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Digital Twin for Field Data Management: Design of a platform to promote FAIR principles and ensure data reusability

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Abstract

While research data volume grows exponentially, its provision does not match this pace, entailing data retrieval challenges in engineering and field-related scenarios. This paper presents a Field Database Platform (FDP), an enriched metadata-based tool within a Digital Twin framework. Designed to digitize the product development process, the FDP enables data preprocessing and visualization, shifting the paradigm from bulky downloads to a more refined, user-centric approach. Built on relational database architecture, the FDP ensures data reusability, closing the data lifecycle loop and promoting data FAIR principles. The specifics of the proposed platform are outlined, demonstrating its application in an automotive use-case.

Keywords: Digital Twin; Field Data Management; FAIR Data Principles; Data Reusability; Metadata; Digital Shadows

1. Introduction

The exponential growth of research data, driven by advancements in Industry 4.0 and the Internet of Things (IoT), has increased the volume of field data—data collected directly from real-world environments [1–3]. In the automotive industry, field experiments and data acquisition efforts, such as creating datasets for proactive vehicle detection at night [4, 5] or investigating the distribution of headlamp radiation for optimized object detection [6], highlight the investments in time, cost, and resources. Field data analysis and the extraction of valuable insights are essential for decision-making, innovation, and technological progress [7, 8]. Moreover, the approval of systems increasingly requires a shared community perspective on data standards, ensuring a foundation for assessing performance. Maximizing the impact of the data requires management practices that ensure its reusability and adherence to FAIR principles, making it Findable, Accessible, Interoperable, and Reusable [9], thereby enhancing its value across the research community [10–12].

Properly managed FAIR data can help prevent redundant work, reduce the need for dedicated system equipment in individual research projects, and increase accessibility and reusability of existing datasets.

Recently, researchers have made significant contributions to establish best practices for Research Data Management (RDM) phases and processes [13, 14] . The phases cover all stages, from initial planning and data acquisition to data analysis, storage, and access. However, the practices often assume that data is acquired under laboratory or controlled conditions. The challenges associated with real-world data collection—such as unpredictable weather conditions (e.g., rain, fog) and unexpected events that frequently occur during data acquisition—are frequently overlooked. This variability of real-world conditions poses obstacles that are not adequately addressed by existing RDM practices.

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In this paper, the use of Digital Twins (DTs) is explored to facilitate Field Data Management (FDM). Unlike traditional Product Lifecycle Management (PLM) and Product Data Management (PDM) systems, which primarily focus on static data storage [15, 16], DTs are presented as an approach to take advantage of the data generated during the system's operational phase within its lifecycle. By leveraging DTs, data collected during operation from a particular physical asset [17] can be stored and made accessible to other researchers, enhancing the exploration of information for the diagnosis and prognosis of technical systems, as illustrated in various use cases [18].

However, if data are accessible through traditional data platforms, researchers may still face some limitations. Conventional platforms emphasize the storage of large datasets, often resulting in gigabytes of data being made available in monolithic files. This method hinders data reusability, as researchers frequently download extensive files without a clear understanding of their contents, obscuring the data's value.

To address this limitation, the Field Database Platform (FDP) is proposed as a metadata-driven platform designed to enhance both the findability, accessibility, and reusability of data within a DT approach. Through the FDP, preliminary insights can be gained by researchers via visualization and filtering tools before downloading, offering a practical, user-centered approach to data management. The underlying problem definition leads to the following research question:

- How to define a DT for FDM?
- How to design a metadata-driven FDP to enhance the findability, accessibility, and thereby the reusability of operational data within the DT?

This paper is organized as follows: Section 2 reviews the related work, while Section 3 introduces the proposed DT for FDM. Section 4 details the development and implementation of the FDP. Finally, Section 5 present an evaluation of the approach and a summary of the findings.

2. Related Works

2.1. Research Data Management

RDM encompasses a structured approach to organizing, storing, and sharing research data. As a key part of research practices, RDM makes it easier to reuse data across different fields. The engineering field, marked by data heterogeneity, especially benefits from RDM practices to enhance accessibility across collaborative platforms [14].

The Research Data Management Organizer (RDMO) is a tool used in the RDM community to help plan, manage, and document research data workflows. RDMO is designed to support the entire data lifecycle and provides researchers and institutions with ready-made templates, which facilitate the creation of Data Management Plans (DMPs) [13, 14].

Although tools like RDMO provide support for RDM, there remains an opportunity to further strengthen RDM practices through increased focus on field data. The integration of field data enhances data authenticity by reflecting conditions encountered in real-world environments.

2.2. Digital Twin

The concept of DTMs has been developed across various fields of study during the last few years. Building on the pioneering work of Grieves [19, 20], who first introduced this concept, different studies have adapted the concept and focused on its various aspects based on their objectives. Nevertheless, a common understanding can be identified, providing a general definition for the DTMs based on three main components. The three components are:

- the physical space, composed of the technical systems being investigated,
- the digital space that encompasses the digital replicas of the physical systems, and
- the digital thread as the communication between the two spaces.

Extending Grieves' foundational work, Stark et al. [17, 21–24] within the German Scientific Society for Product Development (WiGeP) further refined the concept by conceptualizing the DT within the digital space as comprising two distinct parts: a Digital Master (DM) and Digital Shadows (DSs). The DM is defined as containing (meta-)data and general information about the system, while data and the relevant processing are included within the DSs [25, 26].

2.3. Digital Twin in Research Data Management

Dierend et al. [15] introduce a DT framework using the open-source "AASX Package Explorer" to manage research data through an Asset Administration Shell (AAS). The potential of DTs for RDM in engineering is highlighted, and data heterogeneity challenges are addressed. However, some needs for data accessibility and reusability, particularly in DSs, are overlooked. The reliance on the AASX Package Explorer limits adaptability, as it offers few access features and lacks built-in support for FAIR data reuse among researchers.

Lehmann et al. [27] present a structured RDM framework focused on laboratory and experimental data collection, leveraging DTs to facilitate the data management of measuring devices within an interdisciplinary research institute. The framework, built upon a central RDM infrastructure with knowledge graphs and bidirectional DT communication, addresses data management challenges in controlled environments. However, the focus on lab-based settings leaves FDM unexplored, where data conditions are variable and require adaptable FAIR-compliant practices.

2.4. Metadata for Field Data Management

Metadata is fundamental for organizing, storing, and sharing information by providing context—such as location, format, and content descriptions—that supports the data FAIR principles. Systems like relational databases standardize metadata representation, enhancing interoperability across platforms [28].

For cyber-physical systems operating in a field, data reusability is challenged by insufficient metadata and inconsistent data management practices, including the inconsistent tagging of environmental conditions and calibration details [14, 29].

Linnhoff et al. [29] stress the need for metadata in automotive Light Detection and Ranging (LiDAR) research under varied conditions, noting that factors like precipitation and fog are essential for accurate modeling. Schmitt et al. [14] highlight the FAIR principles' role in metadata use, finding that inadequate metadata fosters isolated data silos, limiting accessibility and reusability.

In this paper, challenges of FDM in unpredictable real-world environments, often overlooked by traditional RDM, are addressed. A DT for FDM is defined and technically implemented through the development of the FDP, a metadata-driven platform designed to enhance the findability, accessibility, and reusability of DSs. Visualization and filtering tools are provided by the FDP, allowing researchers to gain preliminary insights before downloading datasets, thereby the need for dedicated system equipment in individual research projects. This approach offers a practical solution that adheres to FAIR principles and advances DT and RDM practices for real-world data.

3. Digital Twin for Field Data Management

To address the challenges of managing field data collected under real-world conditions, a DT designed for FDM in cyber-physical systems is proposed (see Fig. 1).

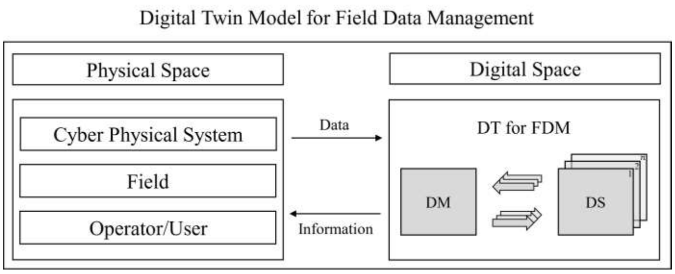

Fig. 1. Digital Twin Model for Field Data Management.

The model is structured into two main spaces: the Physical Space and the Digital Space. The Physical Space consists of the cyber-physical system (CPS), the field, and the operator or user. The CPS is responsible for data acquisition, serving as the primary source of operational data; it includes sensors and computational resources that operate in the physical environment. The field represents the actual environment with varying real-world conditions such as weather (e.g., rain and fog). The operator or user interacts directly with both the CPS and the field by collecting data or serving as a participant in field experiments.

The Digital Space encompasses the DT itself, comprising the DM and DSs. The DM is a virtual representation of the CPS, the field, and the operator or user in their actual states. Continuous updates from operational data ensure that the DM remains accurate and relevant. The DSs include operational status, historical data, and experimental results logged during the CPS's operation. They capture the temporal aspects of the system, allowing for the retrieval of previous versions and states.

The interaction between the physical and digital spaces is facilitated through bidirectional data exchange. Operational data (e.g, sensor measurements) flows from the CPS in the Physical Space to the DSs, while updates from the DM enable real-world adjustments to the CPS. This data flow enables continuous alignment between the physical and digital spaces.

3.1. Use Case: Test Vehicle for Field Data Collection

To illustrate the application of the proposed DT, a sensor-equipped test vehicle is deployed (see Fig. 2).

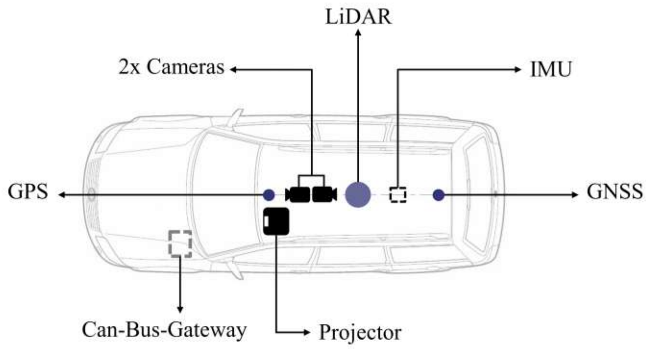

Fig. 2. Sensor’s Setup of the Test Vehicle for Field Data Collection.

The setup includes a LiDAR system, which facilitates distance measurements and 3D environmental mapping. Two high-resolution cameras capture visual data, allowing for analysis of headlamp radiation distribution and its impact on object detection capabilities [6]. An Inertial Measurement Unit (IMU) provides data on the vehicle’s acceleration, orientation, and angular velocity, while GNSS and GPS systems provide location and time data, enabling tracking of the vehicle’s movements and synchronization with other sensors. A projector projects symbols and light patterns onto the road to investigate how the light projections affect the driver’s behavior [30]. Access to the vehicle’s CAN-bus enables data collection from internal sensors, such as the steering angle, allowing for dynamic light projection aligned with street lanes [30].

The sensors are integrated into the Robot Operating System (ROS) framework on an onboard computer, powered by the vehicle's battery. Sensors are synchronized at 10 Hz using the IMU's Pulse Per Second (PPS) signal. The synchronization enables integration of additional external data from open-source APIs, enriching the DSs with context. In this use case, the DSs represent the data collected during various research experiments conducted with the test vehicle.

4. Field Database Platform

To enhance the reusability of DSs within the DT, the FDP is introduced as a metadata-driven platform that addresses the limitations of traditional RDM methods. As a practical implementation of a DT for FDM, the FDP organizes and enriches DSs, promoting FAIR principles.

4.1. Development

The FDP's development includes structuring data from the test vehicle in a relational database and enriching it with metadata. This enables the DT to provide insights into real-world conditions while supporting data-driven research processes.

4.1.1. Digital Shadows

The FDP manages the DSs, which include:

- Camera and LiDAR Data: files are named with UNIX timestamps to ensure temporal alignment.
- GPS Data: captured in a CSV format (e.g., "$GPRMC,172034.41,A,5225.427540,N,..."), the data includes timestamps, coordinates, speed, and course.
- IMU Data: stored in CSV format ("$PSONCMS"), IMU readings include acceleration along three axes and orientation (Roll, Pitch, Yaw).

While the DSs are systematically organized, it does not comply with the FAIR principles. To address this limitation, a database is implemented as the backbone of the FDP. This database enriches the data with detailed metadata—including sensor type, data format, measurement specifics, and experimental conditions.

4.1.2. Enriching Digital Shadows

To enrich the DSs and enhance the DT, external data are integrated using open-source APIs. The synchronization of the sensors allows external data to be aligned with the DSs using timestamps and geographic coordinates. External weather data from Open-Meteo, an open-source weather API [31], was integrated. Accessing real-time and historical weather information extends the datasets without the need for additional physical sensors.

The selection of external environmental data focuses on factors influencing sensor performance. The day/night indicator provides lighting context. Weather description accounts for conditions like fog, rain, or snow that impair camera and LiDAR readings. Monitoring visibility levels helps adjust data analysis based on sensor accuracy. Temperature affects the physical and electrical properties of sensor components, impacting performance. High humidity can cause lens condensation and degrade LiDAR measurement quality. Precipitation can obscure lenses, distort LiDAR readings, and degrade GPS signals. Recording wind speed helps isolate its impact on vehicle stability and IMU data. Particulate matter (PM_{10}/$PM_{2.5}$) can scatter light and obscure images, affecting optical sensors. Carbon monoxide levels indicate traffic density, providing context for sensor data interpretation. Lastly, monitoring dust accumulation is important because it can settle on sensor surfaces and impairs optical readings.

4.1.3. Database Architecture Design

- *Database System:*

The choice of an SQL database is driven by the need to handle structured sensor data effectively. SQL databases ensure data integrity through schema-based storage and enable data retrieval with querying capabilities. Using a relational database allows interconnection of data from different sensors, supporting analytics that require data integration. Structured data, such as GPS and IMU, is stored directly in database tables, enabling access through structured queries. However, due to the large size and binary nature of image and LiDAR data, only metadata—such as URL and data type—is cataloged in the database, rather than the files themselves. SQL databases also support integration with external APIs, further justifying this choice for the contribution.

- *Database Schema based on Field Metadata:*

Designing a database schema organizes data in relational databases using tables, columns, rows, and keys. Tables have columns for data types (e.g., integers, strings) and rows representing data items. A primary key uniquely identifies each record in a table and can be a single column or a combination of columns (composite key). A foreign key links tables by referencing another table's primary key, forming relationships like one-to-one, one-to-many, and many-to-many [32].

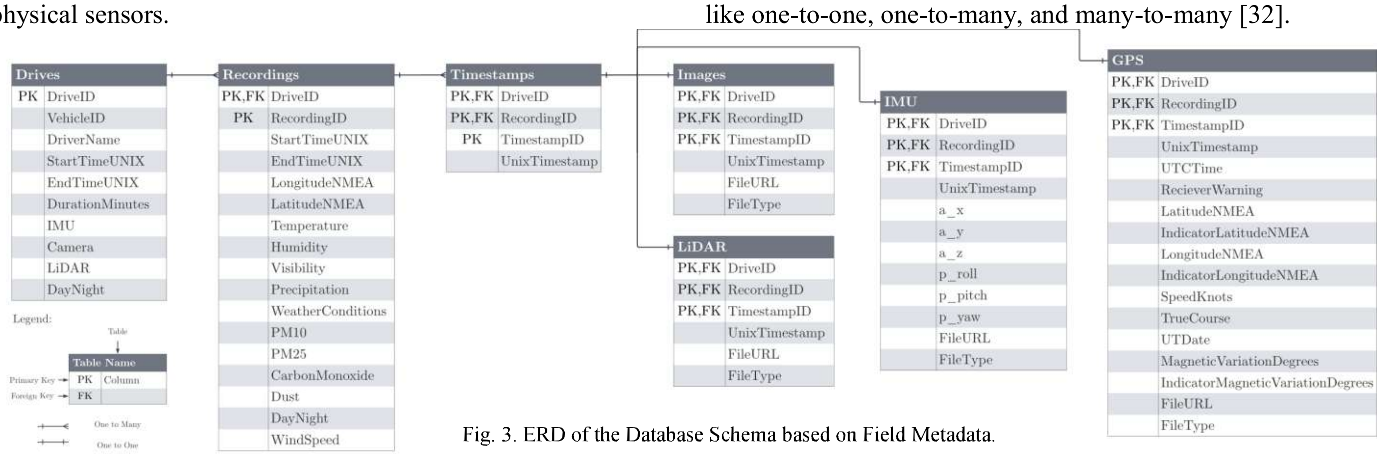

Fig. 3. ERD of the Database Schema based on Field Metadata.

The Entity Relationship Diagram (ERD) in Fig. 3 outlines the relationships and the table structure, providing an overview of the FDP's database architecture.

The implemented schema comprises seven tables: *Drives*, *Recordings*, *Timestamps*, *GPS*, *IMU*, *Images*, and *LiDAR*. The *Drives* table records individual driving sessions, each identified by a primary key "Drive ID". The *Recordings* table, with a composite primary key of "Drive ID" and "Recording ID", logs details of each session and includes external data from the Open-Meteo API. The *Timestamps* table records the multiple timestamps for each session and forms a composite primary key with "Drive ID", "Recording ID", and "Timestamp ID". This structure extends to the *GPS*, *IMU*, *Images*, and *LiDAR* tables, ensuring unique data entries across tables. The database utilizes one-to-one and one-to-many relationships to structure interactions between tables.

4.2. Implementation

The FDP's architecture consists of two main components: the backend, responsible for the DSs processing and database management, and the frontend, which provides the interface for data visualization and the filtering tools. The following sections detail the implementation of the backend and the frontend. A demo version of the FDP is available[1].

4.3. Backend

The DSs are initially saved in ROS-bag—a file format within the ROS framework designed to record and store data streams, where each dataset is timestamped for accurate synchronization. A custom Python script scans the stored ROS-bag data, extracting, timestamping, and populating it into the relevant database tables. This process runs at defined intervals, allowing new DSs to be integrated into the database as they become available.

Built with *Node.js* and utilizing the *Express.js* framework, the backend uses the *mysql2* module to enable database connectivity. It also performs periodic API requests to the Open Meteo server to retrieve environmental data relevant to each dataset, enriching the contextual understanding of the DSs. To perform each external API request, the backend accesses the "Recordings" table to retrieve the necessary data, including latitude, longitude and UNIX Start and End Timestamps.

4.3.1. Frontend

Developed with the *React.js* framework, a component-based approach is followed in the frontend to support modular development. The dashboard is served as the main entry point, where an overview of the DSs is provided. Key statistics, such as total counts of drives, recordings, images, and LiDAR point clouds, are displayed to allow data scope to be quickly assessed by researchers. From this initial overview, visualizations can be explored to summarize operational and environmental conditions:

Day/Night Drives: the ratio of night to day drives is displayed in a pie chart, allowing data collected under specific lighting conditions to be focused on by researchers.

Sensor Availability: a bar chart is used to visualize the availability of different sensors, aiding in the assessment of sensor utilization.

Environmental Statistics: extreme environmental values (e.g., highest temperatures or humidity levels) are presented in a table, providing additional context on field conditions during data collection.

In addition, detailed tables are available for more in-depth analysis, displaying data categories. The calendar component, including a date selector, can also be used by researchers to search for specific recordings, offering access to detailed sensor data (e.g., acceleration, orientation, geographic coordinates) and image previews for selected dates. A map interface is also provided to enhance spatial context by displaying the recorded path. A data export feature is included in the tables, allowing filtered datasets to be downloaded, thus supporting data sharing.

- *Data Filtering and Querying:*

A main objective of the FDP is to enable the identification of relevant datasets, reducing the need for dedicated system equipment in individual research projects. Environmental and operational filtering and querying capabilities are provided in the frontend:

Sensor Availability: recordings containing data from selected sensors can be focused on.

Time of Day: recordings can be chosen based on whether they were taken during the day or night.

Weather Conditions: datasets collected during specific weather conditions (e.g., rain, fog) can be filtered.

Environmental Factors: recordings based on specific ranges for temperature, humidity, or other environmental conditions can be selected.

These viewing options allow researchers to focus only on datasets relevant to their research goals, thereby enhancing data accessibility while reducing unnecessary data exploration.

5. Conclusion and outlook

While DT concepts have gained interest in the engineering field, there remains a lack of technical implementations, particularly in supporting FDM. The FDP contributes to this area by offering a metadata-driven platform aligned with FAIR principles. By adopting a DT approach, the FDP facilitates the organization and retrieval of datasets. The DT-based structure enables continuous data updates, allowing researchers to capture insights from operational data as it evolves, which supports proactive decision-making. The FDP's capabilities ensure that researchers are less dependent on dedicated field equipment, as they can repurpose existing data to suit new research goals, increasing efficiency and reducing costs.

[1] https://fielddatabaseplatform.nfdi4ing.de/

Researchers frequently engage in additional practices, such as modifying data parameters or conducting object detection tasks, which are time-consuming. Future developments of the FDP should include offering data derived from raw datasets, allowing researchers to access both the raw data and versions derived for specific applications. Additionally, expanding the platform for various cyber-physical systems (like robotics) would support enabling hybrid DTs for field operations.

Current limitations of the FDP include the lack of integration for data sources like projector and CAN data, which, if addressed, would enhance the comprehensiveness of the DSs. Further investigation into other aspects of the DT, especially the DM, is needed. In summary, while the FDP advances the application of DT in FDM, addressing these limitations will be essential for creating an adaptable platform that realizes the potential of DTs in data-driven research.

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