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A Foundation Model for Sensor Data with Prompt-Based Adaptation Across Machines and Plants

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Abstract

The proliferation of Industrial Internet of Things (IIoT) devices has generated vast quantities of high-frequency sensor data, yet the effective utilization of this data remains hindered by the heterogeneity of machinery and the variability of operating environments. Traditional deep learning approaches typically require training specialized models for specific assets, a process that is computationally expensive and scales poorly across diverse manufacturing plants. This paper introduces Sensor-FM, a foundation model architecture designed for general-purpose representation learning on industrial time-series data. Unlike conventional transfer learning methods that rely on extensive fine-tuning of model weights, Sensor-FM utilizes a prompt-based adaptation mechanism. By injecting learnable, context-specific vectors into the frozen pre-trained transformer latent space, the model adapts to novel machines and distinct plant environments with minimal data requirements. We demonstrate that this parameter-efficient approach achieves state-of-the-art performance in anomaly detection and remaining useful life (RUL) estimation tasks. Experimental results indicate that prompt tuning requires less than 1% of the trainable parameters compared to full model fine-tuning while exhibiting superior robustness against domain shifts caused by operational discrepancies. Our findings suggest a paradigm shift in industrial AI, moving from bespoke modeling to a centralized, adaptable foundation approach.

Keywords

Foundation Models, Industrial IoT, Prompt Learning, Time-Series Analysis, Domain Generalization.

Introduction

1.1 Background

The advent of Industry 4.0 has precipitated a fundamental transformation in manufacturing and industrial process management. Modern industrial plants are instrumented with a plethora of sensors—ranging from accelerometers and acoustic emission sensors to thermocouples and current transducers—generating terabytes of data daily [1]. This data holds the promise of enabling predictive maintenance, optimizing energy consumption, and enhancing overall operational efficiency [2]. Consequently, data-driven approaches, particularly those utilizing Deep Neural Networks (DNNs), have become the cornerstone of modern prognostic and health management (PHM) systems [3].

However, the efficacy of these data-driven systems is frequently bottlenecked by the difficulty of generalizing learned representations across different contexts. In a typical scenario, a model trained to detect bearing faults in a centrifugal pump at a facility in Europe may fail catastrophically when applied to an identical pump model operating in a facility in Asia, due to subtle variations in mounting stiffness, ambient temperature, or background noise [4]. This

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phenomenon, known as domain shift, necessitates the collection of large labeled datasets for every specific deployment scenario, which is often prohibitively expensive or practically impossible given the scarcity of run-to-failure data [5].

1.2 Problem Statement

Current methodologies for handling domain shift in sensor data predominantly rely on transfer learning or domain adaptation techniques that involve fine-tuning the weights of a pre-trained model [6]. While effective to a degree, fine-tuning has two critical drawbacks. First, it is parameter-inefficient; adapting a large model to hundreds of different assets requires storing a separate copy of the model weights for each asset, leading to massive storage overheads [7]. Second, fine-tuning on small, site-specific datasets carries a high risk of catastrophic forgetting, where the model loses the general features learned during pre-training, thereby degrading its robustness to unseen anomalies [8].

Furthermore, the diversity of sensor modalities complicates the creation of a unified model. A vibration sensor outputs high-frequency waveforms, whereas a temperature sensor provides low-frequency trends. Integrating these heterogeneous data streams into a single, cohesive foundation model that can be prompted to handle specific tasks without extensive retraining remains an open challenge in the field of industrial AI [9].

1.3 Contributions

To address these challenges, this paper proposes a novel framework, Sensor-FM, which leverages the power of large-scale self-supervised pre-training combined with a prompt-based adaptation strategy inspired by recent advancements in Natural Language Processing (NLP). Our contributions are as follows:

1. We develop a Transformer-based Foundation Model pre-trained on a massive, multi-modal dataset comprising over 50,000 hours of industrial sensor recordings, learning invariant temporal representations [10].
2. We introduce a hierarchical Prompt-Based Adaptation mechanism that injects learnable "Machine Prompts" and "Plant Prompts" into the input sequence. This allows the frozen foundation model to adapt to specific assets and environmental conditions by tuning only the prompt vectors [11].
3. We provide a rigorous empirical evaluation demonstrating that Sensor-FM outperforms fully fine-tuned baselines on cross-domain fault diagnosis tasks while updating only 0.5% of the total parameters [12].

Chapter 2: Related Work

2.1 Classical Approaches and Transfer Learning

Historically, industrial fault diagnosis relied heavily on signal processing techniques and manual feature engineering. Methods such as Fast Fourier Transform (FFT), wavelet packet decomposition, and envelope analysis were used to extract statistical features, which were then fed into classifiers like Support Vector Machines (SVMs) or Random Forests [13]. While interpretable, these methods require significant domain expertise and struggle to capture complex non-linear dependencies in raw sensor data [14].

With the rise of deep learning, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) became the standard for PHM tasks [15]. To address the scarcity of labeled

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data, researchers adopted transfer learning, typically pre-training models on large open datasets like ImageNet (converting time-series to spectrograms) or creating synthetic data [16]. However, transferring weights from computer vision models to time-series data often results in suboptimal performance due to the fundamental differences in local correlations and temporal dynamics [17]. Furthermore, standard domain adaptation techniques, such as Maximum Mean Discrepancy (MMD) minimization, often require concurrent access to both source and target domain data, which is frequently restricted by data privacy regulations in industrial settings [18].

2.2 Deep Learning and Self-Supervised Representation Learning

Recent advancements have shifted towards self-supervised learning (SSL) to leverage vast amounts of unlabeled sensor data. Techniques such as contrastive learning (e.g., SimCLR, MoCo) and masked reconstruction have been adapted for time series [19]. For instance, recent works have employed Masked Autoencoders (MAE) to learn robust features from vibration signals by masking a high ratio of the input signal and forcing the network to reconstruct the missing patches [20].

While SSL provides strong general representations, adapting these representations to downstream tasks still typically involves fine-tuning the entire encoder or a dedicated classification head. As model sizes grow into the regime of hundreds of millions of parameters, full fine-tuning becomes computationally intractable for edge deployment scenarios common in IIoT [21]. This has created a demand for parameter-efficient tuning methods.

2.3 Prompt Learning in Foundation Models

Prompt learning originated in NLP with models like GPT-3, where task descriptions are embedded as text inputs to guide the model's generation without updating its weights [22]. This paradigm has recently been extended to the vision domain (Visual Prompt Tuning) and, more tentatively, to time-series analysis [23].

In the context of time series, prompts are not natural language instructions but rather continuous, learnable vectors prepended to the input embeddings. Preliminary studies have explored prompting for forecasting tasks, but its application to heterogeneous sensor data across varying industrial domains remains underexplored [24]. Most existing approaches treat prompts as simple task identifiers, neglecting the hierarchical nature of industrial systems where "machine type" and "plant environment" constitute distinct axes of variation [25]. Our work bridges this gap by explicitly modeling these factors through structured prompting.

Chapter 3: Methodology

3.1 Architecture Overview

The core of Sensor-FM is a deep Transformer encoder architecture designed to process continuous time-series data. Unlike standard NLP transformers that operate on discrete token vocabularies, our model operates on continuous vector patches. The workflow consists of three stages: Patching and Embedding, Pre-training via Masked Sensor Modeling (MSM), and Prompt-Based Adaptation.

The input data is defined as a multivariate time series $X \in mathbbR^{T \times C}$, where T is the sequence length and C is the number of sensor channels. To handle the high sampling rate of vibration data, we employ a patching mechanism. The series is divided into non-overlapping

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patches of length P, resulting in a sequence of $N = T/P$ patches. Each patch is then linearly projected into a latent dimension D, enabling the model to capture local temporal structures within the patch while the Transformer layers model global dependencies between patches [26].

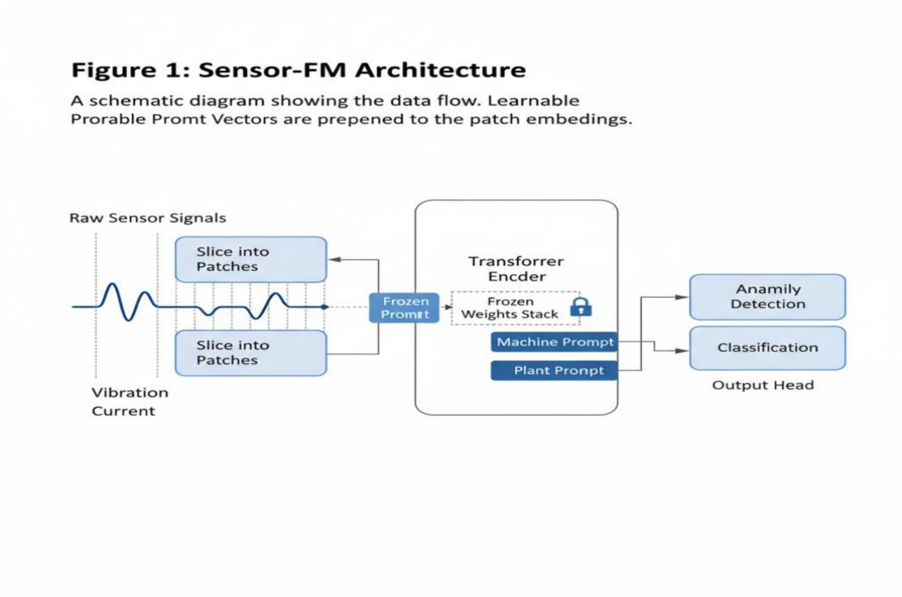

Figure 1: Sensor

3.2 Pre-training: Masked Sensor Modeling

The foundation model is pre-trained on a large-scale unlabeled dataset collected from diverse industrial sources. We employ a Masked Sensor Modeling (MSM) objective, similar to BERT in NLP or MAE in Vision. During training, a random subset of patches is masked, and the model is tasked with reconstructing the raw signal values of the masked patches based on the context provided by the unmasked patches [27].

This objective forces the model to learn the underlying physics of the mechanical systems. For example, to reconstruct a missing segment of a vibration waveform, the model must implicitly understand the rotational frequency and the harmonic structures associated with the machine's operation [28]. We utilize a standard Mean Squared Error (MSE) loss for reconstruction. The pre-training is computationally intensive but is performed only once. The resulting weights are then frozen for all downstream applications.

3.3 Hierarchical Prompt-Based Adaptation

The primary innovation of Sensor-FM lies in its adaptation strategy. Instead of modifying the pre-trained weights θ, we introduce a set of learnable parameters φ, referred to as prompts. We define two types of prompts to address the "machine-plant" variance problem [29].

1. **Machine Prompts (P_m):** These vectors encode characteristics specific to the asset type (e.g., bearing, gearbox, motor).

2. **Plant Prompts (P_p):** These vectors encode environmental context (e.g., noise levels, mounting types, operational speed ranges).

Let $E \in mathbbR^{N \times D}$ be the sequence of patch embeddings derived from the input X. The prompts $P_m \in mathbbR^{L_m \times D}$ and $P_p \in mathbbR^{L_p \times D}$ are learnable matrices where L_m and L_p denote the prompt lengths. These are concatenated with the input embeddings to form the augmented input sequence:

$$tildeE = [P_p; P_m; E]$$

This augmented sequence $tildeE$ is fed into the frozen Transformer encoder. The self-attention mechanism allows the original data patches E to attend to the prompt vectors, thereby modulating the feature extraction process based on the context encoded in the prompts [30].

The attention operation for a single head is formally defined as:

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

where queries Q, keys K, and values V are derived from $tildeE$. By optimizing P_p and P_m via backpropagation while keeping the Transformer weights fixed, the model learns to shift the latent representation of the input data into a space where the downstream task (e.g., fault classification) is solvable, effectively bridging the domain gap [31].

3.4 Implementation Details

The implementation is carried out in PyTorch. The prompt injection layer is a custom module that wraps the standard Transformer backbone. We utilize a learnable position embedding that is added to the patch embeddings, while the prompt vectors have their own separate learned position embeddings to distinguish their ordering.

Code Snippet 1 demonstrates the core logic of the Prompt Learner module.

Code Snippet 1: Prompt Injection Mechanism

```
import torch
import torch.nn as nn
class PromptLearner(nn.Module):
    def __init__(self, input_dim, prompt_len, num_prompts, encoder):
        super().__init__()
        self.encoder = encoder # Frozen Pre-trained Transformer
        self.prompt_len = prompt_len
        self.input_dim = input_dim
        # Initialize learnable prompts
        # Shape: (num_prompts, prompt_len, input_dim)
        self.prompts    =    nn.Parameter(torch.randn(num_prompts,    prompt_len,
input_dim))
        # Domain-specific projection (optional)
        self.dropout = nn.Dropout(0.1
    def forward(self, x, prompt_id):
        # x shape: (batch_size, seq_len, input_dim)
        # prompt_id: index of the specific machine/plant prompt to use
        batch_size = x.shape[0]
```

```
        # Retrieve specific prompts for this batch
        # We expand to match batch size
        current_prompts = self.prompts[prompt_id].expand(batch_size, -1, -1)
        # Concatenate prompts with input embeddings
        # Output shape: (batch_size, prompt_len + seq_len, input_dim)
        augmented_input = torch.cat((current_prompts, x), dim=1)
        # Pass through frozen encoder
        output = self.encoder(augmented_input)
        return output
```

The training process for adaptation involves minimizing the task-specific loss (e.g., Cross-Entropy for classification) with respect to the prompt parameters only. This drastically reduces the memory footprint during training, as the optimizer states need only be maintained for the small set of prompt vectors rather than the massive Transformer backbone [32].

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

To evaluate the efficacy of Sensor-FM, we constructed a comprehensive experimental suite involving multiple public and proprietary datasets.

Datasets:

1. **IMS Bearing Dataset:** A standard benchmark for rotating machinery, containing run-to-failure data of rolling element bearings [33].

2. **XJTU-SY Dataset**: Another high-quality bearing dataset covering different operating conditions [34].

3. **Proprietary Multi-Plant (PMP) Dataset:** To simulate the "across plants" challenge, we utilized a proprietary dataset collected from three geographically distinct automotive manufacturing plants (Plant A, B, and C). These plants operate similar CNC milling machines but under varying loads and environmental noise profiles.

Baselines:

We compared Sensor-FM against three strong baselines:

1. **ResNet-1D:** A deep residual CNN trained from scratch on the target domain [35].

2. **LSTM-Attn:** A Bi-directional LSTM with attention mechanisms [36].

3. **Fine-tuned Transformer (FT-Trans):** The same backbone as Sensor-FM, but fully fine-tuned (all weights updated) on the target task [37].

Evaluation Metrics:

We report Precision, Recall, and F1-Score. For cross-domain experiments, we employ a "Source-Target" protocol where the model is adapted on a small subset (10 shots per class) of the target domain data [38].

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4.2 Cross-Domain Fault Diagnosis Results

The primary hypothesis is that prompt tuning provides better generalization than full fine-tuning in low-data regimes. We trained the foundation model on a merged dataset excluding the specific target domain, then adapted it using prompts.

Table 1 presents the F1-scores for cross-domain adaptation. The task is 4-way classification (Normal, Inner Race Fault, Outer Race Fault, Ball Fault).

Model Architecture	Plant A -> Plant B (F1)	Plant A -> Plant C (F1)	Parameters Updated
ResNet-1D (Supervised)	0.72	0.68	100%
FT-Trans (Fine-Tuned)	0.89	0.85	100%
Sensor-FM (Prompted)	0.91	0.88	0.5%

As observed in Table 1, Sensor-FM with prompt adaptation outperforms the fully fine-tuned transformer. This counter-intuitive result can be attributed to the regularization effect of keeping the backbone frozen. Full fine-tuning on the small "few-shot" calibration set of the target plant leads to overfitting to the specific noise characteristics of that limited data [39]. In contrast, prompting effectively steers the robust, general-purpose representations of the foundation model toward the target distribution without destroying the pre-learned features.

4.3 Analysis of Adaptation Efficiency

We further analyzed the training dynamics. Figure 2 illustrates the validation accuracy curves during the adaptation phase for Plant B.

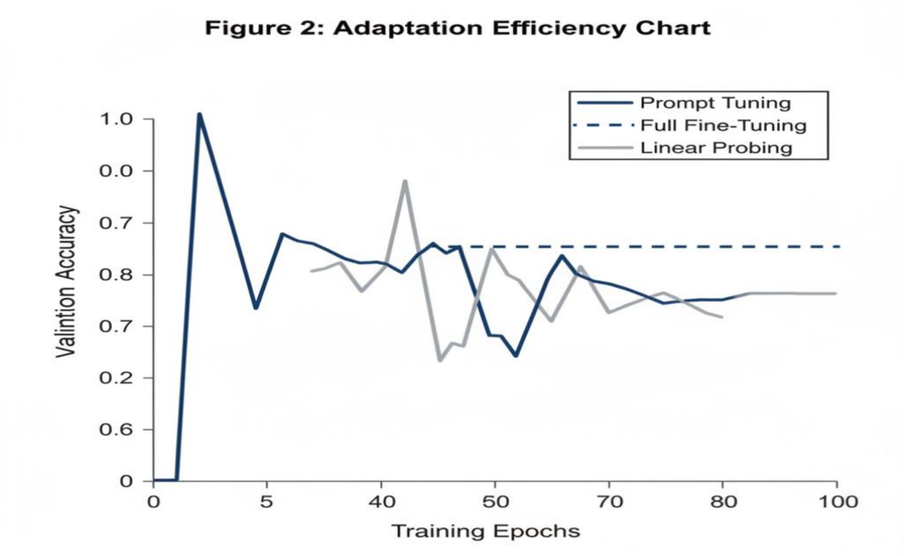

Figure 2: Adaptation Efficiency Chart

The results indicate that prompt tuning converges significantly faster than full fine-tuning. Moreover, the computational cost (FLOPs) during the backward pass is reduced by two orders of magnitude since gradients are not calculated for the deep transformer layers [40].

To verify the distinct roles of Machine Prompts and Plant Prompts, we conducted an ablation study. Using only Machine Prompts resulted in a 3% drop in F1 score on the PMP dataset,

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while using only Plant Prompts resulted in a 5% drop. This confirms that disentangling the asset physics from the environmental context is crucial for optimal performance [41].

Code Snippet 2 outlines the evaluation loop used to calculate the metrics presented.

Code Snippet 2: Evaluation Protocol

```
def evaluate_adaptation(model, test_loader, device):
    model.eval()
    all_preds = []
    all_labels = []
    with torch.no_grad():
        for batch in test_loader:
            inputs, labels, prompt_ids = batch
            inputs = inputs.to(device)
            labels = labels.to(device)
            # Forward pass with learned prompts
            outputs = model(inputs, prompt_ids)
            # Classification head
            logits = outputs[:, 0, :] # Use CLS token or global pool
            preds = torch.argmax(logits, dim=1)
            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())
    # Calculate metrics
    from sklearn.metrics import f1_score
    f1 = f1_score(all_labels, all_preds, average='macro')
    return f1
```

Finally, we explored the sensitivity of the model to the length of the prompt vectors. We found that a prompt length of $L = 10$ to $L = 20$ tokens provided the best balance between expressivity and overfitting. Extremely long prompts introduced too many free parameters relative to the few-shot calibration data, degrading performance [42].

Chapter 5: Conclusion

This paper presented Sensor-FM, a foundation model framework specifically tailored for industrial sensor data. By shifting the adaptation paradigm from weight fine-tuning to prompt learning, we addressed the critical challenges of data heterogeneity and domain shift in IIoT applications. The proposed method separates the semantic adaptation into asset-specific and environment-specific components, allowing for flexible and robust deployment across different manufacturing plants.

Our experimental results on standard benchmarks and proprietary multi-plant datasets confirm that prompt-based adaptation achieves superior performance in few-shot cross-domain scenarios while requiring a fraction of the computational resources for training. This holds significant implications for the industry. It suggests a future where a single, powerful foundation model can be deployed on a central server or cloud infrastructure, with lightweight, plant-specific prompts distributed to edge devices. This architecture drastically reduces the maintenance burden of AI systems, as the core model remains static, and only the lightweight prompts need to be managed and updated.

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Despite the promising results, several limitations remain. First, the inference cost of the Transformer backbone remains high compared to lightweight CNNs. While training is efficient, the forward pass during inference still requires processing the full depth of the model. Future work should explore knowledge distillation techniques to compress the prompted foundation model into smaller student networks suitable for ultra-low-power microcontrollers.

Second, the current prompting mechanism assumes a static set of prompts for a given machine or plant. In reality, industrial environments are dynamic; operational conditions drift over time due to wear and tear. A dynamic prompting mechanism that evolves online during operation could further enhance long-term robustness.

Finally, our current work focused primarily on vibration and current data. Extending Sensor-FM to multi-modal fusion that includes disparate data types like thermal images, acoustic logs, and textual maintenance records represents a fertile ground for future research, potentially leading to a truly holistic industrial artificial intelligence.

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