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EuProGigant: A decentralized Federated Learning Approach based on Compute-to-Data and Gaia-X

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Abstract

Machine learning normally requires a considerable amount of data for model training, limiting the field of usage especially for small manufacturing companies due to their lack of machine data. Federated learning provides an opportunity to enlarge the data basis for model training without the need to directly share the machine data with other participants, addressing concerns regarding to privacy, intellectual property and potential reverse engineering of proprietary process information through competitors. Previous research focused mainly on federated learning models, mostly managed and orchestrated by some kind of centralized authority. The presented approach shows a more decentralized, self-sovereign concept of federated learning for the manufacturing industry, expanding its applicability to a broader range of participants. It combines existing solutions for machine learning and Compute-to-Data by Ocean Protocol with the concept of dataspaces as defined by Gaia-X. The methodology is demonstrated through an use case derived from industry demands involving several CNC milling machines.

Keywords: Federated learning; Gaia-X; Design methodology, tools and technologies

1. Introduction

Machine learning (ML) provides a broad field of possibilities to improve manufacturing processes, but often the data basis of a single organisation is too limited for an effective model training. Concerns regarding privacy or intellectual property and the fear of loss of control on the shared data are still some of the most common barriers in cooperation across company borders [10]. Federated learning (FL) in combination with intellectual property preserving methods represents a solution to address these concerns by preventing the data from leaving the data owner's field of control. Previous research has already presented practical solutions, but is mostly bound on the presence of a centralized entity to manage orchestration and access control or on small groups of participants and requires a lot of manual background tasks, such as building up cooperation networks and negotiating legal agreements. Today, in a world of constant changes and unpredictable interruptions, especially small and medium-sized enterprises (SMEs) need a more agile, self-sovereign and ready-to-use solution that is not tied to a centralized platform operator or implies other forms of lock-in effects by the service architecture. Our approach uses the distributed ledger technology (DLT) based Ocean Protocol to automate data access control with Smart Contracts in a standardised digital form. We extended these concepts by using components of Gaia-X, making it possible to offer and consume FL resources to some extent independent from the used machine learning model on a digital, decentralized and self-sovereign data and service marketplace that opens the reach to a wider range of participants.

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2. Related work

With the increase in adoption of Industry 4.0 in Europe [5], the demands of using its benefits across companies have increased as well [19]. In the current landscape of abundant data and heightened privacy concerns, FL has emerged as an evolved approach to ML, transitioning the emphasis from abstract principles to practical, real-world adjustments and the challenges they entail.

While conventional centralized ML methods are efficient, they raise concerns about data privacy [20]. This issue becomes especially significant when data needs to stay within its security perimeter, which is often the case in healthcare or industrial data protection [24]. FL represents a specific example of the more general approach of "bringing the code to the data, rather than the data to the code." It tackles the essential issues of data privacy, ownership and locality [3]. The distributed ML aspect of FL facilitates further advantages of decentralized data sources [1], allowing industry-typical SMEs with limited processing and data collection capabilities to gain deeper insights into their data and produce well-performing local ML models [27]. Moreover, this aspect enables model training on a large number of devices or data sources [17], rendering it highly scalable. Thus, the adaptability to growing data sets, diverse applications and numerous participants is ensured, making FL a versatile and practical method for a wide range of real-world scenarios from industry edge devices to massive IoT networks or even holistic digital twin platforms, without compromising its effectiveness.

One of the main concerns in FL is the centralization aspect, taking on various forms [21]. For ecosystems with equal partners, a decentralized approach is considerably more practical than a centralized one, because the partners do not need to agree on a central authority [26]. The solution to this problem can be the use of a distributed technology like DLT.

DLT, with its immutable and transparent ledger, can facilitate secure and verifiable transactions within FL ecosystems. Smart Contracts on distributed ledgers can automate participant coordination, access control and data sharing agreements [18], ensuring data provenance and integrity while enabling transparent reward distribution based on data contribution and computation effort. This enables collaboration among disparate and potentially competing entities.

Ocean Protocol, with its self-sovereign Compute-to-Data approach, complements this by allowing data to remain on premises, only granting selected algorithms temporary access to compute on private data [22]. This methodology not only preserves privacy and intellectual property but also reduces data transfer costs. The protocol's use of Smart Contracts to manage access control in a self-sovereign manner and provide data and training audit trails, further strengthens trustless collaboration, which is essential for FL projects among competitors.

But there is a missing link between the trust provided within the DLT and the trust provided from the outside world. Initiatives like Gaia-X with its Trust Framework aim to enhance trust into federated solutions by providing a framework for trusted ecosystem participants and digital services [29].

Gaia-X is a joint European initiative which aims to define a framework and rules for a self-sovereign and secure data exchange and digital service consumption based on a standardized trust model. The concepts are defined in several publications provided by the Gaia-X AISBL which are constantly updated, modified and extended. The Gaia-X Trust Framework e.g. defines four types of rules [12]: (1) Serialization format and syntax; (2) Cryptographic signature validation and validation of the keypair associated identity; (3) Attribute value consistency; (4) Attribute veracity verification.

By unifying these rules, Gaia-X enables an interoperable trust model. This model is built upon self-descriptions, which are technically implemented as verifiable credentials [11]. Several projects are building on Gaia-X principles, for example: Catena-X, Smart Connected Supplier Network, Manufacturing-X and EuProGigant, that aim to utilize Gaia-X for the manufacturing industry [23]. EuProGigant has proposed a concept to bring the Gaia-X Trust model to production machines with an architecture for edge devices [8]. Furthermore, the architecture can be used for a resilience concept based on Gaia-X built upon Self-Descriptions, system theory and control, anomaly detection and self-orchestration [33]. Despite the high potential of Data- and Service Ecosystems, the economic feasibility is not there for every case [25], business models should be developed first [14]. One of these promising use cases will be presented in this paper.

3. Federated Learning based on Compute-to-Data and Gaia-X

3.1. Architecture

Compared to centralized ML, FL introduces additional complexity to the infrastructure as well as to the training process itself through its distributed nature. Figure 3.1 shows an architecture for decentralized FL. There are two forms of participants: (1) data owners, that want to offer their data sets for model training through FL and (2) model owners, that want to consume these data assets to train and improve their new or existing ML models. The decentralized orchestration layer is an abstraction for a set of services which can be provided by the two participants themselves to initiate and conduct the training process through FL without the need of an additional party like a data trustee. It is built on top of Ocean Protocol, which incorporates the necessary services for the participants to create and consume assets, as well as the accounting part for financial transactions related to the procurement of the assets. To make the assets and all needed services accountable and trusted, this layer also includes a Clearing House service, as defined by Gaia-X, and a catalogue service. Therefore, each asset, service and each participant need to be expressed in form of a Self-Description which is verified by an external trust anchor.

As described before, the anchors are implemented as Verifiable Credentials. As basic trust anchor for the participant

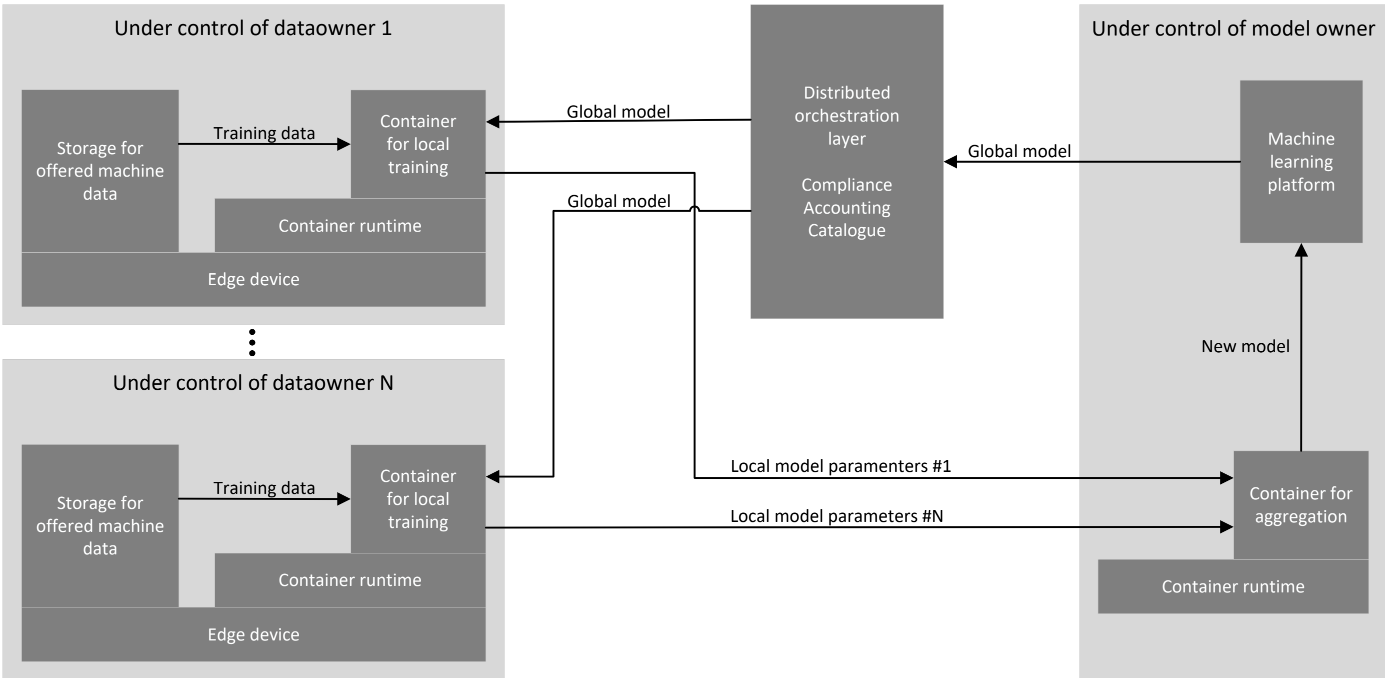

Fig. 1. Federated Learning Architecture

the Gaia-X Clearing Houses are used, that are responsible for linking the digital identity to the real participant by verifying their Decentralized Identities (did) and for enforcing a standardized form of the Self-Description describing the data and services which is called Gaia-X Service Offering. Data owners and model owners can built up trust by providing offerings in the FL ecosystem.

Before FL can take place, the data owners need to decide which access controller and Compute-to-Data environment to use with their data, or provide it themselves entirely. Using Ocean Protocol, the data owners can then publish their respective data services, assigning them did:op identifiers that are then used for further identification. In addition, the data owners can specify within the metadata which parties are allowed to compute on the data. A catalogue service based on Smart Contracts and an off-chain metadata cache is utilized to enable offerings to be searched and filtered based on their metadata. Direct access to the provided datasets is restricted to the access controller chosen by the data owner. In turn a set of whitelisted Compute-to-Data environments can be connected to the access controller to allow Compute-to-Data access. Direct access from outside these instances is not permitted.

A model owner that wants to initialize a FL process creates a new model or takes an existing one from his ML platform. In our present approach an instance of craftworks' navio is used, but compatibility to other platforms, like Software AG's cumulocity, is planned. In the next step, the desired datasets for the training process are selected based on their did:op identifiers. The previously mentioned catalogue services can help finding the appropriate offerings. Any whitelisted third party, including the model owner, can then purchase access to the datasets, Compute-to-Data environments and model, by signing Smart Contract transactions on a supported Ethereum Virtual Machine (EVM) compatible network. Afterwards, a container that contains the global model and the necessary algorithms for training is distributed to the various Compute-to-Data instances. After the local training on the Compute-to-Data instances is finished, the newly trained local models are returned to the model owner for further aggregation to a new global model.

FL includes a variety of methods for aggregating local model updates to a central instance. One example of this is Federated Averaging, whereby local models compute gradients on their respective data, which are then averaged on the central aggregation instance, i.e. under the control of the model owner, to promote the newly aggregated model as the global model. Another approach, known as Federated Proximal Gradient Descent, enables local models to take gradient descent steps on their respective data. The aggregation instance then combines these updated models by applying a proximal operator to ensure fairness and convergence. The model itself is typically structured as either a global parameter server, where the model owner's ML platform maintains the global model, or as a weighted combination of local models. The specific formatting of the model depends on the objectives and setup of FL.

Crucially, FL preserves data privacy and intellectual property by sharing only model updates, such as gradients or model parameters, while the actual data owner's raw data remains securely stored on local devices. However, the current approach lacks model protection, enabling the owner of the Compute-to-Data instance to access the ML model distributed by the model owner. Although this issue may not be significant for an early stage demonstration, it should be taken into account for production-level implementations.

3.2. Usage in manufacturing

Predictive analyses of manufacturing processes are playing an increasingly important role in maintaining the competitiveness of production companies. With the help of predictive maintenance, productivity increases of up to 25% can be achieved by detecting the failure of machine tool components at an early stage. In addition, unplanned downtime is expected to be reduced by up to 70% and maintenance costs by up to 25% [7]. Data-driven modeling using the available data from the computerized numerical control (CNC) [16] is a promising approach for predictive maintenance, if the concept on which the models are trained remains as similar as possible. In the case of machine tools, changes to the concept, which are subject to the data, are e.g. machine tools of different providers or design using different components and sensor systems. In order to achieve a high level of accuracy in data-driven models, a large amount of data from the same or similar machines is therefore required. The quality and quantity of the data is hereby the limiting factor for improving the prediction quality [7].

Since the development of predictive maintenance models additionally requires a high degree of domain knowledge for a complete and correct mapping of the structure and states of a given system or component [13], solutions in the form of predictive maintenance services can often only be achieved with the expertise of component manufacturers.

SMEs, which make up the majority of companies in the German manufacturing industry [28], may lack the necessary domain knowledge and commission component and service developers to implement data-driven models for predictive maintenance. However, due to lack of identical machines, they are often unable to aggregate an adequate database for the training of reliable data-driven models. Usually it is not possible to extend the database by adding data of similar machines of other manufacturers, as this requires companies to share their data, resulting in the risk to disclose know-how that is tied up in the data and thus the sovereignty over the company's own data cannot be maintained. This results in many closed data silos in the landscape of manufacturing companies in Germany, which means that the technical possibilities available are not being used sufficiently and there is no broad-based scaling of information provision and use [31].

The use of the proposed decentralized and privacy-preserving FL approach in manufacturing companies can contribute to overcoming these hurdles in this exemplary use-case. As described above, the paradigm shift to the Code-to-Data approach eliminates the need to disclose or share data. The federated model training takes place exclusively on decentralized local container runtimes. This way it is guaranteed that proprietary knowledge in the process data of the manufacturers stays within the company and isn't accessible by others. This and the principles of Gaia-X foster trustful cooperation and knowledge exchange across company boundaries may solve the problem that in today's industrial practice, information is only provided to the necessary extent. This allows component manufacturers and service developers to access a larger amount of data from the same or similar machine tools for the development of predictive services with higher accuracy an thus higher reliability in model-based decisions. The usage of Gaia-X ensures that not only the provided training data itself, which is usually available in the form of time series, but also the machine is described by metadata. Furthermore, in the future this approach will allow the machine vendor to hand out a verifiable product pass of the machine. This can than be extended with other component vendor information. With these information and the possibility of selective disclosure with verifiable credentials insights into the machines can easily be shared in a self-sovereign way. This ensures that, despite decentralized data sets, only data from the same or similar machines can be matched and used for training and applying the specific models, so that the concept remains the same. This means that a holistic representation of different machine tool designs does not have to be taken into account when creating the model.

The within EuProGigant developed validation platform can be used for demonstration of the developed FL approach. The HELLER CNC-ProfiTrainer forms the basis of the validation platform. It is a portable machine tool for training and demonstration purposes, which faithfully reproduces a fully-fledged machine with industrial components such as a CNC and drive control on a scale of 1:4. The validation platform is a further development of our demonstrator, which has been presented for the first time at the Hannover Messe 2022. Since then, the current implementation of Gaia-X Compliance (currently 22.10) and self-sovereign Compute-to-Data have been presented here.

The validation platform addresses the use case of tool condition monitoring as subdomain of predictive maintenance with the central question: how can medium-sized companies, with often small machinery, benefit from an experience of many processes on similar machines by a cross-company, sovereign exchange of information, so they are able to adapt their machining processes more effectively regarding tool wear [9]?

For this purpose, three identical machine tools are used to record data from the CNC during manufacturing of a workpiece using the machines' OPC UA servers and make the data available as an asset in the ecosystem in a self-determined manner. Based on the process information contained in the data, a service developer can create data-driven models that can make an automated statement about the condition of the tool. The Gaia-X Framework creates a basis of trust with the help of data usage agreements, which enables service developers to consume and aggregate data for training the models outside the IT system environments of the data owners. On the other hand, an existing Compute-to-Data instance is used for executing process analyses on production data. This enables the execution of the trained models on the data owner's IT system environment without the need to share any further data.

Despite the established trust layer the above described concerns of the manufacturing companies still limit the willingness to provision the process data for model training. With the help of decentralized FL, the existing use case can be augmented by data sovereign training of the models demonstrating the architecture developed in this paper. For this purpose, 4 similar Heller CNC-ProfiTrainers are available, which are located at PTW — TU Darmstadt (2), TU Wien and IGH Infotec AG. In the first iteration one of the machines at PTW using Beckhoff instead of Siemens components isn't considered because of its incongruent concept to the other machines in form of different drives, CNC and drive control. By using very similar constructed machines the deviation in behaviour is expected to be minimal. But the validity of the described FL-approach has to be proofed for different machine types and concepts in future works. The only difference of the remaining three machines is that one of them has 5-axis kinematics. The remaining two machines only have 4-axis kinematics due to the absence of the rotary A-axis. However, this is negligible for the following implementation, as the manufacturing processes used to show the approach are only carried out using the three translatory axes.

Our solution prioritizes flexibility by remaining agnostic to the explicit implementation of machine learning models and the federation approach. This allows the model owner to choose the most suitable implementation for their specific use case. The concrete implementation of our validation platform's data model relies on a federated variant of XGBoost classifiers [6]. Following the training of individual XGBoost models at the clients, the model owner aggregates the global model using bagging aggregation techniques [2] and distributes the updated global model to the clients. Bagging, short for Bootstrap Aggregating, is a machine learning ensemble technique designed to improve the stability and accuracy of models and can be leveraged for aggregating federated models [4, 30].

Our dataset comprises 41,501 labeled samples, encompassing 22 columns from the three above mentioned machines. Notably, 16 columns contain numerical sensor readings, while 8 represent categorical parameters. These features describe various aspects of the CNC-ProfiTrainers, including positions, currents, torques, speeds, and tool information. The binary-encoded labels reflect the quality of each sample. Due to the dataset's imbalanced nature, favoring good quality, we assess our results on independent test sets for all clients using the F1-score metric.

With the help of these instances of the validation platform, it is possible to demonstrate that, following component production and the automated provision of data sets as asset in the ecosystem, decentralized training can be carried out on the respective container runtimes on the edge computers of the machine tools. For this purpose, a global model for predicting the tool state is deployed from an instance of craftworks' navio to the edge systems with the help of a container and then returned to navio for aggregation. Using the did:op identifiers and the catalogue service, a description of both the data set and the model to be trained ensures that the data set corresponds to the expected input features of the machine learning model. The trained and aggregated model then can be consumed by the data provider from navio to passively identify outliers and empower the machine operator to make informed decisions. In order to enable the interoperability of different data models of the data sets provided, the use of standards or standardized data models and submodels of the asset administration shell has been envisaged. Specifically, for the application of the proposed FL approach with the validation platform the existing pipeline of collecting data samples semantically described according to the OPC UA companion specifications through the OPC UA servers of the machines was used. These samples with a sampling frequency of 8 Hz were packaged according to the about 90 second long reference face milling process in a standardized JSON-file containing the aforementioned data. These files then can be used for training the XGBoost models.

However, for this FL to work, sufficient edge computing resources have to be provided by the data owners. This may be a problem as most edge devices on the shop floor are to small to train or modify large models [15]. The provision of these computing resources to train the models results therefore in costs for the data owners. For the provided computing power, the ecosystem offers, as described, the possibility of compensation through automated financial transactions. This can create monetary incentives to provide data for component and service developers and opens up new business models for the manufacturing industry. These monetary aspects need to be examined more closely in future studies.

Across a value network, multiple parties, such as component suppliers, assembly plants, and logistics providers, can participate in collaborative model training without revealing their proprietary knowledge. This and the principles of Gaia-X foster trustful cooperation and knowledge exchange across company boundaries, ultimately leading to more reliable and longer use of production facilities as well as improved product quality and process efficiency, but also opening up new business models for different domains and use cases like process planning or peak shaving for energy efficiency [32].

4. Conclusion and outlook

The presented architecture with integration of Web3 and Ocean Protocol's mechanisms as well as Gaia-X into FL could lead to more efficient, transparent and participatory AI development, unlocking value across industries while ensuring compliance with increasingly stringent data protection regulations.

An implementation of the approach is deployed to three very similar ProfiTrainer PT16 CNC milling machines from the EuProGigant validation platform demonstrator network. In a first step the benefits of federally trained ML models over models that are only trained with data from a single machine will be evaluated. Further research should address the possibility to include machines of the same model type but with differences in mechatronic components, in our case the addition of a ProfiTrainer PT16 with a Beckhoff CNC instead of a Siemens CNC, and the therefore necessary enlargement of the data basis for model training in regards to the number of machines and samples. Also an increase of the sampling frequency from the currently used 8 Hz, limited by the OPC UA server, to values of at least 100 Hz is planned.

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