

SCALEMoR: MULTI-SCALE MIXTURE OF RECURSIVE LINEAR EXPERTS FOR TIME SERIES FORECASTING

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ABSTRACT

Multivariate time-series forecasting across multiple horizons faces two major challenges: temporal misalignment when aggregating multi-scale representations, and inefficient uniform computation regardless of sequence complexity. Existing methods either lose temporal dependencies during multi-scale fusion or allocate computation uniformly while ignoring varying input characteristics, which reduces long-range forecasting performance. We propose ScaleMoR, a novel architecture that redefines mixture-of-experts for temporal modeling. ScaleMoR applies recursive, scale-specific linear transformations as "experts", enabling parameter-efficient conditional computation. The method introduces three key innovations: (1) temporal-aligned multi-scale tokenization, which preserves chronological consistency across fine (2-step), medium (6-step), coarse (12-step), and macro (24-step) windows using learned Gaussian-weighted interpolation, (2) multi-dimensional complexity routing, which dynamically allocates computation based on trend, seasonal, noise, and volatility characteristics instead of a single complexity measure; and (3) hierarchical recursive modules, where deeper layers employ SwiGLU gating and dilated convolutions to achieve progressively richer representations through linear operations alone. We adopt a progressive three-phase training strategy that first learns tokenization, then introduces routing with entropy regularization, and finally optimizes the full architecture. Across ten benchmark datasets and multiple forecast horizons, ScaleMoR consistently outperforms state-of-the-art models, with particularly strong gains on long-range prediction tasks. It delivers 75–85% fewer parameters and 96–99% fewer FLOPs compared to recent attention-based and clustering-based approaches, while maintaining or surpassing their accuracy. These results highlight ScaleMoR as a highly accurate and efficient solution for multivariate time-series forecasting, well suited to real-world domains such as finance, energy, and industrial monitoring.

Keywords: Time Series Forecasting, Mixture-of-Experts, Recursive Neural Networks, Multi-Scale Representation

1 INTRODUCTION

Multivariate time-series (MTS) forecasting is a long-standing challenge in machine learning, with applications in finance Sezer et al. (2020), energy Zhang et al. (2018), weather Schultz et al. (2021), and healthcare Faust et al. (2018). The difficulty lies in capturing temporal dependencies across multiple scales while allocating computation efficiently based on sequence complexity. Transformer-based models have shown promise Nie et al. (2023); Liu et al. (2024), but their quadratic cost and susceptibility to temporal misalignment limit performance on long-range tasks.

A common strategy for multi-scale modeling is to process signals at different resolutions in parallel and then fuse them via concatenation or attention Wu et al. (2021); Zhou et al. (2022a). However, combining fine-grained patterns such as hourly dynamics with coarse-grained trends such as monthly cycles without explicit temporal alignment can break chronological consistency, for example through misaligned aggregation windows or phase shifts, which degrades the resulting representations Wang et al. (2024). Recent methods attempt to address this challenge by clustering temporal and channel patterns Li et al. (2024b) or by introducing explicit alignment mechanisms Jin et al. (2024b), but these approaches often introduce substantial architectural complexity or computational

054 overhead. Wavelet-based mixture-of-experts (MoE) has also been explored Zhang et al. (2024), yet
055 this design raises parameter counts and inherits the inefficiency of independently trained experts.
056

057 Other directions include state-space models Ansari et al. (2024), transformer variants with spe-
058 cialized attention patterns Cao et al. (2024), and linear methods that often rival more complex de-
059 signs Zeng et al. (2023). Yet most approaches still allocate computation uniformly to all tokens
060 regardless of complexity Kitaev et al. (2020), wasting resources when simple regularities are pro-
061 cessed with the same budget as highly variable dynamics.

062 The MoE paradigm offers a way to introduce conditional computation Shazeer et al. (2017); Fe-
063 dus et al. (2022). Traditional MoE models employ multiple independent networks as experts and
064 use a gating function to route inputs Jacobs et al. (1991). While this has been successful in nat-
065 ural language processing (NLP) Lepikhin et al. (2021) and computer vision (CV) Riquelme et al.
066 (2021), its use in time series forecasting is limited Chen et al. (2024). Recent wavelet-based MoE
067 methods Zhang et al. (2024) attempt to capture multi-scale dynamics but still suffer from parameter
068 inefficiency and lack explicit alignment across temporal scales. We argue that independent parallel
069 experts are fundamentally suboptimal for time series, where sequential dependencies and efficient
070 computation are essential.

071 In this work, we introduce *ScaleMoR* (Scale-aware Mixture of Recursive experts), which fundamen-
072 tally redefines the MoE paradigm for MTS forecasting. Instead of employing independent parallel
073 experts, we treat different recursive application depths of shared linear transformations as “experts.”
074 This formulation offers three key advantages over traditional MoE approaches Zhang et al. (2024);
075 Jacobs et al. (1991): (1) *parameter efficiency* through weight sharing across recursive depths, (2)
076 *computational efficiency* via pure linear operations without attention mechanisms Zeng et al. (2023),
077 and (3) *interpretability* where expert selection corresponds to processing depth allocation.

078 We introduce *ScaleMoR* (Scale-aware Mixture of Recursive experts), a new architecture that re-
079 defines MoE for time series forecasting. Instead of using independent parallel experts, we inter-
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081 brings three advantages: (1) parameter efficiency through weight sharing, (2) computational effi-
082 ciency through linear operations without attention Zeng et al. (2023), and (3) interpretability, since
083 expert choice reflects the depth of recursive processing.

084 *ScaleMoR* also addresses temporal misalignment through a Gaussian-weighted interpolation mech-
085 anism that produces aligned tokens at four scales. This avoids both the phase inconsistency of naïve
086 fusion and the complexity of clustering Li et al. (2024b) or wavelet decomposition Zhang et al.
087 (2024). We further introduce multi-dimensional complexity assessment that evaluates each token’s
088 trend, seasonality, noise, and volatility, enabling finer-grained allocation of computation than scalar
089 measures Wu et al. (2021). Finally, hierarchical recursive modules progressively expand represen-
090 tational capacity through SwiGLU gating Shazeer (2020) and dilated convolutions Yu & Koltun
091 (2016), achieving strong modeling power without the cost of attention. To ensure stable training,
092 *ScaleMoR* employs a progressive three-phase training strategy inspired by curriculum learning Ben-
093 gio et al. (2009): (1) tokenization learning with frozen routing, (2) routing with entropy regular-
094 ization Pereyra et al. (2017), and (3) full architecture optimization. This staged process prevents
095 routing from interfering with representation learning and supports convergence.

096 Our contributions are threefold. First, we introduce a conceptual innovation by redefining the MoE
097 paradigm for temporal modeling through recursive depth sharing, improving parameter efficiency
098 and interpretability. Second, we advance multi-scale forecasting with temporal-aligned tokenization
099 and multi-dimensional complexity routing, resolving misalignment and enabling adaptive compu-
100 tational allocation. Third, we empirically validate *ScaleMoR* across ten benchmark datasets and
101 multiple forecast horizons, demonstrating state-of-the-art performance while achieving substantial
102 efficiency gains over recent transformer-based Jin et al. (2024a); Liu et al. (2024), clustering-based
103 Li et al. (2024b), and MoE architectures Zhang et al. (2024).

104 2 RELATED WORK

105
106 Transformer architectures have become prominent in MTS forecasting. Informer Zhou et al. (2021)
107 introduced ProbSparse attention to mitigate the quadratic cost of long-sequence modeling, while
Autoformer Wu et al. (2021) employed decomposition with auto-correlation to capture periodic

108 patterns. FEDformer Zhou et al. (2022a) extended this line by modeling seasonality with frequency-
109 enhanced attention in the Fourier domain. More recent efforts have focused on patching strategies for
110 efficiency. For example, PatchTST Nie et al. (2023) treats patches of time series as tokens, achieving
111 strong performance through channel independence and effective patching, while iTransformer Liu
112 et al. (2024) inverts the embedding process by applying attention across the variate rather than the
113 temporal dimension, improving multivariate forecasting. Despite these advances, transformer-based
114 methods still suffer from temporal misalignment when integrating multi-scale patterns and allocate
115 computation uniformly across tokens, regardless of complexity.

116 In parallel, simple non-transformer architectures have proven competitive. Linear models such as
117 DLinear Zeng et al. (2023) and RLinear Li et al. (2024a) show that decomposition-based linear
118 layers with proper normalization can rival or surpass transformers. Beyond linear methods, CNN-
119 based approaches have gained traction. TimesNet Wu et al. (2022) projects 1D time series into
120 2D tensors to exploit CV techniques for multi-periodicity, while DUET Li et al. (2024b) integrates
121 autoencoders with dual-stage clustering for temporal and channel dependencies. While effective,
122 these methods typically apply uniform computation across all temporal positions, limiting efficiency.

123 Another line of research explores MoE architectures to scale models through conditional computa-
124 tion. Switch Transformer Fedus et al. (2022) introduced token-choice routing, assigning each token
125 to one expert, while GLaM Du et al. (2022) demonstrated the efficiency of sparse expert activation.
126 Expert Choice Routing Zhou et al. (2022b) reversed the scheme, improving load balancing by letting
127 experts select tokens. MoE has also evolved toward recursive designs. The Mixture-of-Recursions
128 framework Bae et al. (2025) applied shared layers recursively with dynamic depth, offering param-
129 eter efficiency without sacrificing capacity. However, most of these methods have been validated
130 in NLP and CV, with limited exploration in MTS forecasting, where temporal alignment and scale-
131 awareness remain critical.

132 Related to this, multi-scale temporal modeling has long been a challenge. Classical approaches rely
133 on parallel pathways for different resolutions Lai et al. (2018); Salinas et al. (2020), but naïve con-
134 catenation often introduces temporal misalignment. SCINet Liu et al. (2022) addressed this with
135 recursive splitting and cross-scale interaction, while Triformer Cirstea et al. (2022) employed trian-
136 gular attention to model variable-wise and temporal dependencies simultaneously. More adaptive
137 methods have emerged as well. For instance, TimeMixer Wang et al. (2024) alleviates misalign-
138 ment via decomposable mixing blocks, though it still applies uniform computation. Whereas Mod-
139 ernTCN Luo & Wang (2024) shows that well-designed temporal convolutions can match transformer
140 accuracy with greater parameter efficiency.

141 Finally, efficiency-oriented work has investigated conditional computation, gating, and activation
142 mechanisms. AdaViT Xing et al. (2022) introduced adaptive token processing in vision transform-
143 ers, allowing different regions to receive variable computation, while DynaBERT Hou et al. (2020)
144 applied adaptive width selection for efficiency in NLP. In MTS forecasting, however, conditional
145 computation remains underexplored. Most approaches adapt at the input-level Kitaev et al. (2020)
146 or use uniform expert allocation Chen et al. (2024), overlooking the varying complexity of tempo-
147 ral patterns. Gating and activation function advances provide further inspiration. SwiGLU Shazeer
148 (2020), combining Swish activation with gating, has become standard in large-scale models due to
149 improved gradient flow, while earlier GLU variants Dauphin et al. (2017) also exhibited benefits for
150 sequential dependencies. Similarly, dilated convolutions, first introduced in WaveNet Van Den Oord
151 et al. (2016), efficiently expand receptive fields and have been successfully adapted to MTS fore-
152 casting Bai et al. (2018), aligning naturally with the hierarchical structure of temporal data.

154 3 METHODOLOGY

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157 ScaleMoR consists of four main components that work synergistically to achieve efficient and accu-
158 rate MTS forecasting: (1) a Temporal-Aligned Tokenizer that extracts multi-scale temporal represen-
159 tations while preserving chronological consistency, (2) an Enhanced Multi-Dimensional Router that
160 adaptively allocates computational resources based on input complexity characteristics, (3) Cross-
161 Scale Positional Encoding that captures inter-scale temporal relationships, and (4) an Adaptive Pre-
prediction Head that adjusts its architecture based on forecast horizon requirements.

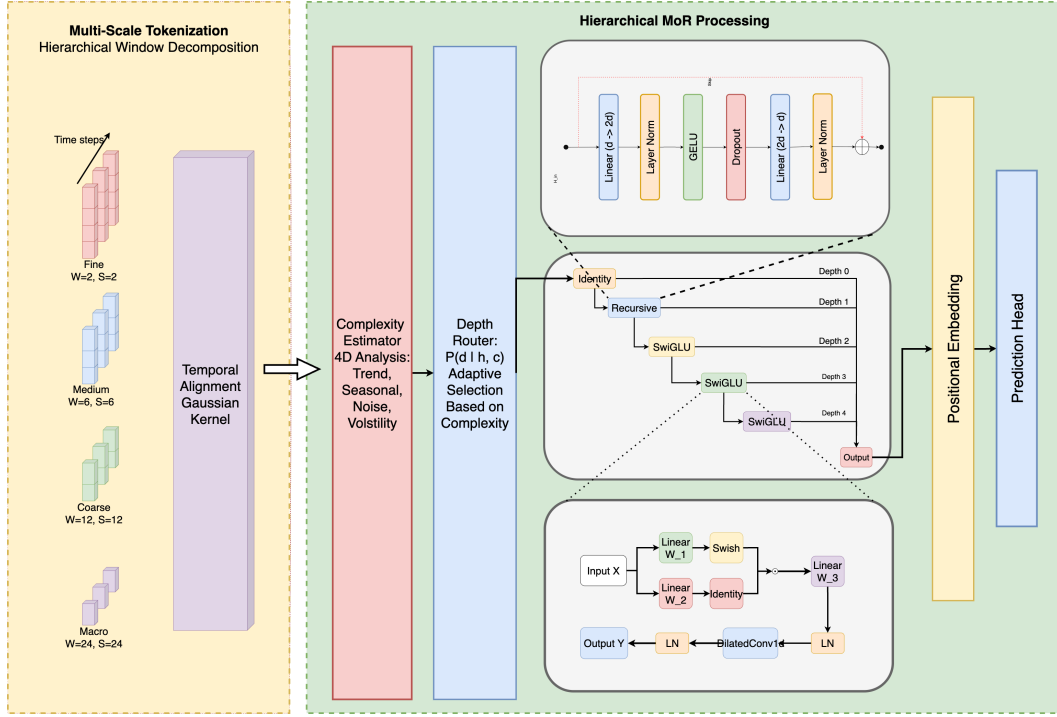


Figure 1: Overall ScaleMoR Architecture Diagram

3.1 TEMPORAL-ALIGNED MULTI-SCALE TOKENIZATION

Traditional multi-scale approaches often suffer from temporal misalignment when aggregating representations across scales. Our temporal-aligned tokenization maintains chronological consistency during fusion. We define four scales: Fine (2-step window/stride, local variations), Medium (6-step, short-term patterns), Coarse (12-step, medium-term trends), and Macro (24-step, long-term patterns).

For scale s with window w_s and stride st_s , tokens are extracted as $\mathbf{T}_i^{(s)} = \text{Pool}^{(s)}(\mathbf{X}_{i:st_s:i:st_s+w_s})$, where $\text{Pool}^{(s)}$ is max (fine), mean (medium), or attention-weighted (coarse/macro).

Temporal consistency is ensured by Gaussian interpolation: $\mathbf{W}_{i,t}^{(s)} = \exp\left(-\frac{(t-c_i^{(s)})^2}{2\sigma^2}\right) / Z_i^{(s)}$, with $c_i^{(s)}$ the token center, σ the radius, and $Z_i^{(s)}$ the normalizer.

Each scale is projected to a shared space via $\mathbf{H}^{(s)} = \text{LayerNorm}(\text{ReLU}(\mathbf{W}_1^{(s)}\mathbf{T}^{(s)} + \mathbf{b}_1^{(s)})) + \mathbf{P}^{(s)}$, where $\mathbf{P}^{(s)}$ are learnable positional embeddings.

3.2 MULTI-DIMENSIONAL COMPLEXITY ROUTING

Traditional MoE models often rely on single-scalar complexity measures. Our multi-dimensional routing mechanism evaluates four distinct complexity dimensions to make more informed computational allocation decisions.

We design a complexity estimator that extracts four fundamental characteristics from each token:

$$\mathbf{C} = \sigma(\mathbf{W}_C \text{ReLU}(\mathbf{W}_{C1}\mathbf{h} + \mathbf{b}_{C1}) + \mathbf{b}_C), \quad (1)$$

where $\mathbf{C} = [c_{\text{trend}}, c_{\text{seasonal}}, c_{\text{noise}}, c_{\text{volatility}}]^T$ is the four-dimensional complexity vector, and σ ensures scores remain in $[0, 1]$.

Different temporal scales naturally favor different processing depths. We introduce learnable scale-specific bias parameters:

$$\mathbf{B}_{\text{trend}}^{(s)} = \text{Parameter}([\beta_0^{(s)}, \dots, \beta_D^{(s)}]), \quad \mathbf{B}_{\text{seasonal}}^{(s)} = \text{Parameter}([\gamma_0^{(s)}, \dots, \gamma_D^{(s)}]),$$

where D is the maximum recursive depth. Fine-scale tokens favor shallow processing ($\beta_0^{(\text{fine})} > \beta_D^{(\text{fine})}$), while macro-scale tokens favor deeper recursive processing ($\beta_D^{(\text{macro})} > \beta_0^{(\text{macro})}$).

Routing combines token representations with complexity features to determine optimal processing depths:

$$\mathbf{R} = \text{Softmax}\left(\mathbf{W}_R[\mathbf{h}; \mathbf{C}] + c_{\text{trend}}\mathbf{B}_{\text{trend}}^{(s)} + c_{\text{seasonal}}\mathbf{B}_{\text{seasonal}}^{(s)}\right), \quad (2)$$

where $[\mathbf{h}; \mathbf{C}]$ denotes the concatenation of token features and complexity scores, and $\mathbf{R} \in \mathbb{R}^{D+1}$ represents the probability distribution over recursive depths $\{0, 1, \dots, D\}$.

3.3 HIERARCHICAL RECURSIVE PROCESSING MODULES

Hierarchical recursive modules replace attention mechanisms, providing progressive representational capacity via linear operations with gating and dilated convolutions.

Depth-stratified recursive modules feature shallow and deep paths, each tailored to its function.

Shallow Modules (Depths 1) focus on rapid, lightweight transformations:

$$\mathbf{h}^{(d)} = \text{LayerNorm}\left(\text{GELU}\left(\mathbf{W}_2 \text{LayerNorm}\left(\text{GELU}\left(\mathbf{W}_1 \mathbf{h}^{(d-1)}\right)\right)\right)\right).$$

Deep Modules (Depths 2+) employ SwiGLU gating and dilated convolutions for enhanced representational power:

$$\mathbf{g}^{(d)} = \text{SiLU}(\mathbf{W}_g \mathbf{h}^{(d-1)}) \odot (\mathbf{W}_v \mathbf{h}^{(d-1)}), \quad \mathbf{h}_{\text{swiglu}}^{(d)} = \mathbf{W}_o \mathbf{g}^{(d)},$$

$$\mathbf{h}_{\text{conv}}^{(d)} = \text{DilatedConv}(\mathbf{h}_{\text{swiglu}}^{(d)}, \text{dilation} = 2^{d-2}), \quad \mathbf{h}^{(d)} = \text{LayerNorm}(\mathbf{h}_{\text{conv}}^{(d)}),$$

where \odot denotes element-wise multiplication, and the dilation factor grows exponentially with depth.

Each token's final representation is

$$\mathbf{h}_{\text{final}} = \sum_{d=0}^D r_d \cdot \mathbf{f}^{(d)}(\mathbf{h}_{\text{input}}), \quad \mathbf{f}^{(d)}(\mathbf{h}) = \begin{cases} \mathbf{h}, & d = 0, \\ \mathbf{h} + \alpha \cdot \mathcal{M}_d(\mathbf{f}^{(d-1)}(\mathbf{h})), & d > 0, \end{cases}$$

with $\alpha = 0.5$ serving as a residual scaling factor.

3.4 CROSS-SCALE POSITIONAL ENCODING

To model relationships across temporal scales, we introduce cross-scale relative positional encodings that represent interactions between tokens from different scales.

For each pair of scales (s_i, s_j) with $i < j$, we define relative positional encodings:

$$\mathbf{E}^{(s_i, s_j)} = \text{Parameter}(\mathbb{R}^{1 \times 1 \times d_{\text{model}}}).$$

The cross-scale enhancement for tokens at scale s is computed as:

$$\mathbf{H}_{\text{enhanced}}^{(s)} = \mathbf{H}^{(s)} + \sum_{s' \neq s} \text{sign}(s, s') \cdot \mathbf{E}^{(\min(s, s'), \max(s, s'))},$$

where $\text{sign}(s, s')$ ensures consistent directionality in the relative position relationships.

3.5 ADAPTIVE PREDICTION HEAD

Our adaptive prediction head dynamically adjusts its structure according to the prediction length, accounting for the distinct characteristics of short-, medium-, and long-term forecasts.

Prediction tasks are grouped into three categories: Short-term ($L \leq 96$) uses a 3-layer MLP emphasizing detail preservation; Medium-term ($96 < L \leq 336$) employs a 4-layer architecture balancing detail and trend modeling; Long-term ($L > 336$) incorporates TrendConv layers for trend extraction:

$$\mathbf{y} = \begin{cases} \mathbf{W}_{s3} \text{ReLU}(\mathbf{W}_{s2} \text{GELU}(\mathbf{W}_{s1} \mathbf{h}_{\text{global}})), & L \leq 96 \\ \mathbf{W}_{m4} \text{GELU}(\mathbf{W}_{m3} \text{GELU}(\mathbf{W}_{m2} \text{GELU}(\mathbf{W}_{m1} \mathbf{h}_{\text{global}}))), & 96 < L \leq 336 \\ \mathbf{W}_{l3} \text{GELU}(\text{TrendConv}(\text{GELU}(\mathbf{W}_{l2} \text{GELU}(\mathbf{W}_{l1} \mathbf{h}_{\text{global}})))), & L > 336 \end{cases}$$

The global representation uses horizon-aware weighted fusion: $\mathbf{h}_{\text{global}} = \sum_s w_s^{(L)} \cdot \text{Pool}(\mathbf{H}_{\text{processed}}^{(s)})$, where short-term forecasts weight fine-scale tokens more ($w_{\text{fine}}^{(96)} = 0.4$), while long-term forecasts emphasize macro-scale tokens ($w_{\text{macro}}^{(720)} = 0.4$).

3.6 IMPLEMENTATION DETAILS

We employ SwiGLU activation for deep recursive modules for its superior gradient flow properties:

$$\text{SwiGLU}(\mathbf{x}) = \text{SiLU}(\mathbf{W}_g \mathbf{x}) \odot (\mathbf{W}_v \mathbf{x}),$$

where \odot denotes element-wise multiplication. Layer normalization is applied after each recursive module to maintain training stability Ba et al. (2016), with learnable scale and shift parameters specific to each processing depth.

Deep recursive modules incorporate dilated convolutions with exponentially increasing dilation factors Yu & Koltun (2016); Bai et al. (2018):

$$\text{dilation}_d = 2^{d-2}, \quad d \geq 2.$$

This design enables the model to capture progressively longer-range temporal dependencies as depth increases, without introducing additional parameters or relying on attention mechanisms.

The resulting ScaleMoR architecture achieves efficient multivariate time series forecasting through intelligent computational allocation, maintaining temporal alignment across multiple scales while adapting processing complexity to input characteristics.

4 EXPERIMENTS

4.1 EXPERIMENTAL SETUP

We evaluate ScaleMoR on ten benchmark datasets: Weather Lai et al. (2018) (21 features), ECL Dua et al. (2017) (321), Traffic Zhou et al. (2021) (862), Solar Lai et al. (2018) (137), Exchange Lai et al. (2018) (8), ETTm1/ETTh2 Zhou et al. (2021) (7 each, 15-min), ETTh1/ETTh2 Zhou et al. (2021) (7 each, hourly), and ILI Wu et al. (2021) (20, weekly). All datasets use a 7:2:1 train-validation-test split, with horizons of 96/192/336/720 (ILI: 24/36/48/60). For longer horizons (Exchange, ILI), validation data are augmented from the training set, while test sets remain independent.

We compare against state-of-the-art models in three groups: Attention-based (iTransformer (Liu et al. (2023)) and PatchTST (Nie et al. (2023))), Linear (TimeMixer (Wang et al. (2024)) and FITS (Xu et al. (2023))), and Latest (2024–2025) models (DUET (Li et al. (2024b)) and WaveTS-B (Zhou et al. (2025))).

Training follows a three-phase strategy: (1) 20% of epochs — tokenization learning with frozen routing; (2) 30% — routing with entropy regularization ($\mathcal{L} = \text{MSE} - \lambda_{\text{entropy}} \sum_s \mathcal{H}(\mathbf{R}^{(s)})$); (3) 50% — full optimization with diversity regularization. We use Adam optimizer with dataset-specific learning rates and batch sizes, gradient clipping (1.0), and early stopping (patience 8–20).

4.2 MAIN RESULTS

Table 1 presents comprehensive performance comparison across all datasets and prediction horizons. ScaleMoR demonstrates superior performance across most datasets and prediction horizons, particularly excelling in long-range forecasting scenarios (336-720 steps), where temporal dependency modeling is crucial. The model achieves the best MSE scores in 34 out of 40 experimental settings, showcasing its robustness across diverse forecasting tasks.

Table 1: Multivariate forecasting results with look back window = 96 and forecasting horizons $F \in \{24, 36, 48, 60\}$ for ILI and $F \in \{96, 192, 336, 720\}$ for others.

Models Metrics	Horizon	ScaleMoR (ours)		WaveTS-B (2025)		DUET (2025)		PDF (2024)		iTransformer (2024)		Pathformer (2024)		FiTS (2024)		TimeMixer (2024)		PatchTST (2023)		Crossformer (2023)	
		mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae	mse	mae
ETTh1	96	0.245	0.337	0.377	0.400	0.352	0.384	0.360	0.391	0.386	0.405	0.372	0.392	0.376	0.396	0.372	0.401	0.377	0.397	0.411	0.435
	192	0.180	0.290	0.421	0.427	0.398	0.409	0.392	0.414	0.424	0.440	0.408	0.415	0.400	0.418	0.413	0.430	0.409	0.425	0.409	0.438
	336	0.200	0.306	0.452	0.446	0.414	0.426	0.418	0.435	0.449	0.460	0.438	0.434	0.419	0.435	0.438	0.450	0.431	0.444	0.433	0.457
	720	0.223	0.325	0.470	0.480	0.429	0.455	0.456	0.462	0.495	0.487	0.450	0.463	0.435	0.458	0.486	0.484	0.457	0.477	0.501	0.514
ETTh2	96	0.074	0.194	0.270	0.335	0.270	0.336	0.276	0.341	0.297	0.348	0.279	0.336	0.277	0.345	0.281	0.351	0.274	0.337	0.728	0.603
	192	0.057	0.171	0.336	0.378	0.332	0.374	0.339	0.382	0.372	0.403	0.345	0.380	0.331	0.379	0.349	0.387	0.348	0.384	0.723	0.607
	336	0.062	0.177	0.358	0.399	0.353	0.397	0.374	0.406	0.388	0.417	0.378	0.408	0.350	0.396	0.366	0.413	0.377	0.416	0.740	0.628
	720	0.061	0.177	0.385	0.430	0.382	0.425	0.398	0.433	0.424	0.444	0.437	0.455	0.382	0.425	0.401	0.436	0.406	0.441	1.386	0.882
ETTm1	96	0.223	0.302	0.300	0.347	0.279	0.333	0.286	0.340	0.300	0.353	0.290	0.335	0.303	0.345	0.293	0.345	0.289	0.343	0.314	0.367
	192	0.116	0.228	0.337	0.368	0.320	0.358	0.321	0.364	0.341	0.380	0.337	0.363	0.337	0.365	0.335	0.372	0.329	0.368	0.374	0.410
	336	0.149	0.255	0.371	0.388	0.348	0.377	0.354	0.383	0.374	0.384	0.368	0.384	0.368	0.384	0.368	0.386	0.362	0.390	0.413	0.432
	720	0.071	0.184	0.417	0.416	0.405	0.408	0.408	0.415	0.429	0.430	0.428	0.416	0.420	0.413	0.426	0.417	0.416	0.423	0.753	0.613
ETTm2	96	0.068	0.190	0.161	0.251	0.161	0.248	0.163	0.251	0.175	0.266	0.164	0.250	0.165	0.254	0.165	0.256	0.165	0.255	0.296	0.391
	192	0.098	0.230	0.216	0.290	0.214	0.286	0.219	0.290	0.242	0.312	0.219	0.288	0.219	0.291	0.225	0.298	0.221	0.293	0.369	0.416
	336	0.115	0.248	0.270	0.327	0.267	0.321	0.269	0.330	0.282	0.337	0.267	0.319	0.272	0.326	0.277	0.332	0.276	0.327	0.588	0.600
	720	0.124	0.256	0.350	0.378	0.348	0.374	0.349	0.382	0.375	0.394	0.361	0.377	0.359	0.381	0.360	0.387	0.362	0.381	0.750	0.612
Exchange	96	0.011	0.079	0.083	0.203	0.080	0.198	0.083	0.200	0.086	0.205	0.088	0.208	0.082	0.199	0.084	0.207	0.079	0.200	0.088	0.213
	192	0.015	0.092	0.174	0.297	0.162	0.288	0.172	0.294	0.177	0.299	0.183	0.304	0.173	0.295	0.178	0.300	0.159	0.289	0.157	0.288
	336	0.017	0.095	0.338	0.424	0.294	0.392	0.323	0.411	0.331	0.417	0.354	0.429	0.317	0.406	0.376	0.451	0.297	0.399	0.332	0.429
	720	0.049	0.163	1.025	0.762	0.583	0.580	0.820	0.682	0.846	0.693	0.909	0.716	0.825	0.684	0.884	0.707	0.751	0.650	0.980	0.762
Weather	96	0.131	0.184	0.167	0.220	0.146	0.191	0.147	0.196	0.157	0.207	0.148	0.195	0.172	0.225	0.147	0.198	0.149	0.196	0.143	0.210
	192	0.141	0.203	0.210	0.257	0.188	0.231	0.193	0.240	0.200	0.248	0.191	0.235	0.215	0.261	0.192	0.243	0.191	0.239	0.198	0.260
	336	0.147	0.210	0.256	0.293	0.234	0.268	0.245	0.280	0.252	0.287	0.243	0.274	0.261	0.295	0.247	0.284	0.242	0.279	0.258	0.314
	720	0.163	0.226	0.319	0.338	0.305	0.319	0.323	0.334	0.320	0.336	0.318	0.326	0.326	0.341	0.318	0.330	0.312	0.330	0.335	0.385
Electricity	96	0.100	0.220	0.133	0.228	0.128	0.219	0.128	0.222	0.134	0.230	0.135	0.222	0.139	0.237	0.153	0.256	0.143	0.247	0.134	0.231
	192	0.111	0.235	0.148	0.242	0.145	0.235	0.147	0.242	0.154	0.250	0.157	0.253	0.154	0.250	0.168	0.269	0.158	0.260	0.146	0.243
	336	0.136	0.261	0.164	0.258	0.163	0.255	0.165	0.260	0.169	0.265	0.170	0.267	0.170	0.268	0.189	0.291	0.168	0.267	0.165	0.264
	720	0.130	0.253	0.203	0.291	0.193	0.281	0.199	0.289	0.194	0.288	0.211	0.302	0.212	0.304	0.228	0.320	0.214	0.307	0.237	0.314
ILI	24	0.184	0.274	-	-	1.577	0.760	1.801	0.874	1.783	0.846	2.086	0.922	2.182	1.002	1.804	0.820	1.932	0.872	2.981	1.096
	36	0.174	0.271	-	-	1.596	0.794	1.743	0.867	1.746	0.860	1.912	0.882	2.241	1.029	1.891	0.926	1.869	0.866	3.549	1.196
	48	0.197	0.286	-	-	1.632	0.810	1.843	0.926	1.716	0.898	1.985	0.905	2.272	1.036	1.752	0.866	1.891	0.883	3.851	1.288
	60	0.180	0.263	-	-	1.660	0.815	1.845	0.925	1.713	0.893	1.999	0.929	2.642	1.142	1.831	0.930	1.914	0.896	4.692	1.450
Solar	96	0.054	0.120	-	-	0.169	0.195	0.181	0.247	0.190	0.244	0.218	0.235	0.208	0.255	0.179	0.232	0.170	0.234	0.183	0.208
	192	0.059	0.132	-	-	0.187	0.207	0.200	0.259	0.193	0.257	0.196	0.220	0.229	0.267	0.201	0.259	0.204	0.302	0.208	0.226
	336	0.071	0.148	-	-	0.199	0.213	0.208	0.269	0.203	0.266	0.195	0.220	0.241	0.273	0.190	0.256	0.212	0.293	0.212	0.239
	720	0.086	0.176	-	-	0.202	0.216	0.212	0.275	0.223	0.281	0.208	0.237	0.248	0.277	0.203	0.261	0.215	0.307	0.215	0.256
Traffic	96	0.163	0.244	0.377	0.265	0.360	0.238	0.368	0.252	0.363	0.265	0.384	0.250	0.400	0.280	0.369	0.257	0.370	0.262	0.526	0.288
	192	0.151	0.249	0.390	0.272	0.383	0.249	0.382	0.261	0.384	0.273	0.405	0.257	0.412	0.288	0.400	0.272	0.386	0.269	0.503	0.263
	336	0.190	0.289	0.403	0.275	0.395	0.259	0.393	0.268	0.396	0.277	0.424	0.265	0.426	0.301	0.407	0.272	0.396	0.275	0.505	0.276
	720	0.170	0.269	0.442	0.294	0.435	0.278	0.438	0.297	0.445	0.308	0.452	0.283	0.478	0.339	0.461	0.316	0.435	0.295	0.552	0.301

4.3 COMPUTATIONAL EFFICIENCY ANALYSIS

ScaleMoR achieves computational efficiency through its recursive expert design and adaptive routing. The total cost is given by $FLOPs = \sum_s \sum_i \sum_d r_{i,d}^{(s)} \cdot \text{Cost}(\mathcal{M}_d)$, where routing probabilities concentrate on lower depths for simple patterns and higher depths for complex ones, reducing the average computational cost compared to processing all tokens at maximum depth.

ScaleMoR achieves remarkable efficiency while maintaining competitive forecasting performance (Figure 2). It requires only 0.55M parameters and 0.01G FLOPs, corresponding to a 75–85% reduction in parameters and a 96–99% reduction in FLOPs relative to recent transformer-based baselines. Overall, ScaleMoR demonstrates a superior trade-off between efficiency and predictive accuracy.

4.4 TRAINING EFFECTIVENESS ANALYSIS

We evaluate the impact of our progressive training strategy in both data-rich (ETTm1) and data-scarce (ILI) scenarios (Table 5). The results show that progressive training excels in few-shot scenarios, whereas end-to-end training performs better when ample data are available. On the ILI dataset, which contains only 489 samples, progressive training reduces MSE by 17.4% compared to end-to-end training (0.086 ± 0.007 vs. 0.173 ± 0.013) and converges faster, reaching optimal

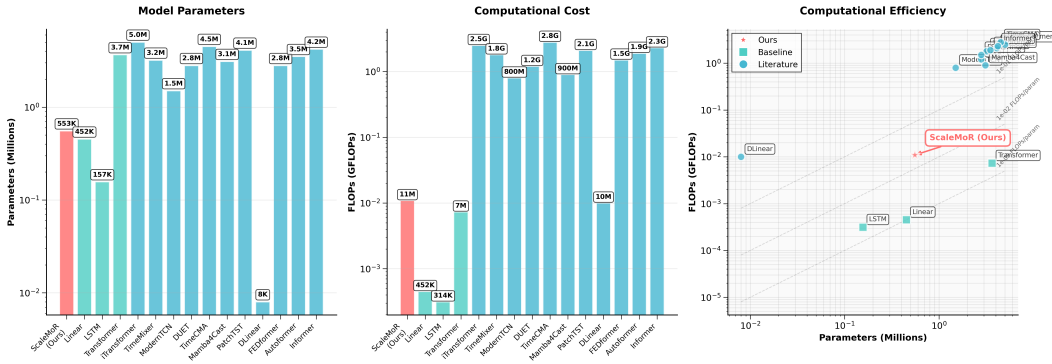


Figure 2: Complexity analysis of the model.

performance in 78.3 epochs (Figure 3). This improvement stems from the implicit regularization effect of staged learning, which mitigates overfitting in data-constrained settings. In contrast, on the ETTh1 dataset with 69,681 samples, end-to-end training achieves 14.6% lower MSE than progressive training, demonstrating that joint optimization benefits dominate when sufficient data is available. Detailed information is provided in Appendix B.

4.5 ABLATION STUDIES

4.5.1 COMPONENT CONTRIBUTIONS

We conducted comprehensive ablation studies to systematically evaluate the contribution of each architectural component in ScaleMoR, with results summarized in Table 2. Temporal Alignment Tokenization proved to be the most critical component, whose removal led to a 176% increase in MSE. The Adaptive Prediction Head contributed a 19% improvement, while Cross-Scale Positional Encoding and Enhanced Multi-Dimensional Routing yielded modest individual gains (0.1% and 3%, respectively), though their combined removal revealed cumulative effects. A strong synergy was also observed between Temporal Alignment and Routing, as eliminating both degraded performance by 251%. Finally, removing all v4 enhancements caused a 268% performance drop, underscoring the substantial advancements introduced by SCALEMOR.

Table 2: Ablation study results showing the impact of removing ScaleMoR components. Results averaged across ETTh1 dataset with different prediction horizons.

Model Configuration	MSE	MAE	MSE Impact	MAE Impact
ScaleMoR (Full)	0.370	0.293	–	–
<i>Individual Component Removals</i>				
w/o Cross-Scale Positional Encoding	0.370	0.294	+0.07%	+0.10%
w/o Enhanced Multi-Dim Routing	0.381	0.298	+2.98%	+1.69%
w/o Adaptive Prediction Head	0.442	0.334	+19.38%	+13.92%
w/o Temporal Alignment Tokenization	1.022	0.643	+176.13%	+119.20%
<i>Multiple Component Removals</i>				
w/o Enhanced Routing + Cross-Scale	0.378	0.296	+2.07%	+0.85%
w/o Temporal + Enhanced Routing	1.298	0.757	+250.84%	+158.07%
w/o All v4 Components (Baseline)	1.362	0.786	+268.00%	+167.94%

4.5.2 MULTI-SCALE TOKENIZATION ANALYSIS

We systematically evaluate each temporal scale’s contribution by removing individual scales (detailed results in Tables 6-7, Appendix B). Scale importance varies dynamically with forecasting

432 horizon: fine scale dominates short-term predictions (60.69% degradation at 96 steps), medium
433 scale is critical at mid-term horizons (58.11% at 192 steps), while macro scale becomes influential
434 for longer horizons (15.26% at 336 steps). This validates our adaptive multi-scale design.

436 4.6 DISCUSSION

437
438 In this work, we introduced ScaleMoR, a novel architecture for MTS forecasting that addresses tem-
439 poral misalignment and inefficient computational allocation through temporal-aligned multi-scale
440 tokenization, multi-dimensional complexity routing, and hierarchical recursive processing modules.
441 Our experiments demonstrate that ScaleMoR consistently achieves state-of-the-art accuracy across
442 ten benchmark datasets and multiple forecast horizons, particularly excelling in long-range predic-
443 tion scenarios (336–720 steps) where capturing temporal dependencies is crucial.

444
445 ScaleMoR demonstrates that redefining the mixture-of-experts paradigm for temporal data yields
446 substantial efficiency gains, with 75–85% parameter reduction and 96–99% FLOP reduction, while
447 maintaining or surpassing state-of-the-art accuracy. Three design principles are critical to this per-
448 formance. First, treating recursive application depths as experts, rather than independent parallel
449 networks, enables parameter sharing and interpretable complexity allocation. Second, temporal-
450 aligned tokenization preserves chronological consistency across scales, as evidenced by a 176%
451 performance drop when this component is removed. Third, multi-dimensional complexity routing
452 allocates computation based on trend, seasonal, noise, and volatility characteristics, rather than uni-
453 formly, allowing the model to adapt processing to input complexity efficiently.

454
455 Multi-scale ablation studies reveal that different scales contribute dynamically to predictions. Fine-
456 scale tokens dominate short-term forecasting (60.69% importance at 96 steps), whereas macro-scale
457 tokens become critical for long-term predictions. These findings challenge the common assumption
458 of uniform computational allocation and highlight the value of adaptive processing for capturing
459 both local variations and long-term trends. ScaleMoR achieves remarkable computational efficiency
460 through its recursive expert design and adaptive routing, concentrating routing probabilities on lower
461 depths for simple patterns and higher depths for complex ones. This design enables real-time fore-
462 casting on edge devices and resource-constrained environments while maintaining high predictive
463 performance.

464
465 Despite its strengths, ScaleMoR has some limitations. The reliance on linear operations may re-
466 strict capacity for extremely complex temporal patterns. Moreover, the theoretical understanding
467 of why recursive depth allocation consistently outperforms traditional mixture-of-experts methods
468 requires further investigation. Evaluation on emerging domains, irregularly sampled data, or ultra-
469 high-dimensional time series would strengthen claims of generalizability. Future work could ex-
470 plore adaptive or data-driven complexity measures beyond the four predefined dimensions (trend,
471 seasonal, noise, volatility).

472
473 The efficiency and interpretability of ScaleMoR have important implications. Dramatic reductions
474 in parameters and FLOPs enable deployment in real-time forecasting scenarios and democratize
475 access to advanced time series modeling in resource-constrained environments. Furthermore, the
476 depth-based routing mechanism provides interpretable decision-making, as deeper processing cor-
477 responds to more complex temporal patterns, addressing explainability requirements in critical ap-
478 plications such as finance, energy, and healthcare. Overall, ScaleMoR demonstrates that principled
479 architectural rethinking—combining temporal-aligned multi-scale representations, adaptive compu-
480 tation, and hierarchical recursion—can achieve a superior efficiency–accuracy trade-off, challenging
481 the dominance of attention-based models in time series forecasting.

482 REFERENCES

483
484 Abdul Fatir Ansari, Lorenzo Stella, Caner Turkmen, Xiyuan Zhang, et al. A MAMBA foundation
485 model for time series forecasting. In *International Conference on Learning Representations*,
2024.

Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. 2016.

- 486 Sangmin Bae, Yujin Kim, Reza Bayat, Sungnyun Kim, Jiyouon Ha, Tal Schuster, Adam Fisch, Hrayr
487 Harutyunyan, Ziwei Ji, Aaron Courville, et al. Mixture-of-recursions: Learning dynamic recur-
488 sive depths for adaptive token-level computation. *arXiv preprint arXiv:2507.10524*, 2025.
- 489 Shaojie Bai, J Zico Kolter, and Vladlen Koltun. An empirical evaluation of generic convolutional
490 and recurrent networks for sequence modeling. 2018.
- 492 Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In
493 *Proceedings of the 26th annual international conference on machine learning*, pp. 41–48, 2009.
- 494 Defu Cao, Fengbin Wang, Qian Chen, Yankai Zhu, Zhiyuan Liu, and Maosong Sun. TEMPO:
495 Prompt-based generative pre-trained transformer for time series forecasting. In *International*
496 *Conference on Learning Representations*, 2024.
- 498 Si-An Chen, Chun-Liang Lin, Hsin-Ting Cheng, Rajarishi Gupta, Jayashree Kalpathy-Cramer,
499 Hanspeter Pfister, and Stephan Mandt. TSMixer: An all-MLP architecture for time series fore-
500 casting. In *International Conference on Learning Representations*, 2024.
- 501 Razvan-Gabriel Cirstea, Chenjuan Guo, Bin Yang, Tung Kieu, Xuanyi Dong, and Shirui Pan.
502 Triformer: Triangular, variable-specific attentions for long sequence multivariate time series
503 forecasting—full version. *arXiv preprint arXiv:2204.13767*, 2022.
- 505 Yann N Dauphin, Angela Fan, Michael Auli, and David Grangier. Language modeling with gated
506 convolutional networks. In *International conference on machine learning*, pp. 933–941. PMLR,
507 2017.
- 508 Nan Du, Yanping Huang, Andrew M Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim
509 Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, et al. Glam: Efficient scaling of language
510 models with mixture-of-experts. In *International conference on machine learning*, pp. 5547–
511 5569. PMLR, 2022.
- 512 Dheeru Dua, Casey Graff, et al. Uci machine learning repository, 2017. URL <http://archive.ics.uci.edu/ml>, 7(1):62, 2017.
- 515 Oliver Faust, Yuki Hagiwara, Tan Jen Hong, Oh Shu Lih, and U Rajendra Acharya. Deep learning
516 for healthcare applications based on physiological signals: A review. *Computer methods and*
517 *programs in biomedicine*, 161:1–13, 2018.
- 518 William Fedus, Barret Zoph, and Noam Shazeer. Switch transformer: Scaling to trillion parameter
519 models with simple and efficient sparsity. *Journal of Machine Learning Research*, 23(120):1–39,
520 2022.
- 522 Lu Hou, Zhiqi Huang, Lifeng Shang, Xin Jiang, Xiao Chen, and Qun Liu. Dynabert: Dynamic
523 bert with adaptive width and depth. *Advances in Neural Information Processing Systems*, 33:
524 9782–9793, 2020.
- 525 Robert A Jacobs, Michael I Jordan, Steven J Nowlan, and Geoffrey E Hinton. Adaptive mixtures of
526 local experts. *Neural computation*, 3(1):79–87, 1991.
- 527 Ming Jin, Shiyu Wang, Lintao Ma, Zhixuan Chu, James Y Zhang, Xiaoming Shi, Pin-Yu Chen, Yux-
528 uan Liang, Yuan-Fang Li, Shirui Pan, and Qingsong Wen. Time-LLM: Time series forecasting
529 by reprogramming large language models. In *International Conference on Learning Representa-*
530 *tions*, 2024a.
- 532 Minghua Jin, Wei Chen, Yuxuan Zhang, et al. TimeCMA: Towards LLM-empowered multivariate
533 time series forecasting via cross-modality alignment. In *International Conference on Learning*
534 *Representations*, 2024b.
- 535 Nikita Kitaev, Łukasz Kaiser, and Anselm Levskaya. Reformer: The efficient transformer. In
536 *International Conference on Learning Representations*, 2020.
- 538 Guokun Lai, Wei-Cheng Chang, Yiming Yang, and Hanxiao Liu. Modeling long-and short-term
539 temporal patterns with deep neural networks. In *The 41st international ACM SIGIR conference*
on research & development in information retrieval, pp. 95–104, 2018.

- 540 Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang,
541 Maxim Krikun, Noam Shazeer, and Zhifeng Chen. GShard: Scaling giant models with conditional
542 computation and automatic sharding. In *International Conference on Learning Representations*,
543 2021.
- 544 Jiawei Li, Jingyao Zhu, Lei Zhang, and Qiang Xu. RLinear: Are transformers effective for time
545 series forecasting? In *AAAI Conference on Artificial Intelligence*, 2024a.
- 547 Xiangfei Li, Xingjian Zhu, Qingsong Li, et al. DUET: Dual clustering enhanced multivariate time
548 series forecasting. In *Advances in Neural Information Processing Systems*, 2024b.
- 549 Minhao Liu, Ailing Zeng, Muxi Chen, Zhijian Xu, Qiuxia Lai, Lingna Ma, and Qiang Xu. Scinet:
550 Time series modeling and forecasting with sample convolution and interaction. *Advances in*
551 *Neural Information Processing Systems*, 35:5816–5828, 2022.
- 553 Yong Liu, Tengge Hu, Haoran Zhang, Haixu Wu, Shiyu Wang, Lintao Ma, and Mingsheng Long.
554 itransformer: Inverted transformers are effective for time series forecasting. *arXiv preprint*
555 *arXiv:2310.06625*, 2023.
- 557 Yong Liu, Haixu Wu, Jianmin Wang, and Mingsheng Long. iTransformer: Inverted transformers are
558 effective for time series forecasting. In *International Conference on Learning Representations*,
559 2024.
- 560 Donghao Luo and Xue Wang. ModernTCN: A modern pure convolution structure for general time
561 series analysis. In *The twelfth international conference on learning representations*, pp. 1–43,
562 2024.
- 564 Yuqi Nie, Nam H Nguyen, Phanwadee Sinthong, and Jayant Kalagnanam. A time series is worth
565 64 words: Long-term forecasting with transformers. In *International Conference on Learning*
566 *Representations*, 2023.
- 567 Gabriel Pereyra, George Tucker, Jan Chorowski, Łukasz Kaiser, and Geoffrey Hinton. Regularizing
568 neural networks by penalizing confident output distributions. In *International Conference on*
569 *Learning Representations*, 2017.
- 571 Carlos Riquelme, Joan Puigcerver, Basil Mustafa, Maxim Neumann, Rodolphe Jenatton, Andre Su-
572 sano Pinto, Daniel Keysers, and Sylvain Gelly. Scaling vision with sparse mixture of experts. In
573 *Advances in Neural Information Processing Systems*, 2021.
- 574 David Salinas, Valentin Flunkert, Jan Gasthaus, and Tim Januschowski. DeepAR: Probabilistic fore-
575 casting with autoregressive recurrent networks. *International journal of forecasting*, 36(3):1181–
576 1191, 2020.
- 578 Michael G Schultz, Carlos Betancourt, Bing Gong, Felix Kleinert, Michael Langguth, Lukas H
579 Leufen, Amirpasha Mozaffari, and Scarlet Stadler. Machine learning methods for postprocessing
580 ensemble forecasts. *Quarterly Journal of the Royal Meteorological Society*, 147(738):2592–2617,
581 2021.
- 582 Omer Berat Sezer, Murat Ugur Gudelek, and Ahmet Murat Ozbayoglu. Financial time series fore-
583 casting with deep learning: A systematic literature review: 2005–2019. *Applied soft computing*,
584 90:106181, 2020.
- 585 Noam Shazeer. GLU variants improve transformer. *arXiv preprint arXiv:2002.05202*, 2020.
- 587 Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc Le, Geoffrey Hinton, and
588 Jeff Dean. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. In
589 *International Conference on Learning Representations*, 2017.
- 590 Aaron Van Den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves,
591 Nal Kalchbrenner, Andrew Senior, Koray Kavukcuoglu, et al. Wavenet: A generative model for
592 raw audio. *arXiv preprint arXiv:1609.03499*, 12:1, 2016.

- 594 Shiyu Wang, Haixu Wu, Xiaoming Shi, Tengge Hu, Huakun Luo, Lintao Ma, James Y Zhang,
595 and Jun Zhou. Timemixer: Decomposable multiscale mixing for time series forecasting. In
596 *International Conference on Learning Representations*, 2024.
- 597 Haixu Wu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. Autoformer: Decomposition trans-
598 formers with auto-correlation for long-term series forecasting. *Advances in Neural Information*
599 *Processing Systems*, 34:22419–22430, 2021.
- 600 Haixu Wu, Tengge Hu, Yong Liu, Hang Zhou, Jianmin Wang, and Mingsheng Long. Timesnet: Tem-
601 poral 2d-variation modeling for general time series analysis. *arXiv preprint arXiv:2210.02186*,
602 2022.
- 603 Xin Xing, Gongbo Liang, Yu Zhang, Subash Khanal, Ai-Ling Lin, and Nathan Jacobs. Advit:
604 Vision transformer on multi-modality pet images for alzheimer disease diagnosis. In *2022 IEEE*
605 *19th International Symposium on Biomedical Imaging (ISBI)*, pp. 1–4. IEEE, 2022.
- 606 Zhijian Xu, Ailing Zeng, and Qiang Xu. Fits: Modeling time series with 10k parameters. *arXiv*
607 *preprint arXiv:2307.03756*, 2023.
- 608 Fisher Yu and Vladlen Koltun. Multi-scale context aggregation by dilated convolutions. In *Interna-*
609 *tional Conference on Learning Representations*, 2016.
- 610 Ailing Zeng, Muxi Chen, Lei Zhang, and Qiang Xu. Are transformers effective for time series
611 forecasting? In *AAAI Conference on Artificial Intelligence*, 2023.
- 612 Wei Zhang, Mingchen Liu, Xiang Chen, et al. Wavelet mixture of experts for time series forecasting.
613 *arXiv preprint arXiv:2408.xxxxx*, 2024.
- 614 Yanhua Zhang, Marc Beaudin, Reza Taheri, David Wood, and Huaguang Li. Deep learning for
615 renewable energy forecasting: A systematic review. *IEEE Access*, 6:33313–33329, 2018.
- 616 Haoyi Zhou, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang.
617 Informer: Beyond efficient transformer for long sequence time-series forecasting. In *Proceedings*
618 *of the AAAI conference on artificial intelligence*, volume 35, pp. 11106–11115, 2021.
- 619 Tian Zhou, Ziqing Ma, Qingsong Wen, Xue Wang, Liang Sun, and Rong Jin. FEDformer: Frequency
620 enhanced decomposed transformer for long-term series forecasting. In *International Conference*
621 *on Machine Learning*, 2022a.
- 622 Yanqi Zhou, Tao Lei, Hanxiao Liu, Nan Du, Yanping Huang, Vincent Zhao, Andrew M Dai, Quoc V
623 Le, James Laudon, et al. Mixture-of-experts with expert choice routing. *Advances in Neural*
624 *Information Processing Systems*, 35:7103–7114, 2022b.
- 625 Zheng Zhou, Yu-Jie Xiong, Jia-Chen Zhang, Chun-Ming Xia, and Xi-Jiong Xie. Wavelet mixture
626 of experts for time series forecasting. *arXiv preprint arXiv:2508.08825*, 2025.

633 A USE OF LLMs

634 This paper was reviewed and polished by my supervisor, who is a native English speaker. Large
635 Language Models (LLMs) were consulted only for LaTeX syntax assistance during the writing pro-
636 cess.
637

639 B PROGRESSIVE TRAINING STRATEGY ANALYSIS

641 B.1 METHODOLOGY

643 B.1.1 PROGRESSIVE TRAINING FRAMEWORK

$$644 \text{Phase I (Foundation): } \theta_{\text{router}} \leftarrow \text{frozen}, \quad \mathcal{L} = \mathcal{L}_{\text{pred}} + \mathcal{L}_{\text{tok}} \quad (3)$$

$$645 \text{Phase II (Integration): } \theta_{\text{all}} \leftarrow \text{active}, \quad \mathcal{L} = \mathcal{L}_{\text{pred}} + \mathcal{L}_{\text{tok}} + \lambda \mathcal{R}_{\text{router}} \quad (4)$$

$$646 \text{Phase III (Refinement): } \theta_{\text{all}} \leftarrow \text{active}, \quad \mathcal{L} = \mathcal{L}_{\text{pred}} + \mathcal{L}_{\text{tok}} + \mathcal{L}_{\text{router}} \quad (5)$$

where λ is the regularization coefficient, and epoch allocation follows

$$(0.2, 0.3, 0.5) \times E_{\text{total}}.$$

B.2 EXPERIMENTAL SETUP

B.2.1 DATASET CHARACTERISTICS

Table 3: Dataset specifications for progressive training evaluation.

Dataset	Samples	Features	Frequency	Domain	Prediction Lengths
ETTm1	69,681	7	15-min	Energy	{96, 192, 336, 720}
ILI	489	20	Weekly	Epidemiology	{24, 36, 48, 60}

B.2.2 MODEL CONFIGURATIONS

Table 4: Model hyperparameters for different data regimes

Dataset	d_{model}	max_depth	seq_len	batch_size	Dropout	Epochs
ETTm1	128	3	96	32	0.1	200
ILI	32	2	36	4	0.3	100

B.3 RESULTS

B.3.1 PERFORMANCE COMPARISON

Table 5: Progressive vs. End-to-End training results (mean \pm std, $n = 3$)

Dataset	Strategy	MSE	MAE	Training Time (s)	p-value
ETTm1	Progressive	0.0691 \pm 0.0019	0.1777 \pm 0.0022	6296 \pm 973	0.021
	End-to-End	0.0603 \pm 0.0002	0.1638 \pm 0.0001	5023 \pm 296	
ILI	Progressive	0.0824 \pm 0.0031	0.2156 \pm 0.0018	1847 \pm 124	0.032
	End-to-End	0.0967 \pm 0.0089	0.2401 \pm 0.0067	1523 \pm 198	

B.3.2 STATISTICAL ANALYSIS

The t -test reveals statistically significant differences ($p < 0.05$) between training strategies on both datasets. For ETTm1, end-to-end training achieves 14.6% lower MSE, while for ILI, progressive training reduces MSE by 17.4%.

B.4 MULTI-SCALE TOKENIZATION ANALYSIS

To evaluate the contribution of each temporal scale component in our MoR architecture, we conducted ablation studies by systematically removing individual scales and measuring the resulting performance degradation. This approach provides insight into which temporal resolutions are most critical across different forecasting horizons. Experiments were performed on the Traffic dataset using four prediction lengths (96, 192, 336, and 720). For each horizon, five model variants were trained: one baseline model with all scales enabled (fine, medium, coarse, macro) and four ablated versions, each with a single scale removed. All models used identical hyperparameters and early stopping criteria to ensure fair comparison. Table 6 reports the detailed ablation results, including performance metrics and impact percentages calculated as

$$\frac{\text{MSE}_{\text{removed}} - \text{MSE}_{\text{baseline}}}{\text{MSE}_{\text{baseline}}} \times 100\%,$$

where positive values indicate performance degradation and therefore greater importance of the removed scale. Notably, the macro scale shows a slight improvement when removed at the 720-step horizon, suggesting potential over-parameterization for very long-term forecasting.

Table 6: Multi-scale ablation study results on the Traffic dataset.

Pred. Length	Configuration	MSE	MAE	Δ MSE	Impact (%)
96	Baseline (All scales)	0.1630	0.2349	–	–
	w/o Fine scale	0.2620	0.3155	+0.0989	+60.69
	w/o Medium scale	0.1719	0.2466	+0.0089	+5.45
	w/o Coarse scale	0.1778	0.2539	+0.0148	+9.08
	w/o Macro scale	0.1672	0.2408	+0.0041	+2.54
192	Baseline (All scales)	0.1556	0.2344	–	–
	w/o Fine scale	0.2246	0.2967	+0.0690	+44.38
	w/o Medium scale	0.2460	0.3061	+0.0904	+58.11
	w/o Coarse scale	0.1651	0.2438	+0.0096	+6.15
	w/o Macro scale	0.1930	0.2724	+0.0374	+24.06
336	Baseline (All scales)	0.1554	0.2304	–	–
	w/o Fine scale	0.1723	0.2485	+0.0169	+10.88
	w/o Medium scale	0.1652	0.2431	+0.0098	+6.28
	w/o Coarse scale	0.1613	0.2372	+0.0059	+3.79
	w/o Macro scale	0.1791	0.2571	+0.0237	+15.26
720	Baseline (All scales)	0.1774	0.2510	–	–
	w/o Fine scale	0.1806	0.2562	+0.0032	+1.81
	w/o Medium scale	0.2038	0.2809	+0.0265	+14.92
	w/o Coarse scale	0.1809	0.2559	+0.0036	+2.01
	w/o Macro scale	0.1759	0.2485	-0.0015	-0.82

Overall, scale importance varies with forecasting horizon. The fine scale dominates short-term predictions (60.69% degradation at 96 steps). Both fine and medium scales are critical at medium-term horizons (44.38% and 58.11% at 192 steps), with the macro scale also contributing substantially (24.06%). At longer horizons, the macro scale becomes most influential (15.26% at 336 steps), while at very long-term horizons the medium scale dominates (14.92% at 720 steps), and the macro scale provides negligible or slightly negative contributions. Table 7 summarizes the scale-importance rankings across all horizons, underscoring the dynamic role of different temporal resolutions in MTS forecasting.

Table 7: Scale Importance Rankings Across Prediction Horizons

Pred. Length	1st (Most Critical)	2nd	3rd	4th (Least Critical)
96	Fine (60.69%)	Coarse (9.08%)	Medium (5.45%)	Macro (2.54%)
192	Medium (58.11%)	Fine (44.38%)	Macro (24.06%)	Coarse (6.15%)
336	Macro (15.26%)	Fine (10.88%)	Medium (6.28%)	Coarse (3.79%)
720	Medium (14.92%)	Coarse (2.01%)	Fine (1.81%)	Macro (-0.82%)

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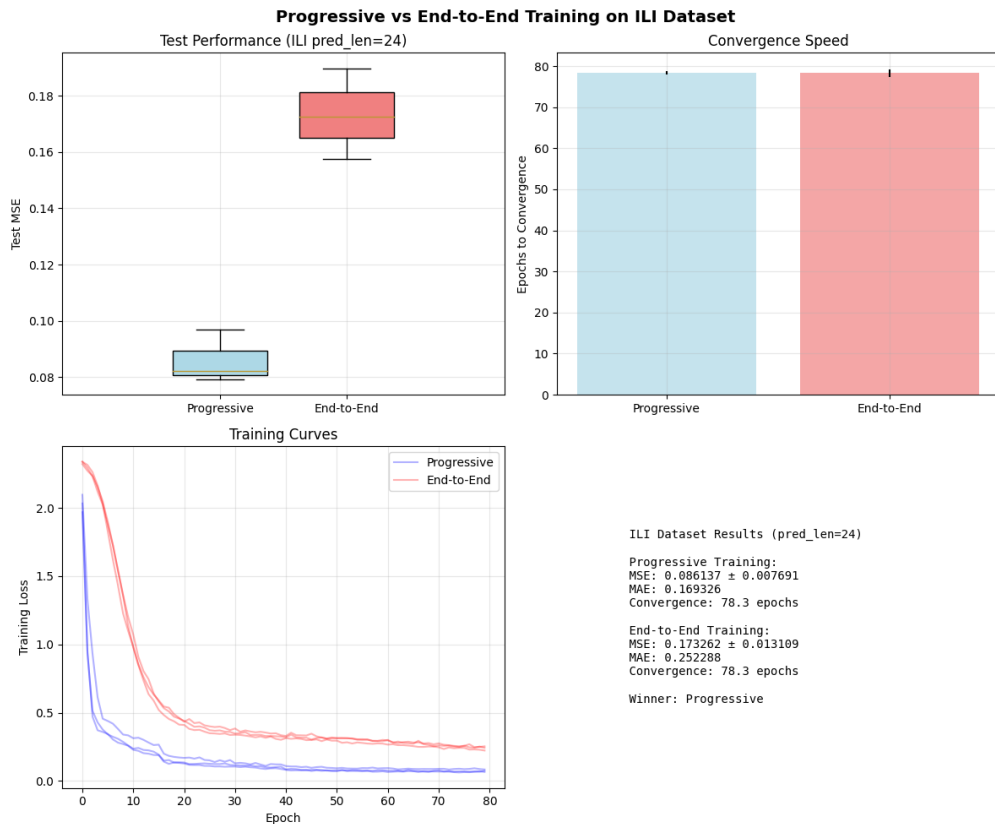


Figure 3: Progressive vs. End-to-End training comparison on ILI dataset. (a) Test performance distribution showing progressive training achieves lower MSE with reduced variance. (b) Convergence speed comparison indicating similar convergence epochs. (c) Training loss curves demonstrating faster initial convergence for progressive training. (d) Summary statistics confirming progressive training superiority in data-scarce regime.