Are Time-Indexed Foundation Models the Future of Time Series Imputation?

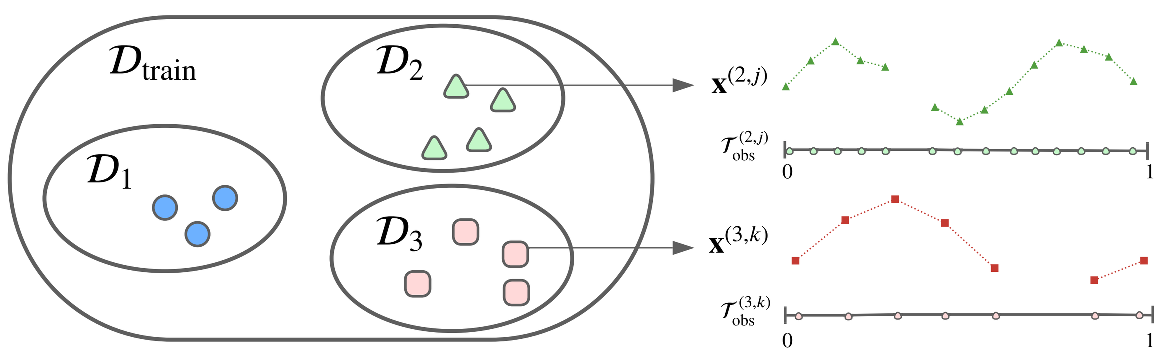
Etienne Le Naour [1*] Tahar Nabil [1*] Adrien Petralia [1] Ghislain Agoua [1]

[1]EDF R&D, Palaiseau, France

[*] Equal contribution

Context

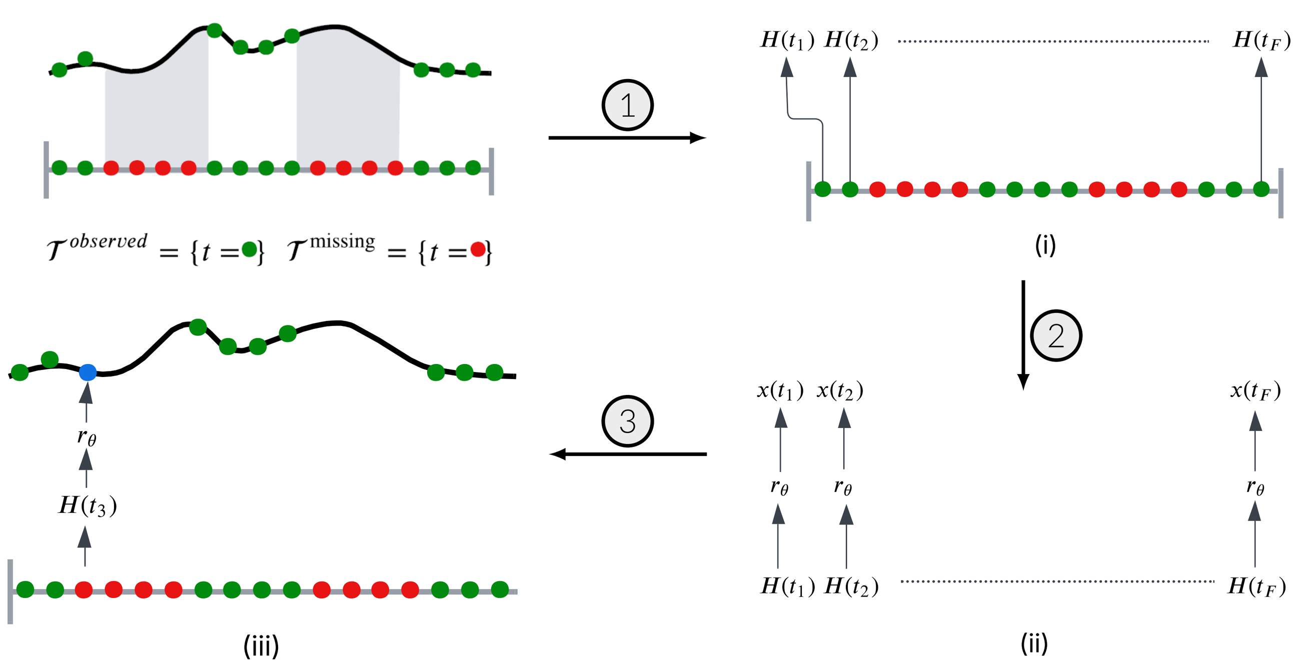
- **Time Series Foundation models** are a promise of **flexible** and **high-performing** models that compensate for the lack of data, withstand regime shifts, and democratize the use of advanced methods.
- These models have been widely studied for forecasting purposes, but they have been **much less explored for imputation**.
- **Patch-based** models are **not inherently designed** to handle the diverse missingness patterns of time series, which may be unaligned, irregular, and collected at varying sampling rates.



Time-Indexed Foundation Models

These models operate in three stages: (i) **encoding time**; (ii) **solving the regression problem** based on the observed context; and (iii) **inferring the values**.

1. `TabPFN-TS`: handcrafted time features + deep regressor pretrained on synthetic toy problems with *in-context learning* [1]
2. `MoTM`: deep adaptive features of time + ridge regressor [2]



Large-scale Univariate Benchmark

- 33 Out-of-Domain univariate datasets (climate, ernergy, traffic, etc.) with sampling freq from 5min to 1h
- 4 imputation settings: (i) 50% or (ii) 70% of observations missing at random, (iii) 2 or (iv) 4 one-day missing blocks
- **1.3M windows to impute in total**
- 6 supervised baselines: `BRITS`, `CSDI`, `SAITS`, `TimesNet`, `TimeMixer++`, `TSLANet`
- 3 local baselines: `Linear Interpolation`, `Seasonal Naive`, `LOCF`

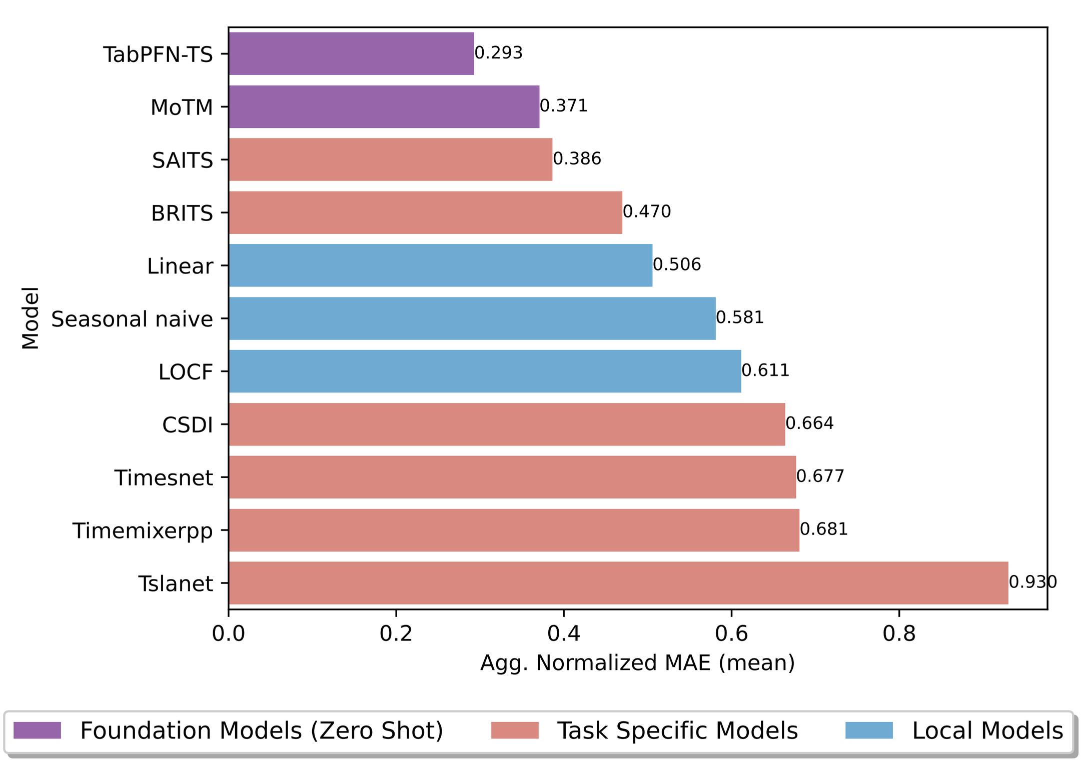


Figure 1. Univariate Benchmark (z-normalized MAEs) on 33 Out-of-Domain datasets.

1. Time-index foundation models lead the benchmark
2. Task-specific models show limited robustness
3. Local baselines remain resilient

Uncertainty Quantification

`TabPFN-TS` & `MoTM` natively support quantile estimation: experiments on 11 datasets show the superiority of `TabPFN-TS` and limited generalization abilities of supervised baselines `CSDI` & `SAITS`.

Table 1. Weighted Quantile Loss (WQL) average scores on eleven representative univariate datasets.

	`TabPFN-TS`	`MoTM`	`CSDI`	`SAITS-Q`
WQL	**0.241**	<u>0.316</u>	0.453	0.476

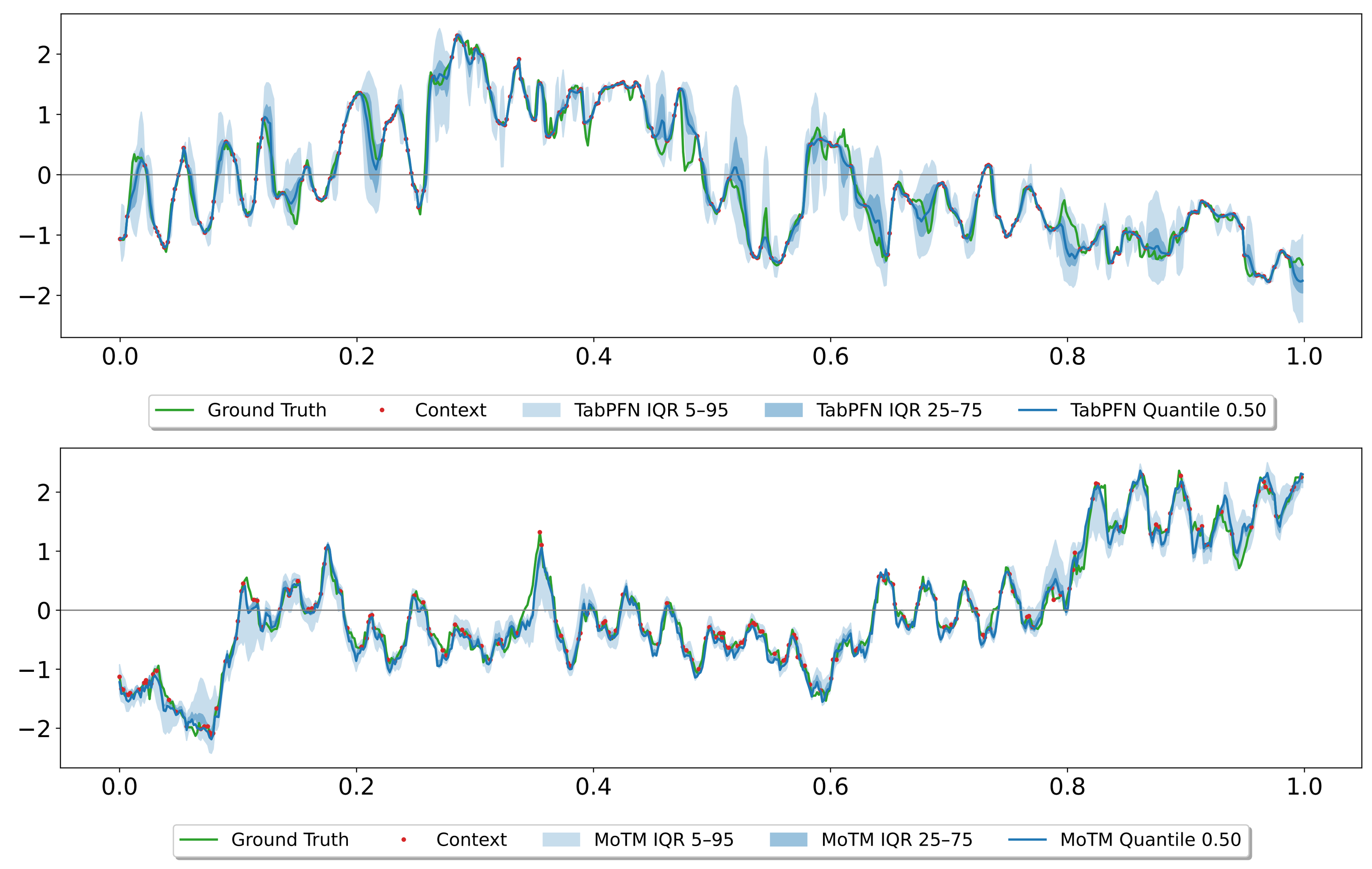


Figure 2. Qualitative quantile results for the 70% missing values scenario, resp. `TabPFN-TS` and `MoTM`.

Zero-shot Integration of Covariates

- Additional covariates $x(t)$ integrated at test-time by simple concatenation to the time features $H(t) \rightarrow$ **no finetuning**
- Yields substantial gains when the covariate strongly informs about the target

Table 2. Complete MAE results on datasets with covariates.

Dataset	Setting	`TabPFN-TS` TabPFN-TS (W/ Covar)	`TabPFN-TS` TabPFN-TS (W/o Covar)	`MoTM` MoTM (W/ Covar)	`MoTM` MoTM (W/o Covar)	`Other baselines` Ridge on Covar	`Other baselines` SAITS Multivar
PV-France	*Pointwise 1*	**0.045**	0.109	<u>0.054</u>	0.102	0.115	0.390
	Pointwise 2	**0.051**	0.160	<u>0.069</u>	0.131	0.123	0.443
	Blocks 1	**0.052**	0.175	<u>0.086</u>	0.191	0.104	0.496
	Blocks 2	**0.049**	0.190	<u>0.086</u>	0.179	0.106	0.485
Wind-France	*Pointwise 1*	<u>0.101</u>	**0.098**	0.128	0.186	0.318	0.359
	Pointwise 2	**0.138**	<u>0.153</u>	0.161	0.244	0.322	0.408
	Blocks 1	**0.275**	0.470	0.335	0.600	<u>0.321</u>	0.590
	Blocks 2	**0.248**	0.470	<u>0.317</u>	0.594	0.335	0.581
Load-France	*Pointwise 1*	**0.037**	<u>0.037</u>	0.138	0.146	0.667	0.292
	Pointwise 2	**0.056**	<u>0.059</u>	0.158	0.164	0.667	0.321
	Blocks 1	**0.143**	<u>0.146</u>	0.236	0.243	0.669	0.490
	Blocks 2	**0.170**	<u>0.178</u>	0.262	0.270	0.674	0.498
W. Covariate improvement		/	31.54%	/	31.03%	/	/

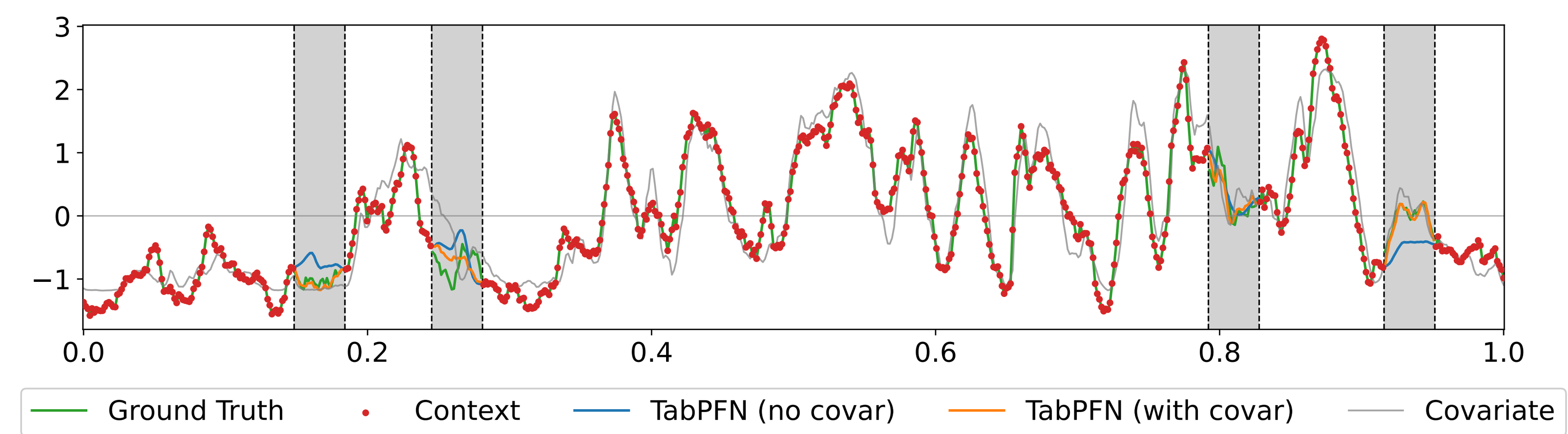


Figure 3. *Wind-France dataset.* `TabPFN-TS` qualitative results W. and W/o covariates.

Link to Paper

[1] Shi Bin Hoo, Samuel Müller, David Salinas, and Frank Hutter. From tables to time: How tabpfn-v2 outperforms specialized time series forecasting models. *arXiv preprint arXiv:2501.02945*, 2025.

[2] Etienne Le Naour, Tahar Nabil, and Ghislain Agoua. MoTM: Towards a foundation model for time series imputation based on continuous modeling. *ECML / PKDD 2025 AALTD Workshop*, 2025.

NeurIPS 2025 Workshop on *Recent Advances on Time Series Foundation Models: Have We Reached the BERT Moment?*