WFTNet: Exploiting Global and Local Periodicity in Long-term Time-Series Forecasting

Peiyuan Liu[1,2,4], Beiliang Wu[1,4], Naiqi Li[2], Tao Dai[1,2], Fengmao Lei[3], Jigang Bao[2], Yong Jiang[2], Shu-tao Xia[2]

1. College of Computer Science and Software Engineering, Shenzhen University, Shenzhen, China
2. Shenzhen International Graduate School, Tsinghua University, Shenzhen, China
3. Ping An Bank Co., Ltd., Shenzhen, China 4. WeBank Institute of Financial Technology, Shenzhen University, Shenzhen, China

1. MOTIVATION

(1) Inadequacy in Existing Time Series Forecasting Methods:

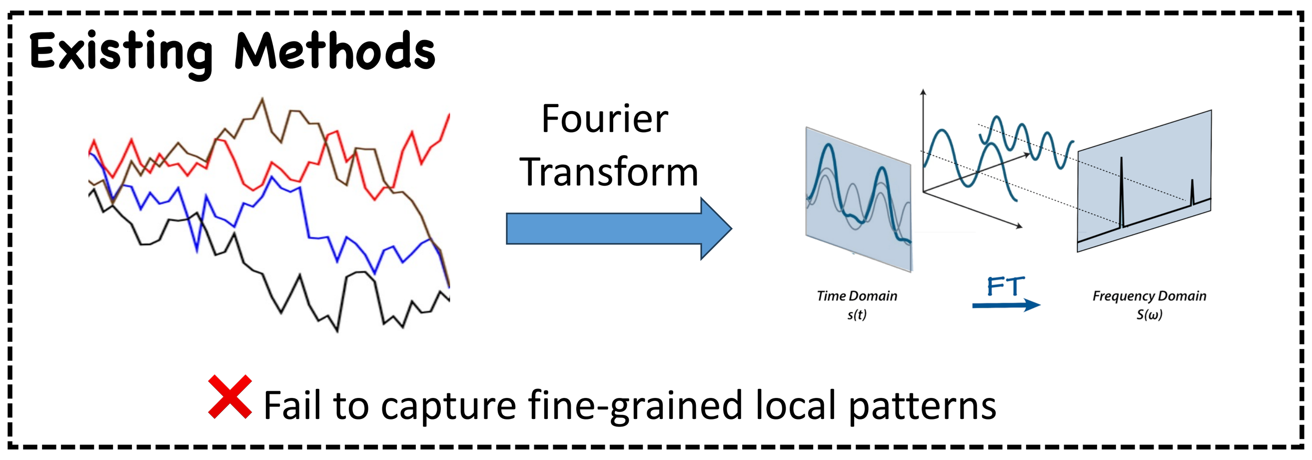
Current models, mainly relying on Fourier transforms, **fail to capture local periodicity**, essential for accurate long-term forecasting.

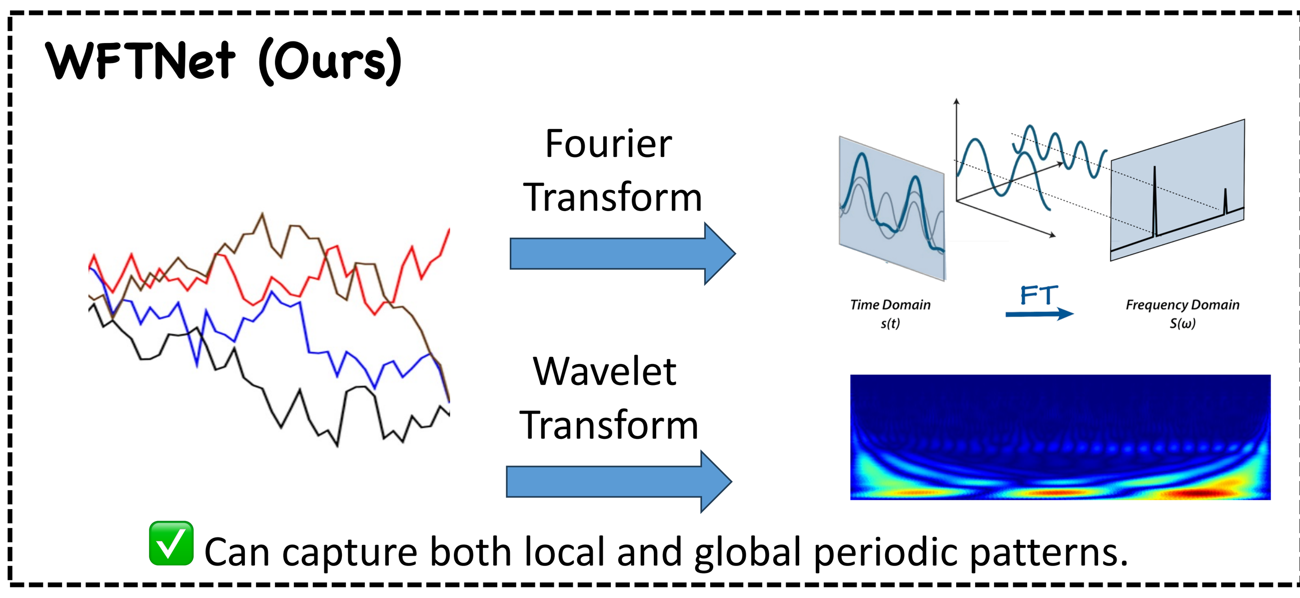
(2) Need for Integrated Global and Local Periodic Analysis

A gap in existing methods: the necessity to **combine the global perspective of Fourier transform with the local insight of wavelet transform** for comprehensive time series analysis.

(3) Innovation with WFTNet:

Introduction of Wavelet-Fourier Transform Network (WFTNet) **incorporating both Fourier and wavelet transforms**, along with a unique **Periodicity-Weighted Coefficient (PWC)**, to significantly enhance long-term time series forecasting accuracy.





2. RELATED WORK

CNN-based and Transformer-based Forecasting method

- **CNN** is good at modeling local features.
- **Transformer** has the ability to capture long-term dependencies.

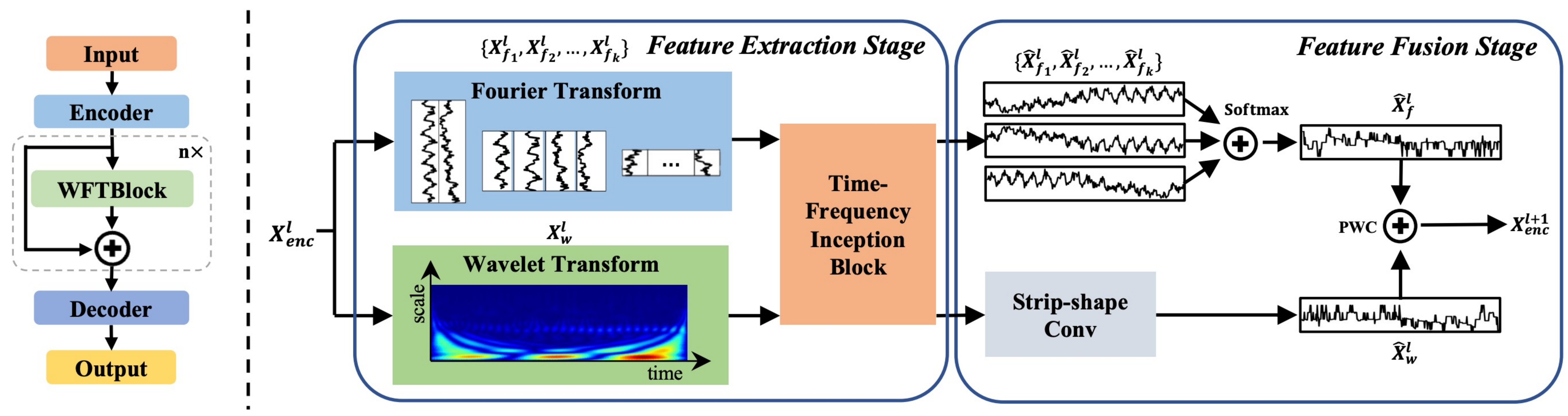
Frequency Enhanced Forecasting Model

- **FEDformer** falls short of fully exploiting periodic patterns in the signa
- **TimesNet** is based on Fourier transform, and thus only captures the global frequency of the entire time series and ignores local frequency variations.

CNN-based	Transformer-based
TimesNet*, MICN...	Autoformer, FEDformer*, Informer, ETSformer...

* means frequency enhanced method

3. PROPOSED APPROACH



Overall architecture of WFTNet (left) and details of WFTBlock (right). The encoder and decoder manage input normalization, embedding, and output projection. WFTBlocks transform the 1D time series into 2D representations using FFT for global periodic patterns and CWT for local features.

WFTNet

- Employs several WFTBlocks in a residual way
- Each WFTBlock use Fourier and wavelet transform to capture global and local information.
- Periodicity-Weighted Coefficient (PWC) adaptively balances global and local information.

4. EXPERIMENTS

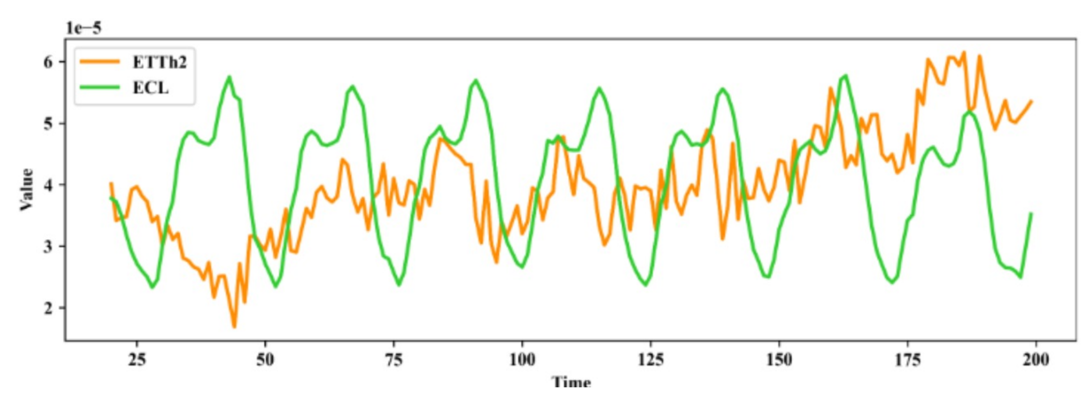
Experiment settings

- **Dataset:** Electricity Transformer Temperature (ETTh1, ETTh2, ETTm1, ETTm2), Traffic, ECL, and Weather.
- Baseline: TimesNet, ETSformer, DLinear, FEDformer, Autoformer.
- Setups: look-back window length is set to 96 for all baselines. Prediction length is set to {96, 192, 336, 720}.
- Metrics: Mean Square Error (MSE) and Mean Absolution Error (MAE).

Models		**WFTNet**		TimesNet [11]		ETSformer [8]		DLinear [10]		FEDformer [7]		Autoformer [5]	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ECL	96	**0.164**	**0.267**	0.167	0.271	0.187	0.304	0.197	0.282	0.193	0.308	0.201	0.317
	192	**0.181**	**0.282**	0.187	0.290	0.199	0.315	0.196	0.285	0.201	0.315	0.222	0.334
	336	**0.194**	**0.295**	0.202	0.303	0.212	0.329	0.209	0.301	0.214	0.329	0.231	0.338
	720	0.230	0.325	**0.220**	**0.318**	0.233	0.345	0.265	0.360	0.246	0.355	0.254	0.361
Traffic	96	0.594	0.316	0.590	**0.314**	0.607	0.392	0.650	0.396	**0.587**	0.366	0.613	0.388
	192	0.624	0.332	0.616	**0.322**	0.621	0.399	**0.598**	0.370	0.604	0.373	0.616	0.382
	336	0.631	0.339	0.634	0.339	0.622	0.396	**0.605**	0.373	0.621	0.383	0.622	**0.337**
	720	0.664	0.360	0.659	**0.349**	0.632	0.396	0.645	0.394	**0.626**	0.355	0.660	0.408
Weather	96	**0.161**	**0.210**	0.169	0.219	0.197	0.281	0.196	0.255	0.217	0.296	0.266	0.336
	192	**0.211**	**0.254**	0.226	0.266	0.237	0.312	0.237	0.312	0.276	0.336	0.307	0.367
	336	**0.271**	**0.296**	0.281	0.303	0.298	0.353	0.283	0.335	0.339	0.380	0.359	0.395
	720	0.347	0.346	0.357	0.353	0.352	**0.288**	**0.345**	0.381	0.403	0.428	0.419	0.428
ETT*	96	**0.323**	**0.365**	0.332	0.369	0.340	0.391	0.333	0.387	0.358	0.397	0.346	0.388
	192	0.403	**0.409**	**0.396**	0.410	0.430	0.439	0.477	0.476	0.429	0.439	0.456	0.452
	336	**0.427**	**0.433**	0.446	0.447	0.485	0.479	0.594	0.541	0.496	0.487	0.482	0.486
	720	**0.430**	**0.445**	0.434	0.448	0.500	0.497	0.831	0.657	0.463	0.474	0.515	0.511
1^{st} Count		**19**		6		1		3		2		1	

* ETT means the ETTh2. Experiments were also conducted on ETTm1, ETTm2, and ETTh1 datasets, but are omitted here due to space constraints.

ECL has stronger periodicity compared with ETTh2



Significance of PWC
(Ablation Study)

Models		WFTNet		Fourier-Only		Wavelet-Only	
Metric		MSE	MAE	MSE	MAE	MSE	MAE
ECL	96	**0.164**	**0.267**	0.168	0.273	0.196	0.301
	192	**0.181**	**0.282**	0.187	0.290	0.209	0.309
	336	**0.194**	**0.295**	0.201	0.300	0.217	0.318
	720	0.230	0.325	**0.218**	**0.320**	0.247	0.347
ETTh2	96	**0.323**	0.365	0.332	0.369	0.329	**0.362**
	192	**0.403**	**0.409**	0.406	0.412	0.404	0.410
	336	**0.427**	**0.433**	0.446	0.447	0.433	0.437
	720	0.430	0.445	0.434	0.448	**0.421**	**0.439**

- Fourier-Only is advantageous for the ECL, which has the stronger periodicity.
- Wavelet-Only proves more beneficial for the less periodic ETTh2 datasets.
- WFTNet, by leveraging PWC for dynamic feature balancing, consistently outperforms these specialized branches.