Multi-Partner Project: Electric Vehicle Data Acquisition and Valorisation: A Perspective From the OPEVA Project

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***Abstract*—The OPtimization of Electric Vehicle Autonomy (OPEVA) project enhances data aggregation for Electric Vehicles (EVs) by collecting critical real-time data (i.e., vehicle performance, battery health, charging behaviours) through heterogeneous data acquisition devices built on robust HW and integrated with Internet of Things (IoT) protocols. By combining internal sensor data and driver-specific behaviours with external information (e.g., road conditions, charging station availability), OPEVA maximizes vehicles performance, establishing secure and seamless data communication between EVs and the infrastructure, and using IoT and cloud computing tools alongside Vehicle-to-Everything (V2X) devices and networks. This paper focuses on the extensible data model ensuring semantic data integrity considering *in-* and *out-vehicle* factors, presenting data acquisition solutions dealing with OPEVA's semantic data model and their use in various Artificial Intelligence (AI)-powered use cases (e.g., range prediction, route optimization, battery management).**

***Index Terms*—Internet of Things, Electric Vehicles, cloud computing, Federated Learning, Machine Learning**

I. Introduction and Motivations

The OPtimization of Electric Vehicle Autonomy (OPEVA) project [1], [2] focuses on pioneering advancements in Electric Vehicles (EVs) data aggregation, extending beyond battery monitoring to include data from internal sensors and driver-specific behaviours, targeting to develop personalized performance and consumption models. By integrating real-time data on road conditions, weather, and charging stations availability, OPEVA aims at optimizing each driving episode, enhancing the EV driving experience through contextual awareness. Moreover, OPEVA also addresses the critical communication link between EVs and the infrastructure, enabling seamless data flow from back-end systems to EVs, thereby improving recharging applications and battery management. From embedded vehicle systems to cloud-based support, OPEVA seeks to achieve a level of mobility efficiency within one decade that took fossil fuel-based systems nearly a century to realize. Additionally, the EU project considers economic, legal, ethical, and environmental factors to boost societal acceptance and awareness of EV technologies, fostering a sustainable and efficient future for personal mobility.

This paper overviews on the progresses of multi-dimensional data modelling, encompassing both *in-vehicle* and *out-vehicle* sources, with a focus on advancements in data generation and collection critical for the EVs ecosystem. In fact, the OPEVA solution portfolio centers on developing a comprehensive data acquisition system collecting real-time metrics from EVs—such as battery health, energy consumption, vehicle positioning, and grid interactions. This system, integrated with Controller

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Area Network (CAN) Bus [3] and Message Queuing Telemetry Transport (MQTT) [4] protocols, supports remote, *in-vehicle*, and *on-site* data collection interfaces for EVs and charging infrastructures, establishing secure mechanisms for reliable data handling within the back-end system. Then, OPEVA's key components include resilient Internet of Things (IoT) and communication infrastructures essential for maintaining seamless connectivity across vehicles, infrastructure, and cloud systems. Advanced storage solutions, V2X devices, and cloud computing tools (such as Docker [5], Kubernetes [6], Kafka [7], and AWS [8]) compose the foundation of this infrastructure, supporting scalable data processing and real-time analytics. Additionally, the integration of next-generation networks (XG), LTE, and IEEE 802.11p ensures a robust and interoperable system, fostering reliability and safety across diverse communication technologies and vehicle types, while enabling predictive maintenance, energy forecasting, and route optimization essential to EV operation. The structure of the paper is the following. In Section II foundational elements and objectives of the OPEVA project are presented. Section III describes different aspects of OPEVA data collection systems, while Section IV provides an overview on different project use cases. Finally, in Section V we draw our conclusions.

II. OPEVA Project Fundamentals and Semantic Data Integrity

The primary goal of OPEVA is to enhance the adoption and market reach of EVs by addressing key psychological barriers, including concerns about range anxiety, high costs, limited charging infrastructure, and lengthy charging times. The specific objectives of the OPEVA EU project can be summarized as follows.

- Enhance the powertrain energy efficiency integrating advanced battery, power, and AI-based control systems.
- Lower the energy consumption and Improve the EV range considering both external factors (e.g., weather, road conditions) and internal data (e.g., battery health, driver profile) using secure data acquisition.
- Optimize EV-grid integration with Vehicle-to-Grid (V2G) technology and smart charging strategies, supporting large-scale EV adoption in power networks.
- Decrease charging times with advanced methods like inductive charging, wireless battery communication, and advanced diagnostics.
- Strengthen research, innovation, and marketing capacities to support the EU's goals for CO_2-neutral and sustainable mobility through EV adoption.

Hence, in order to achieve these objectives, OPEVA has an ambitious and proactive strategy to collect data and develop a semantic basis to integrate a wide range of HW and SW-based Key Technologies (KTs). This semantic basis forms the multi-dimensional data model of the OPEVA architecture, in detail designed to support innovation across various interconnected domains, and creating a platform for advancements categorized into KTs. Key foundational elements of the architecture include:

1) **Cloud support and communication services**: enhancing connectivity between vehicles, infrastructure, and back-end systems.
2) **Battery Management Systems (BMSs)**: ensuring efficient EV battery performance through advanced monitoring and control.
3) **Energy-aware intelligence and prediction**: using data analytics and Machine Learning (ML) for energy demand forecasting and usage optimization.
4) **Charging and energy grid integration**: facilitating seamless interaction between EVs, grids, and renewable sources for sustainable charging and grid stability.

These building blocks create a cohesive framework supporting the development of innovative solutions, accelerating the shift to sustainable mobility, and engaging end-users in the long-term adoption of assistive technologies equipping intelligent vehicle. This will improve societal acceptance of EVs, since drivers, passengers, as well as Vulnerable Road Users (VRUs) will benefit from improved safety and lifestyle on the long-term period. Moreover, the semantic data integrity is a key aspect in the OPEVA data modelling, as it is defined as the accuracy, consistency, and contextual relevance of data within EVs and grid relationships, ensuring that it aligns with project's requirements and architectural specifications. To maintain data integrity, a data governance strategy has been implemented within the OPEVA framework, encompassing clear policies and standards for data management. This framework includes a JSON-based messaging system enriched with metadata, linked to superclasses to provide contextual clarity, aiding user understanding of data origin, structure, and interrelations. Then, security measures span from low-level components—such as secure IoT gateways, Trusted Platform Modules (TPMs), and HW Security Modules (HSMs)—to advanced proximity control solutions, safeguarding data from edge devices through the entire network. Error-correcting codes are also employed, reinforcing data integrity across the data flow.

The developed data model, shown in Fig. 1, comprises superclasses returning the relationships among EVs, charging infrastructure, last-mile delivery services, and external entities. Designed for extensibility, the model primarily focuses on optimizing EVs and batteries but can incorporate additional superclasses, such as drivetrain models and climate impact considerations.

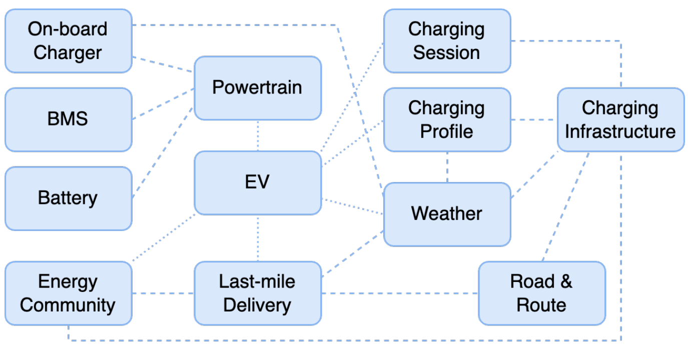

Fig. 1. Developed data model and integrity in the OPEVA project.

More in detail, a central superclass is the EV, where the powertrain and related modules are integral, particularly for battery's State-of-Health (SoH) assessment. Other key components include the electric traction motor, power electronics, *on-board* charger, battery, BMS, and DC/DC converter. To support a comprehensive charging management, the proposed model introduces superclasses for the Charging Infrastructure (considering both wired and wireless stations), Charging Session (managing operations for individual/fleet EVs), and Charging Profile (linking driving behaviour and route conditions to battery performance).

High-level superclasses represent last-mile delivery and routing, integrating single or fleet of EVs usage with factors such as weather and road conditions to assess impacts on battery State-of-Charge (SoC) and overall energy efficiency. Additionally, the Energy Community superclass addresses energy production, storage, demand-response, economic benefits, and social impacts, creating a complete model of EV interaction within broader energy ecosystems.

The OPEVA layered architecture, built on the Open Systems Architecture for Enterprise Application Integration (OSA-EAI) [9], consolidates design, maintenance, operational, and diagnostics data into a unified model, ensuring data integrity and minimizing inconsistencies. This framework enhances data accuracy, reliability, and accessibility, supporting informed decision-making and efficiency across the EV ecosystem.

Finally, to reduce battery weight and improve both scalability and versatility, a wireless BMS is also developed within the OPEVA framework, with energy autonomous transponders able to acquire and communicate sensor data in real time are conceived in order to operate within the battery while exclusively relying on energy harvesting, thereby relaxing maintenance requirements, reducing costs and improving reliability.

III. Data Collection from EVs

A critical aspect of the integration between EVs and smart grids is the collection of real-time data from EVs, providing information on vehicle performance, battery health, charging behaviour, and grid interactions, and serving many purposes, such as optimizing charging schedules, monitoring battery performance, and contributing to grid stability. The literature suggests various solutions, e.g., using CAN Bus systems to acquire *in-vehicle* data and IoT protocols (e.g., MQTT) to transmit this information to centralized platforms [10], [11]. Furthermore, ML- and AI-based algorithms can be used to interpret this data, enabling predictive maintenance, energy forecasting and real-time route optimization. More advanced data collection systems are needed to achieve these outputs and to handle the dynamic nature, increasing complexity and volume of data of energy demand and EV use.

So as, the design and implementation of an advanced data acquisition system for EVs, focusing on real-time transmission and analysis of vehicle and battery data, is presented. Using a Jetson Nano Developer Kit [12]-based data acquisition system, it is possible to harvest data from the vehicle's CAN Bus network, then processing and transmitting it to a platform using MQTT for further analysis. This system is built with various sensors and HW, including GPS to track the EV's position and a 12V-5V converter to ensure compatibility with the vehicle's power system.

A. Development of the Data Collection Systems

OPEVA foresees different HW solutions are designed for collecting data. The first is a data acquisition system to be used in HW-in-the-Loop (HIL) systems (as shown in Fig. 2), whose key components are the following.

- A Jetson Nano Developer Kit, selected for high-performance data processing thanks to its optimal balance of performance and cost, and support to edge AI applications (e.g., image classification, object detection). It was tested and validated for *in-vehicle* use with advanced thermal management solutions.
- A Korlan USB2CAN module [13] to interface with the EV's CAN Bus and collect key data such as battery health, speed, and energy consumption.
- GPS and tilt sensors.
- An Human-Machine Interface (HMI) panel displaying critical information on the vehicle (as shown in Fig. 3).

Fig. 2. EV Data Collection Box & integrity (provided by ACD).

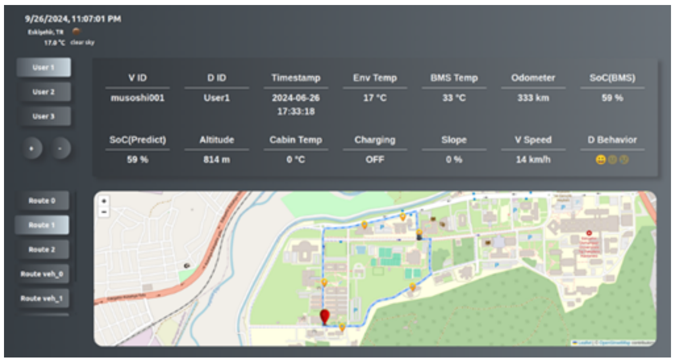

Fig. 3. HMI panel.

Then, Fig. 4 depicts the essential role of the edge device in the data acquisition process. The Musoshi vehicle generates *raw* CAN Bus data, which requires decoding and contextualization before their storage in a database or their usage for high-level analytics. This edge device locally pre-processes *raw* data, converting them into a human-readable format via specialized decoding SW. By performing this conversion *at the edge*, the system reduces the complexity and bandwidth requirements for transmitting *raw* CAN data directly to a cloud or external server. Moreover, this approach ensures compatibility with third-party applications and supports the seamless integration of decoded data into dynamic routing, fleet management, and diagnostic platforms. Direct reliance on CAN Bus data without such pre-processing would increase network strain, introduce latency, and limit interoperability, especially in scenarios involving large-scale fleet management.

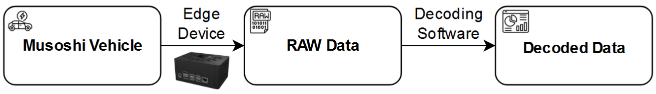

Fig. 4. EV Data Collection Box workflow.

The proposed system not only captures and transmits data, but also enables data to be fed into the database to support dynamic routing decisions, fleet management and vehicle diagnostics, which are critical for optimizing energy use and reducing grid load.

Alternatively, a general-purpose and low-cost gateway is also designed in OPEVA to collect data from the CAN-bus or OBD port of an EV. Such gateway encrypts at high speed data at edge (vehicle in this case) and transmits the encrypted data to any third party service, say a cloud service, securely. As

Fig. 5. PRIGM Midi-3 Secure Gateway (provided by ERARGE).

shown in Fig. 5, the secure gateway, denoted as PRIGM Midi-3, operates in a working environment that is composed of two areas of operation: (i) vehicle side (*in-vehicle*) and (ii) server side (e.g., cloud back-end servers). The first area is the vehicle itself (so-called *in-vehicle*) on which the PRIGM Midi-3 is installed. The gateway has two connectors, one for the power input, and one for the Ethernet cable connector, the latter used by the Vehicle Control Unit (VCU) to connect to the gateway, while the gateway is connected to the external world via GSM (4G-LTE Modem). Then, when the VCU wants to send data to the server, it establishes a secure connection with the gateway via the local Ethernet network in the vehicle. This connection is automatically accepted by the gateway and a Virtual Private Network (VPN) connection is automatically started with the infrastructure on the server side. The VPN connection is verified by a master device, denoted as PRIGM HSM, and then the secure data channel is established between the vehicle and the server over a two-way connection. After the secure data channel is established, the VCU securely sends any CAN data, message, etc. to the server over a transparent connection. Similarly, this connection allows the server to send data to the vehicle.

Another HW solution for data collection and valorization in the aim of the OPEVA project is a general-purpose Multi-Interface Gateway (MIG) system, equipped with different network interfaces, and based on Commercial-off-the-Shelf (COTS) components. In detail, the main goal of the MIG is to provide fully-customizable internal data and traffic routing protocol (not only to send data to the cloud), allowing information flows between network interfaces, through customizable routing rules. Moreover, the MIG can process the received data streams on the basis of custom processing units. The available interfaces, rules, and custom processing units can be managed through a Web dashboard, that allows users to smoothly control all the configurations.

A prototype of the MIG is under development, as shown in Fig. 6, with the following main components/interfaces:

- a Raspberry Pi 3 (RPi) Model B provided with different communication interfaces, such as *on-board* BLE and IEEE 802.11 (Wi-Fi) interfaces;
- an external BLE USB adapter (namely, LM Technologies LM506);
- an external Wi-Fi USB adapter (namely, TP-Link TL-WN722N);
- a Long Range Wide Area Network (LoRaWAN) gateway Interface (namely, Seeed Studio WM1302 USB);
- a LoRaWAN End-Node module (namely, Microchip RN2483 PICtail).

Fig. 6. MIG prototype under development by the University of Parma.

The MIG internal routing mechanism is managed through the Zero Overhead Network (Zenoh) [14], a publish/subscribe protocol allowing to forward data through running processes in a fast and lightweight way. Finally, the MIG storage support for the routing mechanism definition is based on a NoSQL database (namely, CouchDB [15]) which is also used to store processing rules.

IV. Illustrative Use Cases and Innovations

The following use cases and innovations are designed and planned according to the EV OEMs' needs and current practices of the EVs utilisation in people and goods transportation. The example use cases here show how the collected data can be used in real-life settings and impact the industry.

A. EV Range Prediction

In this use case, the research examines the collected data with variables such as energy consumption (dimension: [kWh]), trip distance (dimension: [km]), vehicle model, driving style, and tire type to improve EV range prediction. Power at the wheels are determined by factoring in forces like aerodynamic drag, rolling resistance, and gravity, as calculated in Eq. 1 [16]:

$$\begin{aligned} P_{wheels}(T) = & \frac{v(t)}{P_{motor}\, P_{driveline}}\Big(a(t) \\ & + mg\cos(\theta)\frac{C_r}{1000}\left(C_1 v(t) + C_2\right) \\ & + 0.5\rho_{air} A_f C_D V_w(t)^2 + mg\sin(\theta)\Big) \end{aligned} \tag{1}$$

where: m is the mass (dimension: [kg]), a is the acceleration (dimension: [m/s^2]), g represents the gravitational acceleration (dimension: [m/s^2]), θ is the road grade (dimension:[%]), C_r is the rolling resistance surface type (dimension: $[kg/t]$), C_1 corresponds to the rolling resistance road condition (dimension: $[kg/t]$), C_2 is the rolling resistance tire type (dimension: $[kg/t]$), ρ_{air} represents the air mass density (dimension: $[kg^3]$), A_f is the frontal area of the EV (dimension: $[m^2]$), C_D corresponds to the drag coefficient, V_w represents the wind speed (dimension: $[km/h]$), $v(t)$ is the EV speed (dimension: $[km/h]$), P_{motor} is the electric motor efficiency (dimension: [%]), $P_{driveline}$ (dimension: [%]) is the driveline efficiency.

The resulting primary metric, "EV range" (dimension: [km/kWh]), is derived by dividing the road distance by power consumption, indicating the maximum achievable range. Then, the Random Forest (RF) algorithm is applied with an 80-20 data split for training and testing, and hyperparameters (e.g., learning rate, tree depth) are optimized to enhance prediction accuracy.This approach utilizes key parameters and refined modelling techniques to improve EV range estimation, providing reliable performance insights. In this use case, data collected from a Tesla Model 3 Long Range Dual Motor [17] are used to predict its range.

B. Data Model Validation via Route Optimization

The OPEVA data model is validated through Routing Markup Language (RoutingML) that is used for EV route planning that gathers information from various data entities in Figure 1. The Demo 5 of OPEVA is mainly focused on dynamic route planning of EVs that is used for last-mile delivery services. A successful route plan is possible by gathering information from various entities such as information of the environment, information about of EVs, details of tasks and information about charging stations. The developed RoutingML shown in Fig. 7 help both validation of information sources and obtain a standardized the routing language for various types of routing problems.

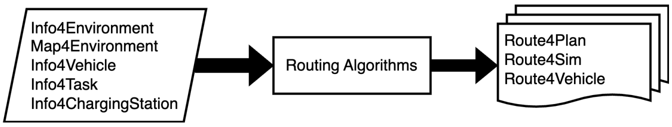

Fig. 7. RoutingML.

The RoutingML diagram in Fig. 7 uses XML/JSON based structured data input. It also generates optimized routes in a structured way for various implementations including benchmarking, real vehicles or simulations. All input and output data are validated using the related schemas.

The implementation of the OPEVA data collection system provides comprehensive data streams for EV in real time. For example, the Route4Vehicle output of RoutingML is used to show the planned route in the HMI of EV, as shown in Fig. 8.

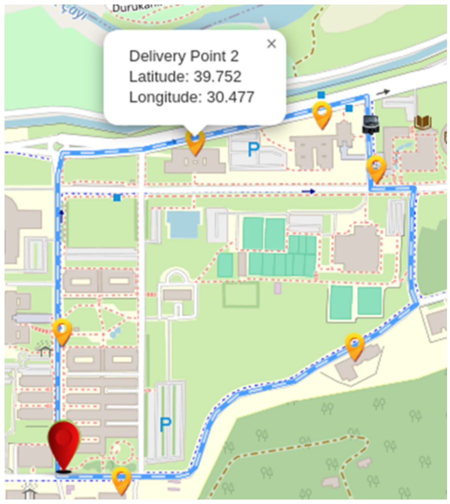

Fig. 8. EV route information.

Furthermore, using this data, location data captured by GPS sensors can be used to dynamically adjust charging points during long-distance journeys, thus optimizing energy consumption and reducing operational costs for fleet operators. To this end, a sample of the collected data during the execution of the route is as follows:

- Battery information: SoC: 82%, average temperature: 35°C.
- GPS Data: latitude: 40.7128° N, longitude: 74.0060° W.
- CAN Bus data: average speed: 34 km/h, energy consumption: 12 kWh/100 km.

C. Wireless Battery Sensing

The development of a Wireless Battery Management System (W-BMS) within OPEVA aims to enhance the scalability and reliability of EV battery management systems. To facilitate the integration of wireless transponders within the battery, the following strategies are employed:

- Ultra-Low Power Transponders: Energy-autonomous wireless sensing solutions are pursued through the evaluation of ultra-low power transponders [18]. These transponders are designed to operate independently of the EV battery, achieving energy autonomy that aligns with the EVs expected lifespan.

- Customized Antennas: Purpose-built antennas with optimized radiation performance for the battery metal-dense environment are developed. This approach minimizes the power required for communication while ensuring reliable coverage across all sensors within the battery [19].

Backscatter radio-based chips, such as commercial UHF RFID transponders, are identified as suitable candidates to meet these objectives. Unlike traditional BMS setups, where each sensor is directly connected to the BMS module, the proposed W-BMS design requires only a UHF RFID reader to connect to the battery. The reader radio-frequency signals serve as both a power source for the transponders internal circuitry and a medium for communication. Leveraging backscatter communication [20], where transponders modulate and reflect the reader signal without generating their own UHF carrier, power consumption is kept exceptionally low (in the range of tens of nanowatts). Thus, these transponders can operate without an onboard energy source, or they can be equipped with an external battery lasting over 10 years. The block diagram of a W-BMS architecture for passive wireless sensing consisting of custom made metal mountable UHF RFID tags, a reader equipped with a custom antenna system is shown in Fig. 9.

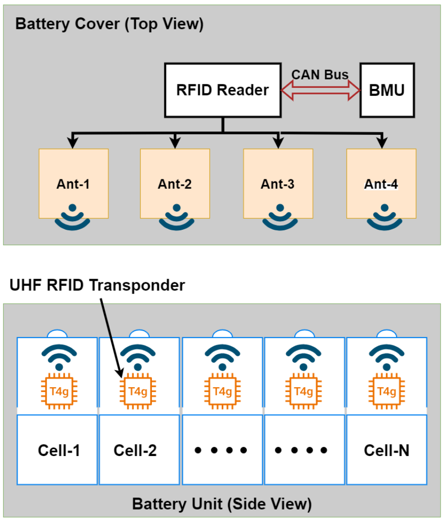

Fig. 9. Passive W-BMS wireless sensing test setup.

D. Federated Learning

Recently, the Federated Learning (FL) concept achieved a considerable success in many research areas, such as, smart city, mobility, healthcare, and service personalization [21]. In general, it can be considered as an evolution of the traditional ML approach that allows models to be trained across many decentralized devices or servers, like, in example, edge devices, smartphones or other, while keeping data localized.

With FL, *raw* data collected from single devices are not sent to a central server, instead, each device is enabled to independently train a model using its own local data. The devices then send only the updated model parameters (not the data itself) to a central (cloud) server, which aggregates these updates to improve a federated, global model. This approach is particularly useful for scenarios where user privacy is a priority (since sensitive data never leaves the device), and it's also beneficial for training models on very large datasets spread across multiple sources without risking data breaches or data centralization issues.

In the OPEVA project the application of FL techniques represents a key aspect, and is applied to effectively combine together data collected from multiple EVs moving on the roads. More in detail, FL will be applied to the distributed routing strategies to improve the overall routing approach by using locally optimized strategies that can be developed on the MIG. Moreover, the FL approach will be beneficial for the definition of a distributed, federated BMS. The status of the batteries on board on each EVs can in fact be monitored locally, through the use of a MIG to create local models. Finally, only relevant updates can be sent to the cloud (using a different MIG network interface) to the integrate them to A general global model.

V. Discussion and Conclusions

The increasing diffusion of EVs is opening new challenges related to technological advancements and socio-economic aspects. In this paper, we have presented the OPEVA project, funded by HE Chips JU, that aims at enhancing vehicle performance, battery management, and charging infrastructure, leveraging external data for optimization and incorporating human factors into vehicle design and functionality. More in detail, we focused on OPEVA fundamentals and data management aspects, describing how innovative HW and SW solutions we developed and integrated in different use cases scenarios, to efficiently collect, process and present EVs related data. The paper has presented a semantic approach where the OPEVA data landscape is modelled in terms of superclasses. These superclasses describe the *in-vehicle* and *out-vehicle* data that can be valorised for the needs of EVs in practical life. The developed data acquisition solutions are showcased in sample use cases such as EV range prediction, wireless battery sensing, route optimization and battery management.

Since the OPEVA project targets cutting edge research with relatively low Technology Readiness Level (TRL)—namely, TRL 5 [22]—, in the future also implementation and maintenance costs will be carefully analysed, since potentially non-negligible HW and implementation-related expenses could impact when deploying these technologies. Nevertheless, the project contributors are ambitious to proceed further in research and innovation also focusing on practical feasibility and scalability. In future studies, the authors and the project consortium will expand this paper with other data acquisition and valorisation systems. Among these, data acquisition from charging infrastructures, diverse data collection and valorisation considering V2X and multi-vehicle settings, improved data valorisation with advanced AI techniques, real-time expert systems and mixed reality simulation techniques will prolong the innovation landscape of the OPEVA project.

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