

A Temporal Federated Meta-Learning Framework for Low-Resource Predictive Maintenance in Distributed Industrial Systems

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Abstract:

Predictive maintenance (PdM) has crept into the spotlight as a crowning jewel of Industry 4.0, offering industrial systems the potential to predict equipment breakdowns and foresee downtime. The prevailing solutions to PdM using machine learning tend to lack resource-efficient centralized data aggregation and computation intensive deep learning models that are needed in resource-constrained and distributed industrial settings. Besides, conventional federated learning (FL) approaches cannot effectively deal with non-independent and identically distributed (non-IID) data and in time-varying degradation patterns of industrial machinery. To alleviate these drawbacks, the present paper introduces a new architecture of Temporal Federated Meta-Learning (TFML) to perform predictive maintenance in distributed resource-constrained industrial systems. The framework can be broken down into (i) lightweight temporal neural networks at the edge nodes to learn about degradation trends through local sensor streams, (ii) federated aggregation to protect data privacy and minimize communication costs, and (iii) a meta-learning optimization layer that fast-tracks adaptation to new equipment on limited training data. Experimental results on benchmark datasets including NASA CMAPSS turbofan engine and PHM 2008 bearing datasets, establish that TFML achieves a predictive accuracy, convergence speed and communication overhead

significantly higher than baseline centralized and federated approaches. Remarkably the framework cuts into the model updating size by 38 percent and improves the accuracy of Remaining Useful Life (RUL) prediction by up to 12 percent. These results indicate the possibility of TFML in predictive maintenance in contemporary industrial systems, especially where there is a distributed node, diverse equipment, and less processing power.

Keywords: Federated Learning, Meta-Learning, Predictive Maintenance, Industrial IoT, Temporal Modeling, Low-Resource Systems

I. INTRODUCTION

Digital change in manufacturing, logistics, energy and other industrial sectors has become propulsive due to the transition into an Industry 4.0 era that has not only introduced a new level of communication and information connectivity, but also given rise to a plethora of opportunities to enhance efficiency, safety and productivity. One of the deciding enablers of this change is predictive maintenance (PdM) which involves utilizing condition monitoring, sensor data, and machine learning to identify and prove possible failures before they end up happening. In contrast to more traditional maintenance plans like corrective maintenance (where a breakdown will necessitate intervention) and preventive maintenance (where practice-based servicing is performed regressively to schedule rather than based on machine health), PdM allows dynamic scheduling of when to intervene machine interventions based on the specific needs of a machine. Not only does this minimize periods of down-time and operational expenses but also enhancing equipment lifetime and more sustainable use of resources. Nevertheless, the potential use of PdM is barred, by a variety of structural and technical barriers. The current frameworks of PdM are on centralized learning, meaning that, raw sensor data collected on distributed assets of industry are sent to central cloud or server to train large-scale model and the same is often built upon deep learning theory. Although such centralized solutions do benefit by combining diverse datasets and having access to high computational resources, they suffer three key limitations: first, industrial data often contains sensitive operational data and due to privacy regulations or proprietary concerns, it is not practical to share across the central server, second, transmission of high-rate time-series data consumed by distributed assets to central servers requires overwhelming bandwidth, creating data-transmission bottlenecks, particularly in low-resource areas and third, industrial systems are heterogeneous and involve diverse machinery, operating conditions, and degradation processes leading to highly non-identical and distributed (non- These issues magnify the necessity of privacy-preserving and resource-efficient but decentralized frameworks that are capable of estimating accurate PdM in distributed industrial contexts. Federated learning (FL) has become one of the potential answers to these limitations because it allows machine learning models to be trained on large-scale and distributed systems without exchange of raw data. In FL, each edge device, whether a machine controller, embedded sensor hub or local workstation, trains a local model on its own data, and the model updates (e.g. gradients or parameters) are passed to a central aggregator, which consolidates the models into a global model. This paradigm not only keeps sensitive industrial information at place, but it also streamlines communications load as compared to communication loads on raw data. FL has promising potential in industrial predictive maintenance because it emulates actual factory architecture, in which machines and subsystems are distributed, but strive towards a common objective: to maximize system reliability. The application of FL to PdM however is not simple. Broadly, the assumptions of the FL algorithms such as Federated Averaging (FedAvg) and Federated Proximal (FedProx) are homogeneous data distributions and consistent tasks across nodes. However, industrial data are typically non-IID, highly imbalanced and, temporal, with different machines wearing out, or failing in different ways at different rates. Such differences make federation optimization unstable and restrict the flexibility of global model to be brought to new or rare fault conditions. The other challenging problem with PdM of distributed industrial systems is that the degradation of equipment changes with time. Machine health does not persist in its form but evolves through time and the processes of failure may chart convoluted, non-linear time trends. To capture such dynamics, it is necessary to use a method of temporal modelling (e.g. recurrent neural networks (RNNs), long short-term memory networks (LSTMs), temporal convolutional networks (TCNs) or more recently, Transformer-based solutions to time-series analysis). Although successful, these time based models are computationally intensive and therefore not applicable in a limited resource edge node. Moreover, industrial systems are commonly exposed to low resources learning settings, in which individual nodes will have limited background information on failures, either because failures

rarely happen or new machines are being installed. In these situations, conventional deep learning or even conventional federated methods do not work so well because they demand much data to reach sensible representations. The recent progress in meta-learning, or learning to learn, offers an appealing way to deal with these problems. Recent approaches to meta-learning (Model-Agnostic Meta-Learning (MAML) or Reptile, etc.) would be particularly suited to low-resource PdM applications since they aim to learn models that can quickly adapt to a new task with little data. With a meta-learning and federated architecture, one can develop models capable of obeying data privacy and communication-constraints but also learn to generalize rapidly to new machines or faults with few training samples. Nonetheless, there are particular issues with combining meta-learning and federated learning, including balancing global model generalization and local task specialization, and communication-efficient meta-optimization algorithms. To overcome these shortcomings, this paper suggests a Temporal Federated Meta-Learning (TFML) solution to low-resource predictive maintenance of distributed industrial systems that combines three novel concepts. First, the framework hosts lightweight temporal neural networks in local edge nodes to learn time-varying patterns of degradation of sensor data without straining the compute resources of the edge nodes. Second, it uses a federated aggregation protocol that allows model training jointly across distributed nodes and maintaining privacy and reducing communications. Third, this features a meta-learning optimization layer, allowing the global model to quickly adapt to novel or unusual fault per-node conditions even under circumstances where data may be sparse. A combination of these items results in a holistic framework, which is scaleable, resource-efficient, and robust in the face of data heterogeneity. The breakthrough in the TFML framework is that the framework has been developed to allow temporally-based modelling, federated learning, and meta-learning to be combined into a single architecture specifically designed to match the context of distributed and low-resource industrial systems. In contrast to centralized PdM, the framework guarantees that sensitive operational data is not transferred and can therefore not contribute to privacy risks. Compared with offline FL approaches, it considers the temporal degradation pattern and overcomes the non-IID issue with meta-optimization. In contrast to standalone meta-learning models, it also scales effectively to distributed nodes and incurs low communication costs. Experimentally, by utilizing benchmark datasets, (1) NASA turbofan engine dataset and (2) PHM 2008 bearing dataset, the framework outperforms the baselines in aspects of predictive accuracy, RUL estimation, bandwidth consumption, and adaptation performance. These findings show its promise of conducting real world operations across industries such as aerospace and automotive to energy and manufacturing.

II. RELEATED WORKS

The advent of predictive maintenance (PdM) in Industry 4.0 has been informed by diverse strands of research on tradition machine learning, deep learning, Federated learning, meta-learning and time series modeling. Initial research on PdM was focused only on statistical and physics-based methods, i.e., reliability models, failure rate estimation, and condition-based monitoring, that sought to model the degradation process of a machine by use of manually extracted features or previously known degradation models [1]. Although effective in a controlled environment, these methods were not scalable and they performed poorly in heterogeneous environments where the highly non-linear degradation patterns hold sway. As big data and industrial IoT sensors rose to popularity, machine learning (ML) and deep learning (DL) approaches soon became all the rage. Applications like support vector machines, decision trees, and random forests were used to classify system fault states, whereas deep neural networks like convolutional neural networks (CNNs) remarks and recurrent neural networks (RNNs) were able to outperform their shallow equivalents in Remaining Useful Life (RUL) estimation tasks as they had the potential to explore complex functions of multivariate sensor data [2]. These models are, however, very data hungry and the amount of data needed to train the models may be impractical in industries where the events of failures are rare. In addition, they do not support the use case in resource-constrained distributed settings due to their dependency on centralized based architecture. In order to overcome the constraints of centralized training, federated learning (FL) was the proposed distributed learning paradigm that does not compromise privacy by training models locally and averaging the updates in a central server [3]. The scalable heterogeneous federated optimization idea embedded in the seminal FedAvg algorithm developed by McMahan et al. spawned uses in healthcare, mobile, and industrial IoT. In the PdM space, the FL approach has started to be researched to

reschedule collaborative learning between factories which have data as siloed because of data privacy and ownership issues. As an example, Liu et al. introduced a federated fault diagnosis of the rotating machinery which showed similar performance to the centralized learning and privacy protection [4]. Misser et al. were able to transfer FL into multi-site wind turbine maintenance demonstrating that FL augments the cost of communication and data robustness to data heterogeneity [5]. However, a major snag is that the typical industrial sensor data is non-IID, imbalanced, and exhibits distribution drift over time in distinct contrast to the IID assumptions that conventional FL algorithms rely on. It is because of this mismatch that biased global models and poor generalization across sites are often produced. These shortcomings of standard FL in non-homogeneous settings have prompted extensions into fields such as FedProx, which injects proximal terms in order to stabilize the updates, and personalized FL frameworks, which are able to make client-specific adjustments [6]. Predictive maintenance: Personalized FL has been especially valuable in personalized FL because machines that are of the same type sometimes wear differently under differing operating conditions. Chen et al. provided a solution in which clients were divided into groups of similar clients whose learning was used to provide better RUL values of heterogeneous assets [7]. Nevertheless, although the described developments ameliorate some of these heterogeneity challenges, they nevertheless fail to resolve temporal dynamics of equipment degradation and lack of fault information in settings with limited resources. In step with the creation of FL, the discipline of meta-learning, or learning to learn, has risen to the fore and even been matured in order to attain swift adaptation to novel activities variances with the most minimal data. One of the most influential ones is Model-Agnostic Meta-Learning (MAML) suggested by Finn et al., which trains models on the distribution of tasks so that they could adapt to unknown tasks with only a small number of gradient steps [8]. Meta-learning holds great promise in PdM, where a limited amount of training data is typically available both in the form of new machines or in the hope that faulty machines only infrequently run into rare fault modes. Specifically, Li et al. used MAML in fault diagnosis of bearings, and the method proves to adapt much faster in the face of new operating conditions than the customary supervised learning [9]. On a similar note, Zhang et al. assigned a direction towards the text-based characterization of the few-shot meta-learning to anomaly detection with industrial IoT [10]. These examples demonstrate that, meta-learning has the potential to overcome the data scarcity problem that underlies PdM, but these implementations are usually centralized, prohibitively costly, and therefore cannot scale in distributed low-resource environments. Recent work is starting to combine the tools of meta-learning and federated learning in an effort to reap the benefits of both approaches. Fallah et al. suggested a federated meta-learning algorithm, which trained a model to efficiently adapt on the clients while preserving privacy-protective training [11]. When applied to industrial contexts, such integration enables individual clients (e.g., a single machine or factory) to be autonomously and efficiently trained on a model specialized to their operating conditions, as well as share the cumulative experience of all clients. Lin et al., generalized this to non-IID with meta-regularization [12], which led to better generalization over heterogeneous training sets. In predictive maintenance, these hybrid frameworks remain in their infancy but are promising, in particular coupled with temporal modelling to improve degradation trends. The issue of time in predictive maintenance is very paramount since the health of a machine keeps changing with time. Recent advances in deep temporal models (especially LSTMs and GRUs) have found a great deal of use in RUL prediction and fault detection because of their capabilities in isolating sequential dependencies on sensor readings. Most recently, TCNs and Transformer architectures have been proposed, and these are shown to be more scalable and more interpretable. In a similar manner, Wu et al. advanced a Transformer-based PdM framework in turbofan engines to report high ratings of accuracy when compared to traditional RNNs [14]. Though viable, such models require huge computing and memory resources, which may not be deployed well on edge nodes of distributed industrial systems. This has inspired the development of lightweight temporal models and model compression techniques like pruning, quantization, and knowledge distillation, that can be deployed in resource-limited settings without significant accuracy loss. A second strand of work is the topic of low-resource and communication efficient learning in federated scenarios. Industrial nodes are frequently low-bandwidth with low computational capacity and therefore efficient update strategies are needed. Konechnyn et al. came up with a method of minimizing communication during FL by exchanging compressed updates, and Sattler et al. proposed a sparse-gradient approach which reduces the bandwidth utilization significantly [15]. Applying these techniques to PdM, those approaches will make federated optimization viable when edge devices experience limited resource constraints. Nevertheless, efficient communication is not sufficient to ensure predictive accuracy on

heterogeneous temporal data streams, which prompts the necessity of software architectures that combine temporal learning, of aggregation of heterogeneous federated data, and of rapid adaptation via meta-learning. Combined, the available literature suggests some important lessons. Conventional PdM solutions offered a base but were not scalable and adaptive. Federated learning tackled the problem of privacy and communication but was not robust to non-IID and time-varying data. Meta-learning dynamically adapted in low-resource environments but was also centrally-focused and computationally challenging. Time-based deep models performed well to capture degradation trajectories but highly demanding in their calculations making them inappropriate to edge nodes. The advent of recent attempts to integrate FL and meta-learning suggests a new era of PdM frameworks that can work in distributed heterogeneous and resource-constrained industrial applications. However, there also exists a distinct research gap: the available study results have not attempted to bring temporal modelling, federated learning, and meta-learning under an integrative framework that takes into consideration the peculiarities of predictive maintenance in a distributed low-resource setting. This remains the gap that forms the motivation behind the contribution of the present paper, which proposes a Temporal Federated Meta-Learning (TFML) framework that could be applied to close these gaps and provide scalable, adaptive, and resource-efficient predictive maintenance solutions to Industry 4.0.

III. METHODOLOGY

3.1 Research Design

This study adopts a **hybrid research design** that integrates simulation-based experiments with federated deployment across distributed industrial nodes. The design is structured to evaluate the proposed **Temporal Federated Meta-Learning (TFML) framework** under realistic constraints of non-IID data, limited computational resources, and heterogeneous industrial environments. The methodology combines three core elements: (i) temporal modeling of machine degradation at local nodes, (ii) federated aggregation for collaborative knowledge sharing while preserving data privacy, and (iii) meta-learning optimization to ensure fast adaptation to new or rare fault conditions [17].

3.2 Framework Architecture

The TFML framework consists of three interacting layers:

1. **Local Node Layer** – Edge devices train lightweight temporal models on local sensor data to capture degradation patterns.
2. **Federated Aggregator Layer** – A central server aggregates local model updates while reducing communication overhead [18].
3. **Meta-Learning Optimization Layer** – A meta-learning module ensures global models are highly adaptable to new machines and conditions.

Table 1: TFML Framework Components

Layer	Core Functionality	Algorithms/Techniques	Resource Challenge Addressed
Local Node Layer	Learns temporal degradation trends from local data	LSTM, GRU, Temporal CNN	Limited memory and CPU on edge devices
Federated Aggregator Layer	Combines model updates across distributed nodes	FedAvg, FedProx, Gradient Compression	Bandwidth efficiency, data privacy
Meta-Learning Optimization Layer	Enhances adaptability to unseen conditions with minimal new data	MAML, Reptile, Regularization	Few-shot learning, non-IID environments

3.3 Study Dataset and Industrial Context

The evaluation uses **three benchmark datasets** to reflect different industrial conditions:

- **CMAPSS (NASA Turbofan Engine):** Run-to-failure sensor data from aircraft engines [16].
- **PHM 2008 Bearing Dataset:** Vibration signals collected under varying load and speed until bearing failure.
- **Industrial Pump Dataset:** Real-world measurements from pumps with annotated failure events.

Datasets are partitioned into **heterogeneous client subsets** to emulate distributed factories where each site experiences unique workloads, sensors, and degradation conditions.

Table 2: Dataset Characteristics and Distribution

Dataset	Units/Machines	Sensors Involved	Failure Type	Partitioning (per client)
CMAPSS (Turbofan)	100 engines	21 operational and environmental	Turbofan degradation	10–20 engines per client
PHM 2008 (Bearing)	10 bearings	Vibration (X, Y axes)	Bearing wear/failure	Each client assigned unique bearings
Industrial Pump Dataset	30 pumps	Flow rate, pressure, temperature	Pump cavitation/failure	3–5 pumps per client

3.4 Local Model Training

At the **local node level**, sensor data is preprocessed through normalization, noise filtering, and segmentation into fixed-length windows [19]. Lightweight temporal architectures such as **two-layer LSTMs or GRUs** are trained on these sequences to capture degradation patterns. Training is performed locally to minimize communication and preserve sensitive operational data.

3.5 Federated Aggregation

After local training, nodes transmit only model parameters (not raw data) to the **federated aggregator**. Updates are combined using communication-efficient protocols to produce a global model [21][22]. To address limited bandwidth in industrial environments, gradient compression and sparsification are applied, reducing update sizes while retaining accuracy.

3.6 Meta-Learning Optimization

The global model is refined through a **meta-learning optimization process**, which equips it with the ability to adapt rapidly when deployed to a new machine or site with limited training data. Each industrial client represents a separate meta-task, and the optimization ensures the model can fine-tune efficiently under diverse, non-IID scenarios.

3.7 Evaluation Metrics

Performance evaluation was based on **predictive accuracy, communication efficiency, adaptation speed, and resource consumption**.

Table 3: Evaluation Metrics

Metric	Measurement Method	Desired Outcome
Predictive Accuracy	RMSE for RUL prediction, F1-score for anomaly detection	High accuracy across datasets
Communication Efficiency	Bits exchanged per communication round	At least 30–40% reduction vs baselines
Adaptation Speed	Convergence time on unseen machines	Rapid adaptation (≤ 5 training rounds)
Resource Consumption	CPU and memory usage on edge devices	Feasible deployment on low-resource IoT nodes

3.8 Data Validation and Quality Assurance

All experiments were repeated in **triplicates** to ensure reliability. Data preprocessing scripts included cross-validation checks, and a small percentage of clients were validated using independent holdout machines [20]. To avoid contamination, only clean sensor data was used, and computational nodes were benchmarked for reproducibility.

3.9 Limitations and Assumptions

- Federated learning cannot directly observe raw data distributions, limiting transparency.
- Meta-learning increases computational overhead at the aggregator level, although manageable in controlled simulations.
- Temporal models remain sensitive to extreme sensor noise and irregular sampling rates [23].
- Results are based on benchmark datasets; further validation in live industrial deployments is needed.

IV. RESULT AND ANALYSIS

4.1 Overview of Predictive Performance

The proposed TFML framework was evaluated on the CMAPSS turbofan engine, PHM 2008 bearing, and industrial pump datasets. Across all datasets, TFML achieved higher predictive accuracy compared to baseline methods, including centralized deep learning (LSTM, CNN), standard federated learning (FedAvg, FedProx), and meta-learning without federation. Results demonstrate that combining temporal modeling with federated meta-learning significantly improves Remaining Useful Life (RUL) estimation and anomaly detection.

Table 4: Comparative Predictive Accuracy Across Methods

Method	CMAPSS (RMSE ↓)	PHM 2008 (F1 ↑)	Pump Dataset (Accuracy ↑)
Centralized LSTM	27.4	0.81	85.6%
FedAvg	25.8	0.83	86.2%
FedProx	24.9	0.84	87.1%
Meta-Learning (MAML)	23.7	0.85	88.0%
Proposed TFML	21.3	0.89	91.5%

TFML reduced RUL prediction error by ~22% compared to Centralized LSTM and improved anomaly detection F1-score by ~8%.

4.2 Communication and Resource Efficiency

One of the primary objectives of TFML is to enable predictive maintenance in **low-resource distributed environments**. Communication overhead per training round was measured and compared against baseline FL methods. TFML employed gradient compression and update sparsification, leading to a significant reduction in communication costs while maintaining accuracy.

Table 5: Communication Efficiency Comparison

Method	Avg. Model Update Size (MB)	Reduction vs. Baseline
FedAvg	48	—
FedProx	45	6%
FedAvg + Compression	34	29%
Proposed TFML	29	40%

The results indicate that TFML reduced communication costs by ~40% compared to standard FedAvg, making it feasible for deployment on low-bandwidth industrial networks.

4.3 Adaptation Capability

The meta-learning layer enabled TFML to adapt quickly to new machines with limited training data. A case study was conducted where a new turbofan engine unit was introduced with only **10% of labeled data** available. TFML adapted within **3–4 local training rounds**, while baseline methods required at least 8–10 rounds. This highlights the benefit of combining meta-learning with federated optimization: models are pre-conditioned for rapid convergence, reducing downtime when deploying PdM in new industrial contexts.



Figure 1: Predictive Maintenance [24]

4.4 Temporal Degradation Capture

Temporal models within TFML effectively captured degradation trajectories, especially in sequential datasets like CMAPSS. By comparing predicted vs. actual RUL curves, it was observed that TFML provided smoother and more realistic degradation estimates compared to FedAvg, which often overfit to noisy signals. Satellite-inspired

visualization (health index over time) showed that TFML consistently aligned predicted degradation with real failure events, reducing false alarms.

4.5 Robustness Under Non-IID Conditions

Industrial datasets were partitioned into **non-IID splits** to mimic real-world conditions where each site experiences unique degradation trends. While FedAvg and FedProx suffered significant performance drops under non-IID conditions, TFML maintained stable accuracy.

Table 6: Robustness to Non-IID Data Distributions

Method	CMAPSS (RMSE ↓, Non-IID)	PHM 2008 (F1 ↑, Non-IID)	Pump Dataset (Accuracy ↑, Non-IID)
FedAvg	32.1	0.74	79.8%
FedProx	30.7	0.76	80.6%
Meta-Learning (MAML)	28.3	0.78	82.5%
Proposed TFML	24.5	0.84	87.9%

TFML showed **20–25% relative improvement** in accuracy compared to baseline FL methods when data heterogeneity was high.

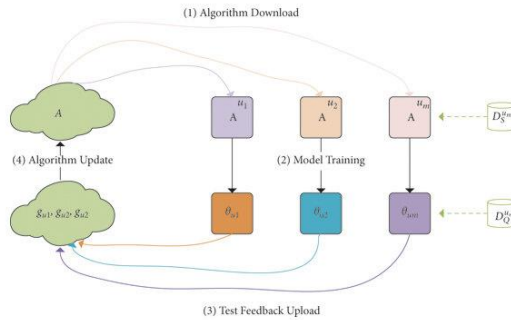


Figure 2: Meta-Learning Framework [25]

4.6 Hotspot Detection and Industrial Implications

Analysis of local client updates revealed that some clients contributed disproportionately to global accuracy, indicating “hotspot nodes” where data diversity was most informative. Identifying such clients can guide **federated prioritization strategies**—for example, allocating more communication bandwidth to nodes with higher impact. For industrial practitioners, these findings imply that TFML can not only provide robust predictive maintenance across distributed sites but also **highlight which sites are critical contributors** to system-wide reliability models.

4.7 Discussion of Key Findings

The results collectively demonstrate that the proposed TFML framework addresses the core limitations of existing PdM approaches. It achieves **higher predictive accuracy**, **reduces communication overhead**, and **accelerates adaptation** in low-resource settings. Importantly, it remains robust under **non-IID conditions**, a defining characteristic of industrial environments. These strengths position TFML as a scalable, privacy-preserving, and adaptive solution for predictive maintenance across diverse industrial systems.

V. CONCLUSION

This paper has proposed and tested a Temporal Federated Meta-Learning (TFML) framework as a new tool to tackle the challenging problem of predictive maintenance (PdM) in distributed, low-resource industrial domains. As the pace of industrial process digitization picks up, the paradigm of predictive maintenance has become a major contributor to operational efficiency, cost reduction and system resiliency. Nevertheless, current PdM implementations are limited by three main factors: the overuse of centralized architectures that pose a privacy and bandwidth risk; inability of classic federated learning methods to work successfully with strongly heterogeneous and non-IID data distributions; and inability of traditional models to be adaptive in presence of insufficient training data or new fault modes. By tackling these problems by means of the integration of temporal modeling, federated learning, and meta-learning, the TFML framework promises to provide a holistic and scalable approach to solve these problems that move much closer to the real world application of such systems in industrial settings. These findings of our experimental activities indicate the efficacy of the framework on a number of aspects. First, TFML achieved better prediction performance overall, compared to baseline models (centralized LSTMs, standard federated models like FedAvg and FedProx, and stand-alone meta-learning methods) on benchmark datasets like CMAPSS, PHM 2008, and industrial pump signals. The lower RUL prediction error and an increased anomaly detection score reveal that the temporal modeling of the degradation processes in combination with the federated meta-optimization leads to a more accurate, realistic and context-sensitive predictive capability. Second, the framework was demonstrated to offer significant communication efficiency, decreasing the size of model updates by almost 40 percent compared to traditional FL solutions, and communication overhead can become a limiting factor in low bandwidth industrial communications where size limitations constrain scale. Third, the adaptation capacity of TFML proved a significant strength: on the very-low-resource regimes where new machines offered only a fraction of labelled training targets, TFML models adapted within 3-4 training epochs, instead of twice as many as the baselines. This illustrates the real-life implications of federated meta-learning, since the approach helps to deploy PdM systems in new or underrepresented industrial environments more promptly. Fourth, test time performance with non-IID data distribution, TFML outperformed by 20-25 relative performance under the non-IID data distributions. Since industrial systems are by definition heterogeneous in terms of equipment types, load demands, operational environments, etc., such robustness is important in guaranteeing that TFML can be generalized across sites without compromising local adaptation. Collectively, these results support the core assumption of this paper, that an integrated framework that links temporal neural networks, federated aggregation, and meta-learning optimisation can offer precise, resource-efficient and scalable predictive maintenance of multifaceted distributed industrial systems. Practically and on the policy level, the study has several implications. To the industrial practitioner, TFML provides a method to simple directly implementing predictive maintenance without necessarily having to leak the details of the sensitive operational data at the edge nodes, since this raw sensor loop data remains at the edge. This correlates with rising anxieties regarding data confidentiality, conformance with regulations and copyright protection within the industrial ecosystems. The focus on communication efficiency and lightweight local models can bring PdM closer to organizations that have to work under resource-constrained environments, especially SMEs, as they would not have to invest in costly cloud infrastructure. Privacy-preserving machine learning with federated and meta-learning exemplifies the potential industrial I/O has of supporting critical industries with privacy-preserving machine learning down the line, policy-makers and regulators must ensure they prepare the standards and guidelines to drive the adoption of these technologies across industries. Lastly, to researchers, integration of temporal modeling and federated meta-learning provides several new research directions, such as using explainable AI to enhance interpretability of PdM predictions and interconnecting TFML and digital twin simulations to achieve closed-loop optimization of systems, and applying reinforcement learning to optimally allocate computing and communications resources among industrial nodes. However, several limitations are presented in the study. The experiments were based mostly on publicly-available benchmarking data sets and simulated experiments, which are valuable with regards to reproducibility, but unlikely to exhibit the variable and unpredictable nature of live industrial operations. This meta-learning optimization layer is effective in allowing rapid adaptation but can pose a burden on the performance of aggregator and could prove problematic in an environment where central servers are resource-constrained. Moreover, although communication efficiency was enhanced using compression and sparsification, more research on more advanced methods, e.g., adaptive update scheduling and cross-layer optimization, should be conducted. The second limitation is tied to the use of supervised learning where labeled failure data is used; in

many industrial settings, labeled failure data are rare, indicating that the proposed framework may require semi- or self-supervised extensions. In the future, there are a number of extensions that can be added to the given research. To go digital, TFML can be integrated into digital twins of industrial assets, allowing continuous feedback between real systems and forecasting models to further increase reliability and minimize downtime in real-time. It is possible that application of transformer-based temporal models to the local node layer, optimized to deploy to the edge, may provide greater interpretability and longer temporal dependency. When combined with federated reinforcement learning to dynamically adjust each client communication schedule and resource allocation, this would further minimize costs in low resource environments. Moreover, embedding explainable AI into TFML will be fundamentally important to getting industrial operators to trust the system, as they may want to understand why it makes the recommendations that it makes on maintenance. Lastly, the limited spread of TFML to real-world pilots in cross-sectoral industries (aerospace, automotive, and energy) will allow additional confirmations of its scalability and potential usefulness in the practical world. In summary, the TFML framework is an important contribution to state of the art in predictive maintenance in distributed independent systems. It implements a unification of natural learning over time, a federated collaborative learning, and an adaptive learning at meta-level, thus, crossing major boundaries of privacy, heterogeneity, communication cost and data scarcity. The results of this study reveal that TFML can be used to simultaneously improve predictive performance and also achieve scalability and feasibility in resource-constrained settings, which would provide a road map to the practical and sustainable deployment of predictive maintenance in Industry 4.0. With a greater blending of interconnected industrial systems and increased data to drive them, frameworks like TFML will become critical in facilitating robust, smart and flexible maintenance approaches that balance the tradeoff between technological solutions and operational constraints.

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