnique de Paris - *École nationale des ponts et chaussées* — *May 2025 - Oct 2025*
- Conducted literature review on **semantic modeling, DT, and EVI**
- Compared different frameworks to identify suitable system architecture
- Built a **NGSI-LD based DT**, to manage both static and dynamic data
- Designed and tested an **optimization scenario** for EVI based on DT

Tech manager of building electrical and intelligence team
Haituo *Construction Engineering Corporation Ltd.* — *Jul 2018 - Jun 2023*
- Optimized technology solution, surpassing profit targets by $550,000 in 2022
- Led an international team of 14 members, earning 'Level-A' performance evaluation in 2022
- Authored two internal research papers, contributed to two company-level guidelines based on TIA/EIA-568 and ISO/IEC 11801 , received € 500 as manuscript fee

Code Competition

3rd Prize "Hackathon Fr 2024" — *Mar 2024*
- Award : 600 euros (Team of 4 members)
- Goal : Secure the route of the Olympic flame in terms of radio coverage
- My responsibility : Designed and implemented a **weighted Dijkstra**-based path planning system to achieve optimal routing

School Project

Big Data & Cloud - *Sales Data Analytics* — *May 2024*
- Deployed **datalake** on **AWS**
- Called **APIs** to extract raw 'JSON' files, cleaned and formatted **'JSON' to 'Parquet'** files
- **Indexed data** in ElasticSearch, created **dashboard** in Kibana
- Managed and scheduled the entire workflow with **Airflow**

Parallel Computing & Deep Learning -
Ultra-Large Size Medical Images Segmentation And Classification — *Jan 2025*
- Split ultra-large 'svs' or 'tif' image into more than 8000 tiles
- Applied **OTSU's** image thresholding and **Canny** edge detection for each tile
- Trained **U-Net** model for segmentation and **EfficientNet** for classification, F1 score: 0.92
- Integrated all processes into a **parallel computing pipeline** in Spark

Data Analysis & Machine Learning - *Bankruptcy Prediction* — *Oct 2024*
- Explored distribution and the correlation of features by **unsupervised learning**
- Applied **re-sampling** to the highly imbalanced dataset
- Applied different **supervised learning models**, and **tuned hyperparameters**
- Evaluated different models by **F1 scores** and **ROC curve**

Annexe 4 - Motivation Letter

Form

ZHAO Chao

(+33) 6 79 86 14 98
zhaochao0739@gmail.com
15 rue Barthelemy danjou,
92100 Boulogne-Billancour

Jan 25, 2025

To

Dr.Daphne Tuncer and Dr.Georgios Bouloukakis

Subject: Application for DigiEV Digital Twin Internship Position

Dear Professors,

My name is ZHAO Chao, a final-year student at ISEP with a background combining construction engineering, computer science, and data science. I am writing to express my strong interest in the 6-month DigiEV internship position. After carefully studying the three core project tasks, I believe my qualifications align perfectly with the role for the following three reasons.

1- **My background uniquely matches the internship requirements.** At Haituo, I implemented serval digital twin models (Honeywell Platform) to monitor and control energy consumption, HVAC system, and data center. I also contributed two company-level guidelines and authored two internal research papers. At ISEP, I gained experience in Python, RESTful APIs, cloud platforms (AWS/Azure), and machine/deep learning frameworks (PyTorch, TensorFlow), alongside Knowledge of Semantic Web (RDF, Ontology). Furthermore, my international experience across both Haituo and ISEP has developed my ability to collaborate effectively within diverse, cross-functional teams.

2- My passion for research and curiosity about the world drive me to seek deeper understanding. I left my previous career to pursue a master's degree because I wanted to understand not only 'what' technical solutions exist, and 'how' to implement them, but also the 'why' behind their design. The DigiEV project's ambition to model EV charging infrastructure as a dynamic ecosystem of energy, data, and human interaction is precisely the type of 'why'-focused challenge that ignites my intellectual curiosity.

3- **This internship aligns with my long-term career goals.** As I plan to pursue a Ph.D. in the intersection of engineering and computer science, this project offers an ideal foundation for exploring digital solutions to real-world energy challenges. The opportunity to work under the joint supervision of ENPC and Telecom SudParis would provide unparalleled exposure to cutting-edge methodologies and interdisciplinary collaboration—key elements for my future academic journey

Thank you for considering my application. I look forward to the opportunity to contribute to this innovative project addressing the crucial challenges of electric vehicle infrastructure development.

Sincerely,

ZHAO Chao

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