



DBLoss: Decomposition-based Loss Function for Time Series Forecasting

Xiangfei Qiu, Xingjian Wu, Hanyin Cheng, Xyuan Liu, Chenjuan Guo, Jilin Hu and Bin Yang

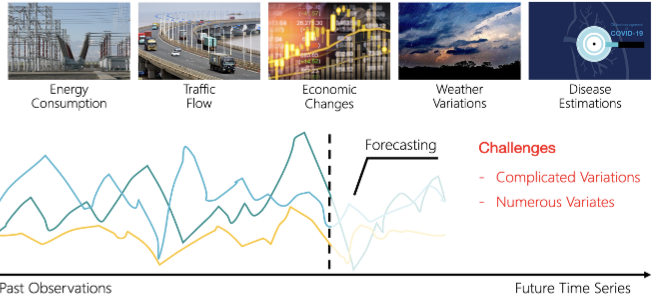
School of Data Science and Engineering, East China Normal University, Shanghai, China



Introduction to Time Series

Time series data refers to data recorded in chronological order, found in various aspects of daily life and industrial production.

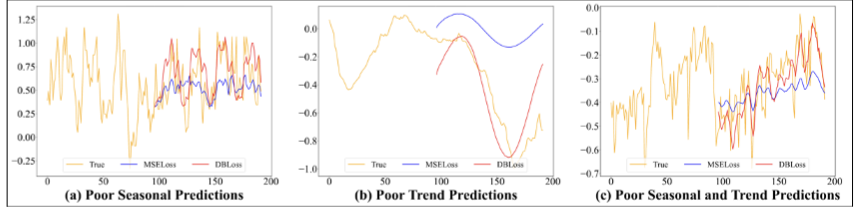
Multivariate Time Series Forecasting aims to predict the next F future timestamps, formulated as $Y = \langle X_{:,T+1}, \dots, X_{:,T+F} \rangle \in \mathbb{R}^{N \times F}$ based on the historical time series $X = \langle X_{:,1}, \dots, X_{:,T} \rangle \in \mathbb{R}^{N \times T}$ with N channels and T timestamps.



Challenges in Time Series Modeling

We observe that current distance-based loss functions (such as MSE) have the following limitations:

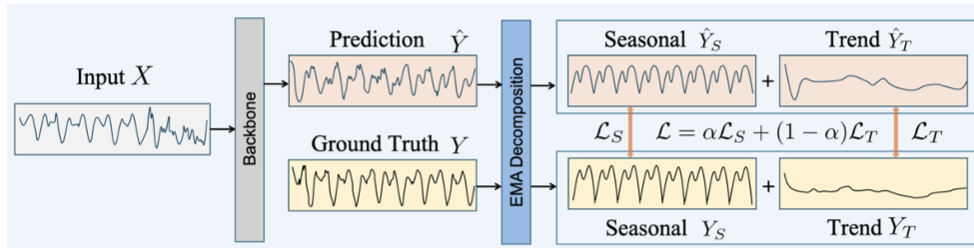
- they may make poor seasonal predictions.
- they may make poor trend predictions.
- they may make both poor seasonal and trend predictions.



Even when decomposition techniques are applied in the forward propagation, the seasonality and trend within the forecasting horizon are not effectively modeled, indicating that the inductive bias is not well applied to the predictions.

DBLoss

- We propose a simple yet effective loss function for time series forecasting, called DBLoss, which can refine the characterization and representation of time series through decomposition within the forecasting horizon.
- The proposed DBLoss is generally applicable to arbitrary deep neural networks with negligible cost. By introducing DBLoss into the baseline, we have achieved performance that generally surpasses the state-of-the-art on eight real-world datasets.



Results

Table 3: Zero-shot forecasting results on ETT datasets. The forecasting horizon is 720. The parameters for the baselines are kept consistent with those of TFB [Qiu et al., 2024]. The better results are highlighted in bold.

Model	T-transformer		Amplifier		PatchTST		DLinear	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETT1→ETT2	0.461	0.470	0.434	0.446	0.393	0.427	0.401	0.431
ETT1→ETTm1	1.061	0.676	0.771	0.592	0.777	0.571	0.758	0.576
ETT2→ETT1	0.672	0.593	0.557	0.521	0.678	0.592	0.530	0.515
ETT2→ETTm1	0.969	0.659	0.802	0.594	0.761	0.585	0.714	0.564
ETT2→ETTm2	0.417	0.428	0.436	0.422	0.403	0.417	0.403	0.415
ETTm1→ETT1	0.705	0.598	0.528	0.516	0.500	0.494	0.482	0.488
ETTm1→ETT2	0.433	0.460	0.409	0.444	0.425	0.446	0.421	0.445
ETTm1→ETTm2	0.369	0.389	0.370	0.387	0.369	0.384	0.372	0.384
ETTm2→ETT1	1.001	0.704	0.775	0.613	0.542	0.524	0.479	0.491
ETTm2→ETT2	0.477	0.486	0.456	0.468	0.444	0.464	0.414	0.439
ETTm2→ETTm1	0.662	0.566	0.551	0.498	0.652	0.547	0.478	0.452

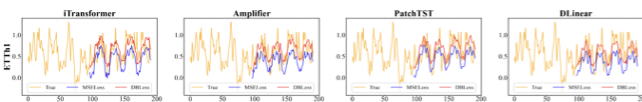


Figure 5: Forecasting visualization comparing DBLoss and MSE loss as objective functions.

Table 2: Comparison between the proposed DBLoss and other loss functions. The model is DLinear and we report the result of three datasets-ETT2, ETTm1, and Traffic. The best results are highlighted in bold, and the second-best results are highlighted in underline.

Dataset	ETT2				ETTm1				Traffic							
	96	192	336	720	Avg	96	192	336	720	Avg	96	192	336	720	Avg	
ORI	MSE	0.300	0.387	0.490	0.704	0.470	0.300	0.336	0.367	0.419	0.356	0.395	0.407	0.417	0.454	0.418
	MAE	0.364	0.423	0.487	0.597	0.468	0.345	0.366	0.388	0.416	0.378	0.275	0.280	0.286	0.308	0.287
TILDE-Q (2022)	MSE	0.287	0.362	0.425	0.599	0.418	0.302	0.336	0.371	0.425	0.359	0.416	0.422	0.423	0.461	0.431
	MAE	0.345	0.395	0.445	0.551	0.434	0.342	0.362	0.386	0.417	0.377	0.294	0.296	0.293	0.316	0.300
FreeDF (2025c)	MSE	0.284	0.362	0.420	0.587	0.413	0.302	0.333	0.363	0.415	0.353	0.398	0.408	0.416	0.452	0.419
	MAE	0.342	0.396	0.445	0.546	0.432	0.344	0.363	0.381	0.411	0.375	0.270	0.275	0.280	0.302	0.282
PSLoss (2025)	MSE	0.283	0.358	0.411	0.614	0.417	0.296	0.332	0.361	0.416	0.381	0.398	0.408	0.416	0.452	0.419
	MAE	0.343	0.393	0.454	0.549	0.430	0.339	0.361	0.380	0.413	0.373	0.270	0.274	0.279	0.299	0.281
DBLoss (Ours)	MSE	0.284	0.357	0.407	0.586	0.409	0.295	0.331	0.361	0.415	0.351	0.396	0.407	0.415	0.449	0.417
	MAE	0.342	0.390	0.430	0.533	0.424	0.337	0.358	0.378	0.409	0.370	0.270	0.274	0.279	0.298	0.280

Table 4: Foundation models results in the 5% few-shot setting. The table reports average MSE and MAE for four forecasting lengths $F \in \{96, 192, 336, 720\}$. The parameters for the baselines are kept consistent with those of TSFM-Bench [Li et al., 2025c]. The better results are highlighted in bold. Full results are provided in Table 10 of Appendix G

Model	GPT4TS				CALF				TTM				Units			
	Loss	ORI	DBLoss	MAE	MSE	MAE	DBLoss	MAE	MSE	MAE	MSE	MAE	DBLoss	MAE	MSE	MAE
ETT1	0.467	0.470	0.453	0.462	0.443	0.454	0.433	0.446	0.405	0.425	0.395	0.417	0.436	0.434	0.425	0.427
ETT2	0.373	0.414	0.368	0.406	0.373	0.407	0.368	0.404	0.342	0.383	0.332	0.378	0.372	0.405	0.357	0.393
ETTm1	0.388	0.401	0.377	0.394	0.372	0.396	0.358	0.382	0.356	0.376	0.354	0.372	0.377	0.402	0.362	0.386
ETTm2	0.278	0.335	0.266	0.330	0.271	0.332	0.259	0.316	0.253	0.315	0.227	0.308	0.292	0.344	0.270	0.320
Solar	0.262	0.335	0.254	0.279	0.229	0.297	0.246	0.300	0.219	0.269	0.224	0.266	0.296	0.261	0.314	0.246
Weather	0.253	0.293	0.248	0.284	0.238	0.277	0.236	0.272	0.225	0.260	0.225	0.256	0.230	0.269	0.231	0.260
Electricity	0.207	0.317	0.207	0.309	0.172	0.268	0.171	0.264	0.179	0.277	0.178	0.274	0.180	0.275	0.181	0.274
Traffic	0.433	0.309	0.428	0.295	0.435	0.316	0.433	0.309	0.484	0.341	0.481	0.339	0.422	0.289	0.420	0.282