Exploring the Hierarchical Sparsity in Long-term Multivariate Energy Data for Effective and Efficient Forecasting

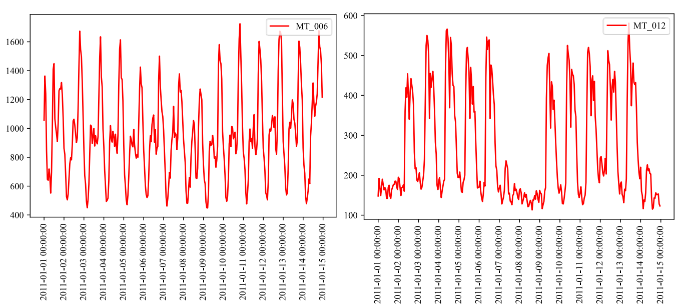
This is the appendix to the paper entitled 'Exploring the Hierarchical Sparsity in Long-term Multivariate Energy Data for Effective and Efficient Forecasting', submitted to IEEE Transactions on Smart Grid.

Appendix A
Periodicity of Energy Data

We present the visualization of the adopted benchmarks to show the corresponding data characteristics, wherein the concrete time and data are presented. It can be observed that all the energy data exhibit periodicity and nonstationarity.

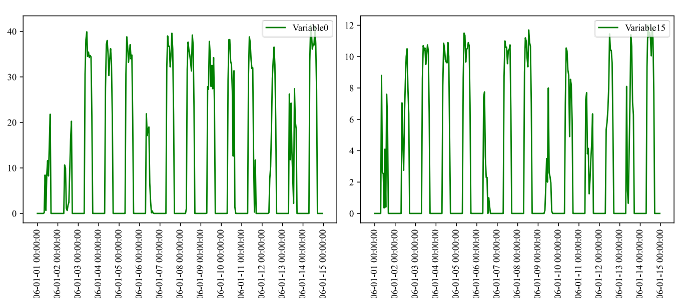
Appendix B
Comparison with GNN-based Models

We adopt two state-of-the-art GNN-based models, Cy2Mixer [2] and Ada-MSHyper [1] for comparison. It can be observed from Table B.1 that neither of these two models outperforms the proposed HST model and their performance is generally worse than the performance of the baselines adopted in the main text.



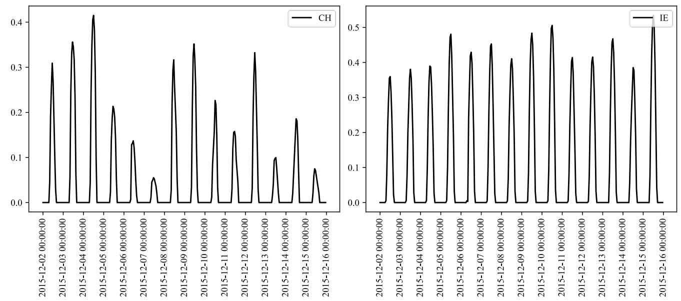
(a) (b)

Fig. A.1. The visualization of two variables ((a) and (b)) from the ECL benchmark.



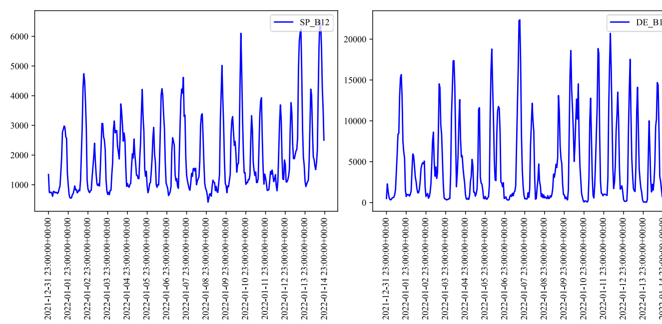
(a) (b)

Fig. A.2. The visualization of two variables ((a) and (b)) from the Solar benchmark.



(a) (b)

Fig. A.3. The visualization of two variables ((a) and (b)) from the Wind benchmark.



(a) (b)

Fig. A.4. The visualization of two variables ((a) and (b)) from the Hydro benchmark.

Appendix C
Comparison with Traditional Models

Two forecasting models based on traditional statistics analysis are adopted in Table C.1 for further evaluation. The first one is ARIMA [3], which is classical and well-known, and the second one is OneShotSTL [4], which is new and state-of-the-art. The experimental results show that the proposed HST model still outperforms these two models, proving the state-of-the-art performance of HST.

References

[1] Z. Shang, L. Chen, B. Wu, and D. Cui, "Ada-mshyper: Adaptive multi-scale hypergraph transformer for time series forecasting," in *Advances in Neural Information Processing Systems*, vol. 37, 2024, pp. 33 310–33 337.

[2] M. Lee, Y. Y. Choi, S. W. Park, S. Lee, J. Ko, and J. Hong, "Enhancing topological dependencies in spatio-temporal graphs with cycle message passing blocks," in *The Third Learning on Graphs Conference*, 2024.

[3] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

TABLE B.1
FORECASTING RESULTS COMPARED WITH TWO GNN-BASED MODELS

Methods	Metrics	ECL				Solar				Wind				Hydro			
		96	192	336	720	96	192	336	720	96	192	336	720	48	96	168	336
HST	MSE	***0.124***	***0.141***	***0.159***	***0.191***	***0.160***	***0.173***	***0.183***	***0.192***	***0.190***	***0.205***	***0.210***	***0.214***	***0.345***	***0.393***	***0.449***	***0.519***
	MAE	***0.227***	***0.243***	***0.261***	***0.290***	***0.208***	***0.217***	***0.223***	***0.227***	***0.219***	***0.225***	***0.229***	***0.232***	***0.388***	***0.420***	***0.455***	***0.502***
Cy2Mixer	MSE	0.223	0.270	0.269	0.303	0.313	0.339	0.320	0.307	0.357	0.376	0.354	0.343	0.620	0.749	0.777	0.831
	MAE	0.320	0.367	0.354	0.418	0.299	0.318	0.319	0.317	0.332	0.327	0.338	0.318	0.594	0.592	0.653	0.664
Ada-MSHyper	MSE	0.165	0.189	0.221	0.278	0.230	0.253	0.250	0.270	0.259	0.272	0.305	0.302	0.463	0.556	0.595	0.721
	MAE	0.260	0.299	0.287	0.338	0.240	0.249	0.252	0.270	0.265	0.274	0.254	0.269	0.458	0.507	0.509	0.588

TABLE C.1
FORECASTING RESULTS COMPARED WITH TWO TRADITIONAL MODELS

Methods	Metrics	ECL				Solar				Wind				Hydro			
		96	192	336	720	96	192	336	720	96	192	336	720	48	96	168	336
HST	MSE	***0.124***	***0.141***	***0.159***	***0.191***	***0.160***	***0.173***	***0.183***	***0.192***	***0.190***	***0.205***	***0.210***	***0.214***	***0.345***	***0.393***	***0.449***	***0.519***
	MAE	***0.227***	***0.243***	***0.261***	***0.290***	***0.208***	***0.217***	***0.223***	***0.227***	***0.219***	***0.225***	***0.229***	***0.232***	***0.388***	***0.420***	***0.455***	***0.502***
ARIMA	MSE	0.902	1.032	1.136	1.251	1.178	1.281	1.336	1.294	1.389	1.460	1.516	1.400	2.510	3.013	3.343	3.556
	MAE	0.769	0.833	0.876	0.933	0.725	0.771	0.740	0.702	0.760	0.753	0.758	0.771	1.290	1.423	1.456	1.575
OneShotSTL	MSE	0.176	0.211	0.289	0.425	0.227	0.245	0.308	0.405	0.271	0.297	0.370	0.492	0.504	0.605	0.772	1.215
	MAE	0.321	0.334	0.436	0.624	0.299	0.318	0.373	0.525	0.315	0.299	0.366	0.519	0.525	0.563	0.777	1.081

[4] X. He, Y. Li, J. Tan, B. Wu, and F. Li, “Oneshotstl: One-shot seasonal-trend decomposition for online time series anomaly detection and forecasting,” *Proc. VLDB Endow.*, vol. 16, no. 6, p. 1399–1412, 2023.