Adaptive Refinement of Time Series Foundation Models via Pattern and Context-Awareness

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Abstract

Time-series forecasting in domains such as ITOps and IoT faces two major challenges: data are non-stationary and multivariate, and state-of-the-art Time-Series Foundation Models (TSFMs) rely on fixed-size windows that miss transient phenomena (e.g., spikes, drifts) and their historical context. Prior efforts address this with seasonal-trend decompositions or frequency-aware pre-training, but these require retraining and offer limited adaptability.

We propose a dynamic two-stream framework that augments any pre-trained TSFM with frequency pattern awareness and contextual retrieval as the two streams. Each input window is decomposed via Fast Fourier Transforms (FFT) and Discrete Wavelet Transforms (DWT) to extract key low- and high-frequency patterns, which are fused into a TSFM through lightweight adapters and gated embedding augmentation. In parallel, frequency pattern signatures are used to retrieve semantically similar historical sequences, enriching long-range context. This approach enhances forecasting robustness of deployed TSFMs without retraining, achieving consistent improvements over baselines on both standard and zero-shot forecasting benchmarks, particularly with abrupt data fluctuations and complex temporal dynamics.

1 Introduction

Time-series forecasting underpins critical decisions in finance, energy, healthcare, and IoT. The emergence of time-series foundation models (TSFMs) such as Chronos [1], TimesFM [4], MOMENT [9], and Time-MoE [13] has demonstrated the promise of large-scale pre-training: by training on massive corpora, these models capture general temporal patterns, enable zero- or few-shot forecasting across diverse tasks, and have the potential to become the default backbone for forecasting. However, deploying TSFMs in practice faces two persistent challenges. First, real-world time series are non-stationary: they exhibit abrupt spikes, irregular cycles, and regime shifts that a fixed sliding window often fails to capture. Second, once a TSFM is deployed in production Fine-tuning or retraining is impractical due to strict latency, compute, and data-sharing constraints. Existing solutions fall short: lightweight adaptation (e.g., adapters, LoRA, prompts) stays confined to the time domain and struggles with transients, while frequency-aware models (e.g., FEDformer[19], CoST, LaST) require training new architectures and are expensive to adapt post-deployment. This leaves a crucial gap: how do we dynamically enhance a pre-trained TSFM at inference to handle real-world temporal dynamics?

We propose a two-stream refinement framework that augments any pre-trained TSFM [1, 4] with frequency pattern awareness and context awareness with historical retrieval, without modifying its core parameters. In the first stream, we apply analytic transforms (FFT and DWT) to decompose the input window into frequency components (details, approx, or trends). This approach exposes transient oscillations and periodic signatures overlooked by time-domain-only encodings. In the second stream, we retrieve semantically similar historical sequences by matching frequency signatures, capturing long-range dependencies and rare patterns beyond the fixed receptive field. Both streams are fused into

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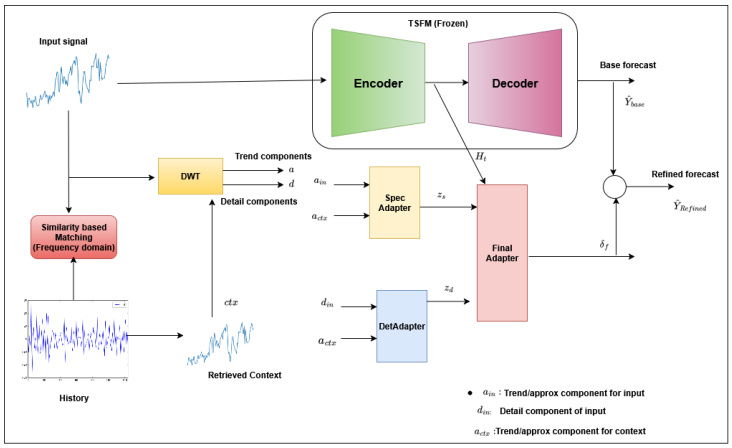


Figure 1: Dynamic two-stage adaptation: (1) decompose the input window into spectral component and detail components; (2) retrieve matching historical windows by frequency signature and integrate them with both components; (3) fuse both streams into a frozen TSFM via adapters

the pre-trained TSFM through lightweight adapters, enriching its representation with the core TSFM untouched. This design offers three deployment-oriented benefits. (i) Plug-and-play adaptability: Our method augments deployed TSFMs without retraining them or additional compute overhead. (ii) Frequency-driven robustness: by conditioning dynamically on the frequency spectrum of the input windows, our framework captures sharp fluctuations and non-stationary patterns that static windows miss. (iii) Scalability across models: large TSFMs gain improved robustness, while compact TSFMs (e.g., TTM) benefit especially from long-range retrieval. Empirical results across cross domain datasets (zero-shot) and long horizon forecasting benchmarks confirm consistent improvements, with notable gains in spiky, irregular, and high-frequency regimes. By coupling frequency decomposition and context retrieval in the two-stream framework, we provide a dynamic, efficient, and generalizable way to refine deployed TSFMs, enabling reliable real-world forecasting.

2 Related Work

TSFMs and Adaptation. TSFMs aim to learn general-purpose representations from massive corpora. Chronos [1] tokenizes series into discrete tokens and trains T5-style transformers, while Moirai [17] employs a masked encoder trained on 27B observations. TimesFM [5] introduces a decoder-only architecture with input patching, and Time-MoE [13] scales this idea via sparse mixture-of-experts. Tiny Time Mixers (TTMs) [6] demonstrate that even lightweight MLP-Mixer–style models (<1M parameters) can achieve strong zero-/few-shot results. Despite their success, these models operate primarily in the time domain with fixed input windows, limiting their ability to capture transient bursts or rare frequency patterns. Adaptation methods have explored parameter-efficient fine-tuning (adapters, LoRA) [10, 8], in-context learning [3], and curriculum-based strategies such as CCL [11]. While effective, these approaches still rely on time-domain adjustments. Some recent works leverage decomposition signals (e.g., trends, seasonality) in diffusion models [12], however involve training models from scratch rather than augmenting existing TSFMs. TSPulse [7] employs a dual-space masked reconstruction strategy, learning from time and frequency domains to capture complementary signal structures in a unified embedding space; however, it is pre-trained from scratch, and does not consume historical context with varying lengths.

Frequency Domain Analysis. Independent of TSFMs, frequency-aware models explicitly exploit spectral structure. FEDformer [19] combines sparse Fourier attention with seasonal-trend decomposition, LaST [16] disentangles latent trends via variational autoencoding, and CoST [18] applies contrastive learning across time and frequency. More integrated designs like TimeMixer++ [15] and TEMPO [2] fuse temporal and spectral patterns through multi-resolution mixing or structured decomposition. While effective, these methods rely on fixed transformation schemes and require full model retraining, limiting their adaptability to accommodate temporal dynamics.

3 Proposed Solution

We propose a **context-guided two-stream adaptation framework** that refines forecasts from any frozen TSFM f_θ without retraining, as demonstrated in Figure 1. Given a query window

$X_{t-k+1:t} \in \mathbb{R}^{k \times C}$, the base TSFM produces

$$\hat{Y}_{\text{base}} = f_\theta(X_{t-k+1:t}), \quad \hat{Y}_{\text{base}} \in \mathbb{R}^{h \times C}. \tag{1}$$

Frequency Decomposition. Each window is decomposed into low-frequency trend $a^{(0)}$ and high-frequency details $d^{(1:L)}$ by DWT:

$$[a^{(0)}, d^{(1)}, \ldots, d^{(L)}] = \mathrm{DWT}(X_{t-k+1:t}). \tag{2}$$

Context Retrieval. To capture long-range patterns, we compute FFT-based embeddings and retrieve the top-1 most similar historical window H^* as:

$$H^* = \arg\max_{H_i \in \mathcal{H}} \frac{\langle\, |\mathrm{FFT}(X)|, |\mathrm{FFT}(H_i)|\,\rangle}{\|\,\mathrm{FFT}(X)\|\;\|\,\mathrm{FFT}(H_i)\|}. \tag{3}$$

We retrieve the adjacent window of the best-matched context H^*, denoted as ctx. Using DWT, we then decompose both the input and context signals into approximation and detail components, represented as (a_{in}, d_{in}) and (a_{ctx}, d_{ctx}), respectively.

Two-Stream Integration. Spectral Adapter stream encodes trend-level signals:

$$z_s = \mathrm{SpecAdapter}([\,\mathrm{FFT}(a_{\text{in}}^{(0)}), \mathrm{FFT}(a_{\text{ctx}}^{(0)})\,]), \tag{4}$$

while the detail stream encodes fluctuations:

$$z_d = \mathrm{DetAdapter}([\,d_{\text{in}}^{(1:L)}, d_{\text{ctx}}^{(1:L)}\,]). \tag{5}$$

Fusion with TSFM. Hidden states of the frozen TSFM are enriched with spectral features:

$$\tilde{H}_t = f_\theta^{\text{enc}}(X_{t-k+1:t}) \tag{6}$$

yielding a refined offset forecast as:

$$\delta_f = FinalAdapter((\tilde{H}_t), z_s, z_t). \tag{7}$$

Then the final refined forecasting is given by:

$$\hat{Y}_{\text{refined}} = \hat{Y}_{\text{base}} + \delta_f \tag{1}$$

Training Objective. All Adapters are optimized with a loss:

$$\mathcal{L} = \frac{1}{hc}\|Y - \hat{Y}_{refined}\|_2^2 \tag{8}$$

ensuring both accurate forecasts and alignment of high-frequency details.

4 Experimental Setup and Results

We follow the similar setting as TimeMixer++ [15], evaluating four horizons (96, 192, 336, 720). In our fine-tuning setup, we train each frozen foundation model (Chronos-Bolt, TimesFM, TTM) for just three epochs using our two-stream adapters. We present the average MSE and MAE across all horizon sizes here, while the appendix (Table 3) provides the detailed results for each individual horizon. In the zero-shot setup, we fine-tune one series (e.g., ETTh1) and directly test on unseen ones (e.g., ETTh2, ETTm1). To demonstrate the robustness of our approach, we report average results over three independent runs.

Table 1 reports long-term forecasting results, showing consistent improvements over most classical baselines (TimeMixer++, PatchTST, FEDformer) and foundation models (Chronos-bolt, TimesFM). Our two-stream injection framework exploits complementary cues: the frequency stream applies DWT to separate smooth trends from rapid fluctuations, enabling targeted corrections, while the context stream captures long-range temporal dependencies beyond the TSFM's receptive field. Injecting both spectral and context signals into the frozen model's latent space refines its inductive biases, preserving short-range accuracy while enhancing medium- and long-horizon forecasts. For short-term settings, results in Appendix Table 5 confirm similar gains over baselines.

4.1 Zero-Shot Forecasting

Table 2 reports zero-shot forecasting under the same TimeMixer++ setup, where our method achieves significant improvements. This cross-dataset success arises because both streams learn abstractions that transfer across domains. This is due to our adapters learn to correct universal frequency motifs (e.g., seasonal cycles vs. noise) and distill recent history into a compact context embedding.

4.2 Refining the Foundation Model's Base Forecast

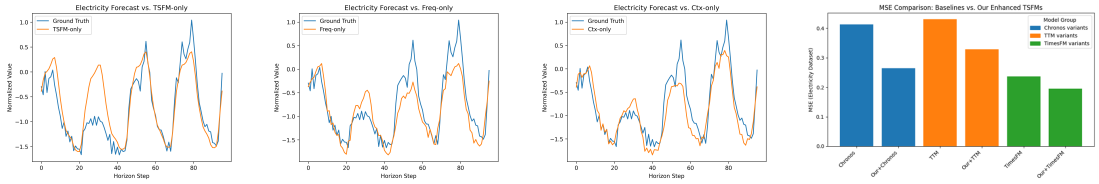
In Tables 1, 2, we report results using the Chronos-Bolt TSFM. To demonstrate the generalizability of our approach, we also evaluated it with TimesFM and TTM, with the corresponding results presented in the Figure 2 and Appendix Table 6. These results clearly show that our method significantly refines the base forecasts produced by pre-trained TSFMs.

Table 1: Long-term forecasting results. We average over horizons {96,192,336,720}. Best results are in red, second best in blue.

	Proposed (Ours)		Chronos-Bolt (2024)		TimesFM (2024)		TimeMixer++		TimeMixer (2024)		iTransformer (2024)		PatchTST (2023)		Crossformer (2023)		TiDE (2023)		TimesNet (2023)		DLinear (2022)		SCINet (2022)		FEDformer (2022)	
Dataset	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Electricity	0.238	0.340	0.326	0.391	0.285	0.357	0.165	0.253	0.182	0.272	0.178	0.270	0.205	0.290	0.244	0.334	0.251	0.344	0.192	0.295	0.212	0.300	0.268	0.365	0.214	0.327
ETT (Avg)	0.236	0.283	0.276	0.325	0.427	0.389	0.349	0.399	0.367	0.388	0.383	0.377	0.381	0.397	0.685	0.578	0.482	0.470	0.391	0.404	0.442	0.444	0.689	0.597	0.408	0.428
Exchange	0.1560	0.2185	0.173	0.235	0.470	0.480	0.357	0.391	0.391	0.453	0.378	0.360	0.403	0.404	0.940	0.707	0.370	0.413	0.416	0.443	0.354	0.414	0.750	0.626	0.519	0.429
Traffic	0.1756	0.2480	0.212	0.272	0.718	0.372	0.416	0.264	0.484	0.297	0.428	0.282	0.481	0.304	0.550	0.304	0.760	0.473	0.620	0.336	0.625	0.383	0.804	0.509	0.610	0.376
Weather	0.091	0.073	0.098	0.0920	0.343	0.365	0.226	0.262	0.240	0.271	0.258	0.278	0.259	0.281	0.259	0.315	0.271	0.320	0.259	0.287	0.265	0.317	0.292	0.363	0.309	0.360
Solar-Energy	0.184	0.209	0.310	0.352	0.559	0.503	0.203	0.238	0.216	0.280	0.233	0.262	0.270	0.307	0.641	0.639	0.347	0.417	0.301	0.319	0.330	0.401	0.282	0.375	0.291	0.381

Table 2: Zero-shot learning results. Results are averaged over horizons {96,192,336,720}. Best results are in red, second best in blue.

	Proposed Approach		Chronos-Bolt (2024)		TimesFM (2024)		TimeMixer++		TimeMixer (2024)		LLMTime (2023)		DLinear (2023)		PatchTST (2023)		TimesNet (2023)		iTransformer (2024)		Crossformer (2023)		Time-LLM (2024)	
Transfer Task	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
$ETT_{h1\to h2}$	0.260	0.322	0.297	0.416	0.446	0.454	0.367	0.391	0.427	0.424	0.992	0.708	0.493	0.488	0.380	0.405	0.421	0.431	0.481	0.474	0.555	0.574	0.353	0.387
$ETT_{h1\to m2}$	0.241	0.346	0.285	0.405	0.478	0.437	0.301	0.357	0.361	0.397	1.867	0.869	0.415	0.452	0.314	0.360	0.327	0.361	0.311	0.361	0.613	0.629	0.273	0.340
$ETT_{h2\to h1}$	0.198	0.341	0.233	0.367	0.510	0.455	0.511	0.498	0.679	0.577	1.961	0.981	0.703	0.574	0.565	0.513	0.865	0.621	0.552	0.511	0.587	0.518	0.479	0.474
$ETT_{m1\to h2}$	0.318	0.407	0.356	0.416	0.431	0.428	0.417	0.422	0.452	0.441	0.992	0.708	0.464	0.475	0.439	0.438	0.457	0.454	0.434	0.438	0.624	0.541	0.381	0.412
$ETT_{m1\to m2}$	0.180	0.320	0.287	0.408	0.441	0.414	0.291	0.331	0.329	0.357	1.867	0.869	0.335	0.389	0.296	0.334	0.322	0.354	0.324	0.331	0.595	0.572	0.268	0.320
$ETT_{m2\to m1}$	0.205	0.304	0.216	0.318	0.417	0.405	0.427	0.448	0.554	0.478	1.933	0.984	0.649	0.537	0.568	0.492	0.769	0.567	0.559	0.491	0.611	0.593	0.414	0.438



(a) Only Chronos-bolt (b) + Frequency (c) + Context (d) Comparison with FMs

Figure 2: Visualization of forecasting results: (a) only Chronos-bolt, (b) with frequency component, (c) with context information, and (d) comparison with other TSFMs.

5 Ablation Study

Table 6 shows that frequency adapters reduce local errors, context adapters improve long-horizon coherence, and their combination yields the best overall performance in both zero-shot and fine-tuned settings. Figure 2 shows that while the frozen TSFM drifts, frequency-only captures bursts but misses trends, and context-only preserves slope but ignores spikes. Only the full two-stream model aligns with both global and local patterns, highlighting the benefit of combining frequency and context. We varied context window sizes (96, 192, 336, 720) with a fixed query of 96 and horizon of 192. Figure 3 shows performance drops when the window is much shorter or longer than the horizon, with the best results when both are similar. We report the computational cost analysis in Table 8 of the Appendix.

6 Conclusion and Limitations

We proposed a dynamic two-stage adaptation framework that augments pre-trained time-series foundation models (TSFMs) with explicit frequency decomposition and retrieval-based long-range context. By integrating short-term spectral features with similar historical patterns via lightweight adapter modules, our method enables zero-shot forecasting without modifying TSFM weights. This design captures both local transients and rare long-range signals.

However, our approach has some limitations. Spectral retrieval may miss semantically relevant patterns in noisy or irregular time series. The added adapters, while efficient, still introduce some inference overhead. Moreover, the framework assumes that informative frequency structures exist—an assumption that may not hold in highly non-periodic or abrupt series. Future work could explore more flexible retrieval objectives and hybrid feature integration to address these challenges.

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A Appendix

B Long-term forecasting

Table 3 presents comprehensive results for the long-term forecasting task, comparing a wide range of competitive models across various prediction lengths. The 'Avg' column represents the average performance over all four prediction horizons: 96, 192, 336, and 720. Our proposed approach consistently outperforms existing state-of-the-art methods.

Table 3: Full results for the long-term forecasting task.

Dataset	Len	Ours (MSE)	Ours (MAE)	TimeMixer++		TimeMixer		iTrans		PatchTST		CrossF		TiDE		TimesNet		DLinear		SCINet		FEDf		Stationary		Autof	
				MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE		
Weather	96	0.0049	0.0544	0.155	0.205	0.163	0.209	0.174	0.214	0.186	0.227	0.195	0.271	0.202	0.261	0.172	0.220	0.195	0.252	0.221	0.306	0.217	0.296	0.173	0.223	0.266	0.336
	192	0.0102	0.0837	0.201	0.245	0.208	0.250	0.221	0.254	0.234	0.265	0.209	0.277	0.242	0.298	0.219	0.261	0.237	0.295	0.261	0.340	0.276	0.336	0.245	0.285	0.307	0.367
	336	0.0095	0.0791	0.237	0.265	0.251	0.287	0.278	0.296	0.284	0.301	0.273	0.332	0.287	0.335	0.280	0.306	0.282	0.331	0.309	0.378	0.339	0.380	0.321	0.338	0.359	0.395
	720	0.0089	0.0749	0.312	0.334	0.339	0.341	0.358	0.347	0.356	0.349	0.379	0.401	0.351	0.386	0.365	0.359	0.345	0.382	0.377	0.427	0.403	0.428	0.414	0.410	0.419	0.428
	Avg	0.0084	0.0730	0.226	0.262	0.240	0.271	0.258	0.278	0.265	0.285	0.264	0.320	0.271	0.320	0.259	0.287	0.265	0.315	0.292	0.363	0.309	0.360	0.288	0.314	0.338	0.382
Electricity	96	0.2625	0.3730	0.135	0.222	0.153	0.247	0.148	0.240	0.190	0.296	0.219	0.314	0.237	0.329	0.168	0.272	0.210	0.302	0.247	0.345	0.193	0.308	0.169	0.273	0.201	0.317
	192	0.2371	0.3583	0.147	0.235	0.166	0.256	0.162	0.253	0.199	0.304	0.231	0.322	0.236	0.330	0.184	0.322	0.210	0.305	0.257	0.355	0.201	0.315	0.182	0.286	0.222	0.334
	336	0.2608	0.3719	0.164	0.245	0.185	0.277	0.178	0.269	0.217	0.319	0.246	0.337	0.249	0.344	0.198	0.300	0.223	0.319	0.269	0.369	0.214	0.329	0.200	0.304	0.231	0.443
	720	0.3138	0.4206	0.212	0.310	0.225	0.310	0.225	0.317	0.258	0.352	0.280	0.363	0.284	0.373	0.220	0.320	0.258	0.350	0.299	0.390	0.246	0.355	0.222	0.321	0.254	0.361
	Avg	0.2686	0.3809	0.165	0.253	0.182	0.272	0.178	0.270	0.216	0.318	0.244	0.334	0.251	0.344	0.192	0.304	0.225	0.319	0.268	0.365	0.214	0.327	0.193	0.296	0.227	0.338
Traffic	96	0.2574	0.3102	0.392	0.253	0.462	0.285	0.395	0.268	0.526	0.347	0.644	0.429	0.805	0.493	0.593	0.321	0.650	0.396	0.788	0.499	0.587	0.366	0.612	0.338	0.613	0.388
	192	0.2616	0.2956	0.402	0.258	0.473	0.296	0.417	0.276	0.522	0.332	0.665	0.431	0.756	0.474	0.617	0.336	0.598	0.370	0.789	0.505	0.604	0.373	0.613	0.340	0.616	0.382
	336	0.2363	0.2925	0.428	0.263	0.498	0.296	0.433	0.283	0.517	0.334	0.674	0.420	0.762	0.477	0.629	0.336	0.605	0.373	0.797	0.508	0.621	0.383	0.618	0.328	0.622	0.337
	720	0.2645	0.3267	0.441	0.282	0.506	0.313	0.467	0.302	0.552	0.352	0.683	0.424	0.719	0.449	0.640	0.350	0.645	0.394	0.841	0.523	0.626	0.382	0.653	0.355	0.660	0.408
	Avg	0.25495	0.30625	0.416	0.264	0.484	0.297	0.428	0.282	0.529	0.341	0.667	0.426	0.760	0.473	0.620	0.336	0.625	0.383	0.804	0.509	0.610	0.376	0.624	0.340	0.628	0.379
Exchange	96	0.0680	0.1968	0.085	0.214	0.090	0.235	0.086	0.206	0.088	0.205	0.256	0.367	0.094	0.218	0.107	0.234	0.088	0.218	0.267	0.396	0.148	0.278	0.111	0.237	0.197	0.323
	192	0.1000	0.2409	0.175	0.313	0.187	0.343	0.177	0.299	0.176	0.299	0.470	0.509	0.184	0.307	0.226	0.344	0.176	0.315	0.351	0.459	0.271	0.315	0.219	0.335	0.300	0.369
	336	0.2429	0.3837	0.316	0.420	0.353	0.473	0.331	0.417	0.301	0.397	1.268	0.883	0.349	0.431	0.367	0.448	0.313	0.427	1.324	0.853	0.460	0.427	0.421	0.476	0.509	0.524
	720	0.4022	0.5270	0.851	0.689	0.934	0.761	0.847	0.691	0.901	0.714	1.767	1.068	0.852	0.698	0.964	0.746	0.839	0.695	1.058	0.797	1.195	0.695	1.092	0.769	1.447	0.941
	Avg	0.203275	0.3371	0.357	0.391	0.391	0.453	0.360	0.403	0.367	0.404	0.940	0.707	0.370	0.413	0.416	0.443	0.354	0.414	0.750	0.626	0.519	0.429	0.461	0.454	0.613	0.539
ETTh1	96	0.1722	0.3044	0.361	0.403	0.375	0.400	0.386	0.405	0.460	0.447	0.423	0.448	0.479	0.464	0.384	0.402	0.397	0.412	0.654	0.599	0.395	0.424	0.513	0.491	0.449	0.459
	192	0.1827	0.3242	0.416	0.441	0.429	0.421	0.441	0.512	0.477	0.429	0.471	0.474	0.525	0.492	0.436	0.429	0.446	0.441	0.719	0.631	0.469	0.470	0.534	0.504	0.500	0.482
	336	0.1956	0.3382	0.430	0.434	0.484	0.458	0.487	0.458	0.546	0.496	0.570	0.546	0.565	0.515	0.491	0.469	0.489	0.467	0.778	0.659	0.530	0.499	0.588	0.535	0.521	0.496
	720	0.1980	0.3413	0.467	0.451	0.498	0.482	0.503	0.491	0.544	0.517	0.653	0.621	0.594	0.558	0.521	0.500	0.513	0.510	0.836	0.699	0.598	0.544	0.643	0.616	0.514	0.512
	Avg	0.1871	0.3270	0.419	0.432	0.447	0.440	0.454	0.447	0.516	0.484	0.529	0.522	0.541	0.507	0.458	0.450	0.461	0.457	0.747	0.647	0.498	0.484	0.570	0.537	0.496	0.487
ETTh2	96	0.2144	0.3584	0.276	0.328	0.289	0.341	0.297	0.349	0.308	0.355	0.745	0.584	0.400	0.440	0.340	0.374	0.340	0.394	0.707	0.621	0.358	0.397	0.476	0.458	0.346	0.388
	192	0.2509	0.3902	0.342	0.379	0.372	0.392	0.380	0.400	0.393	0.405	0.877	0.656	0.528	0.509	0.402	0.414	0.482	0.479	0.860	0.689	0.429	0.439	0.512	0.493	0.456	0.452
	336	0.2675	0.4017	0.346	0.398	0.386	0.414	0.428	0.432	0.427	0.436	1.043	0.731	0.643	0.571	0.452	0.452	0.591	0.541	1.000	0.744	0.496	0.487	0.552	0.551	0.482	0.486
	720	0.2806	0.3992	0.392	0.415	0.412	0.434	0.427	0.445	0.436	0.450	1.104	0.763	0.874	0.679	0.462	0.468	0.839	0.661	1.249	0.838	0.463	0.474	0.562	0.560	0.515	0.511
	Avg	0.2534	0.3874	0.339	0.380	0.364	0.395	0.383	0.407	0.391	0.411	0.942	0.684	0.611	0.550	0.414	0.427	0.563	0.519	0.954	0.723	0.437	0.449	0.526	0.516	0.450	0.459
ETTm1	96	0.1079	0.2380	0.310	0.334	0.320	0.357	0.334	0.368	0.352	0.374	0.404	0.426	0.364	0.387	0.338	0.375	0.346	0.374	0.418	0.438	0.379	0.419	0.386	0.398	0.505	0.475
	192	0.1562	0.2902	0.348	0.362	0.361	0.381	0.390	0.393	0.374	0.387	0.450	0.451	0.398	0.404	0.374	0.387	0.382	0.391	0.439	0.450	0.426	0.441	0.459	0.444	0.553	0.496
	336	0.2206	0.3533	0.376	0.391	0.390	0.404	0.426	0.420	0.421	0.414	0.532	0.515	0.428	0.425	0.410	0.411	0.415	0.415	0.490	0.485	0.445	0.459	0.495	0.464	0.621	0.537
	720	0.2395	0.3709	0.440	0.423	0.454	0.441	0.491	0.459	0.462	0.449	0.666	0.589	0.487	0.461	0.478	0.450	0.473	0.451	0.595	0.550	0.543	0.490	0.585	0.516	0.671	0.561
	Avg	0.1811	0.3131	0.369	0.378	0.381	0.395	0.407	0.410	0.406	0.407	0.513	0.495	0.419	0.419	0.400	0.406	0.404	0.408	0.485	0.481	0.448	0.452	0.481	0.456	0.588	0.517
ETTm2	96	0.2131	0.3455	0.170	0.245	0.175	0.258	0.180	0.264	0.183	0.270	0.287	0.366	0.207	0.305	0.187	0.267	0.193	0.293	0.286	0.377	0.203	0.287	0.192	0.274	0.255	0.339
	192	0.2014	0.3353	0.229	0.291	0.237	0.299	0.250	0.309	0.255	0.314	0.414	0.492	0.290	0.364	0.249	0.309	0.284	0.361	0.399	0.445	0.269	0.328	0.280	0.339	0.281	0.340
	336	0.2983	0.4137	0.303	0.343	0.298	0.340	0.311	0.348	0.309	0.347	0.597	0.542	0.377	0.422	0.321	0.351	0.382	0.429	0.637	0.591	0.325	0.366	0.334	0.361	0.339	0.372
	720	0.3098	0.4120	0.373	0.399	0.391	0.396	0.412	0.407	0.412	0.404	1.730	1.042	0.558	0.524	0.408	0.403	0.558	0.525	0.960	0.735	0.421	0.415	0.417	0.413	0.433	0.432
	Avg	0.2557	0.3766	0.269	0.320	0.275	0.323	0.288	0.332	0.290	0.334	0.757	0.610	0.358	0.404	0.291	0.333	0.354	0.402	0.954	0.723	0.305	0.349	0.306	0.347	0.327	0.371

Table 4: Ablation study: contribution of each component on four datasets (MSE / MAE).

Dataset	Base FM		FM + Frequency		FM + Context		FM + Frequency + Context	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Electricity	0.295	0.379	0.232	0.351	0.235	0.353	0.227	0.346
Traffic	0.237	0.261	0.220	0.290	0.249	0.305	0.201	0.223
Exchange	0.202	0.347	0.0912	0.228	0.0887	0.225	0.069	0.198
Weather	0.021	0.0934	0.0054	0.0614	0.0067	0.0679	0.0102	0.0837

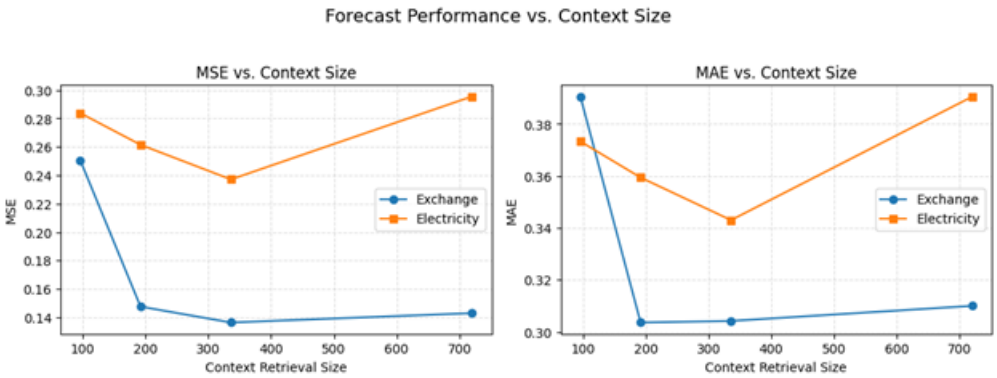

Figure 3: Effect of context size in the forecasting.

C Short-term forecasting

Table 5 presents the experimental results on the M4 dataset for short-term forecasting, demonstrating that our proposed approach leads to significant improvements in forecasting performance.

Table 5: Short-term forecasting results on the M4 dataset (single variate, prediction lengths in [6, 48]). Lower SMAPE and MASE indicate better performance.

Frequency	Metric	Ours	TimeMixer++ (Ours)	TimeMixer (2024b)	iTrans (2024)	TiDE (2023a)	TimesNet (2023)	N-HiTS (2023)	N-BEATS∗ (2019)	PatchTST (2023)	MICN (2023a)	FiLM (2022a)	LightTS (2022a)	DLinear (2023)	FED. (2022b)	Stationary (2022c)	Auto. (2021)
Yearly	SMAPE	**11.675**	13.179	13.206	13.923	15.320	13.387	13.418	13.436	16.463	25.022	17.431	14.247	16.965	13.728	13.717	13.974
	MASE	**2.147**	2.934	2.916	3.214	3.540	2.996	3.045	3.043	3.967	7.162	4.043	3.109	4.283	3.048	3.078	3.134
Quarterly	SMAPE	**3.3665**	9.755	9.996	10.757	11.830	10.100	10.202	10.124	10.644	15.214	12.925	11.364	12.145	10.792	10.958	11.338
	MASE	**1.3325**	1.159	1.166	1.283	1.410	1.182	1.194	1.169	1.278	1.963	1.664	1.328	1.520	1.283	1.325	1.365
Monthly	SMAPE	**1.4036**	12.432	12.605	13.796	15.180	12.670	12.791	12.677	13.399	16.943	15.407	14.014	13.514	14.260	13.917	13.958
	MASE	**0.8780**	0.904	0.919	1.083	1.190	0.933	0.969	0.937	1.031	1.442	1.298	1.053	1.037	1.102	1.097	1.103
Others	SMAPE	**2.980**	4.698	4.564	5.569	6.120	4.891	5.061	4.925	6.558	41.985	7.134	15.880	6.709	4.954	6.302	5.485
	MASE	**2.150**	2.931	3.115	3.940	4.330	3.302	3.216	3.391	4.511	62.734	5.090	11.434	4.953	3.264	4.064	3.865

Table 6: Comparison of Chronos-Bolt, TimesFM, Our+TimesFM, and Our+Chronos on six datasets. Lower MSE/MAE indicate better performance.

Dataset	Chronos-Bolt		Our+Chronos		TimesFM		Our+TimesFM	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Electricity	0.3260	0.3914	0.2319	0.3424	0.1924	0.2650	0.1654	0.2150
Traffic	0.2126	0.2727	0.1722	0.2572	0.6581	0.6890	0.5868	0.3847
Weather	0.0017	0.0287	0.0071	0.0718	0.1488	0.2360	0.1028	0.2116
Exchange	0.0680	0.1947	0.0340	0.1445	0.0924	0.1768	0.0524	0.1739
ETTm1	0.1560	0.2750	0.1079	0.2380	0.4900	0.6860	0.4125	0.5621
ETTh1	0.2133	0.3122	0.1722	0.3044	0.4289	0.5150	0.3924	0.4738

We evaluated our proposed approach on different versions of the Chronos-Bolt model—mini, small, and tiny to demonstrate that our method is not limited to a specific foundation model variant. As shown in Table 4, our approach significantly improves forecasting performance across all model versions.

C.1 Contribution of each component

We present the component-wise performance of our approach in Table 4. In our visual comparisons figure 2, the baseline TSFM produces overly smooth straight-line forecasts that miss both rapid spikes and long-term trend shifts. The Freq-only variant corrects high-frequency oscillations and periodic

Table 7: Performance comparison of Chronos-Bolt (Small, Mini, Tiny) and our approach on four datasets. Lower MSE/MAE indicate better performance.

Dataset	Small		Mini		Tiny	
	Ours (MSE/MAE)	CB (MSE/MAE)	Ours (MSE/MAE)	CB (MSE/MAE)	Ours (MSE/MAE)	CB (MSE/MAE)
Electricity	0.2319 / 0.3424	0.3260 / 0.3914	0.2305 / 0.3413	0.3288 / 0.3963	0.2351 / 0.3499	0.3379 / 0.4059
Traffic	0.1722 / 0.2572	0.2126 / 0.2727	0.1728 / 0.2577	0.2147 / 0.2740	0.1780 / 0.2597	0.2191 / 0.2798
Weather	0.0071 / 0.0718	0.0017 / 0.0287	0.0071 / 0.0718	0.0017 / 0.0291	0.0071 / 0.0718	0.0017 / 0.0289
Exchange	0.0340 / 0.1445	0.0680 / 0.1947	0.0321 / 0.1395	0.0664 / 0.1926	0.0298 / 0.1363	0.0662 / 0.1919

bumps, but, lacking context awareness, its forecasts still drift off the true slow trend over longer horizons. Conversely, the Ctx-only model preserves the overall trajectory and prevents drift, but fails to capture transient spikes and oscillations. Only the full two-stream approach combines both strengths, faithfully tracking global trends while adjusting to every local fluctuation.

C.2 The improvement in forecasting using our proposed approach with FMs

We evaluated our approach in conjunction with the pre-trained Chronos-Bolt, TimesFM, and TTM foundation models. As shown in Figure 2, integrating our method with these pre-trained models leads to significant improvements in forecasting performance.

C.3 Effect of context window size

We evaluated our approach using various context window sizes to assess their impact on forecasting performance. For this experiment, we fixed the input query size at 96 and the forecasting horizon at 192, while varying the context window size across 96, 192, 336, and 720. The results, illustrated in Figure 3, show that forecasting performance declines when the context window is either smaller or much larger than the forecasting horizon. Notably, our model achieves optimal performance when the context window size is approximately equal to the forecasting horizon, as the extracted context segment most closely aligns with the prediction interval in this scenario.

D Computational complexity

In this section, we compare the computational complexity of our adapter layers with computational complexities of original TSFM models. We follow common practices and measure the number of floating point operations (FLOPs) in multiply-accumulate operations (MACs) using batch size of 1 in forward pass. We use `ptflops` [14] utility that estimates FLOPs and number of parameters of PyTorch models. Results of comparison are shown in table 8. For family of Chronos models, the number of parameters in our adapters is only 5.52% of the parameters of the original tiny model, 2.56% of the mini model, 1.27% of the small model and 0.36% of the base model. FLOPs vary from 0.69% for the tiny model to only 0.04% for the base model.

Table 8: Comparison of computation complexity (FLOPs measured in multiply-accumulate operations) of our adaptor layers with original TSFM models. FLOPs and parameters are in millions (M).

Model	Original Model		MLP adaptors		As percents of original models	
	parameters (M)	FLOPs (M)	parameters (M)	FLOPs (M)	parameters (%)	FLOPS (%)
chronos-bolt-tiny	8.65	137.83	0.48	0.95	5.52	0.69
chronos-bolt-mini	21.24	348.08	0.54	1.08	2.56	0.31
chronos-bolt-small	47.72	794.38	0.61	1.21	1.27	0.15
chronos-bolt-base	205.29	3473.93	0.74	1.48	0.36	0.04