Eaton's Centre For Intelligent Power (CIP)

Scalable and Efficient MLP-based Fully Parameterised Quantile for Probabilistic Power Forecasting

Anthony Faustine,
Lead data scientist, *Eaton CIP-Dublin,* Lucas Pereira & Nuno J Nunes
(FEELab, LARSys, Tecnico Lisboa)

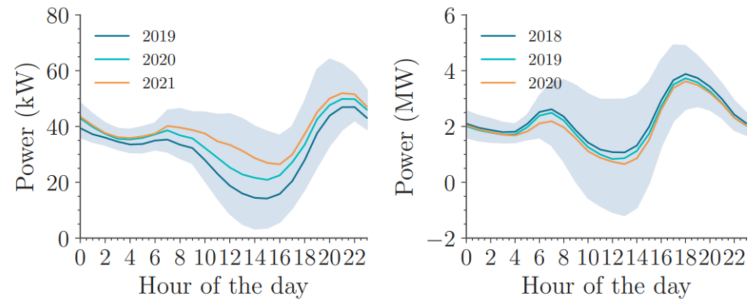
anthonyafaustine@eaton.com *sambaiga.github.io*

Outline

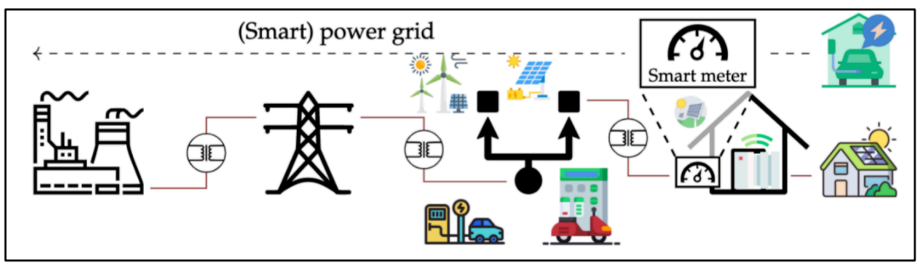
- Load Forecasting for Future Energy Systems .
- Scalable MLPF Architecture.
- MLPFQR: A Novel Approach to Probabilistic Load Forecasting
- Experiment & Benchmark
- Results
- Conclusion

Power Load Forecasting for Future Energy Systems

- More challenging =>Less predictable pattern, B-PV, and volatile RES generation.
- Need for uncertainty quantification=>Growing uncertainty in Load demands and generation.
- Scalability => Numerous LV substations (17K substations in Spain DSO), buildings, etc.

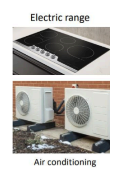


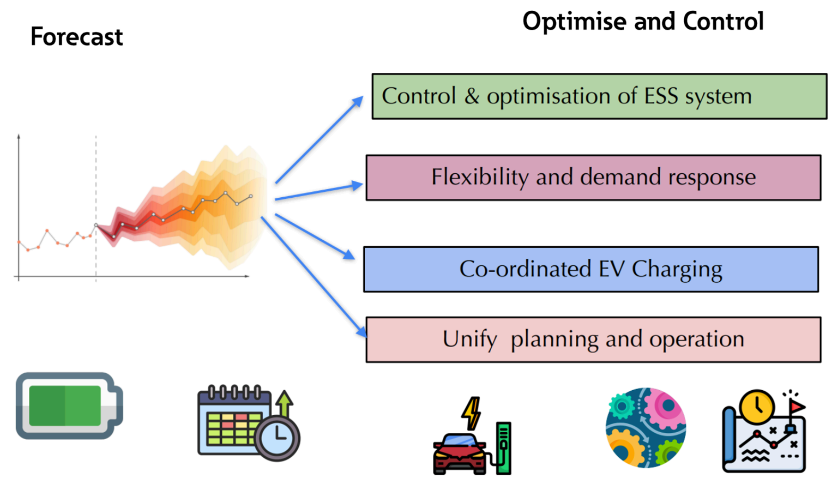
(a) MLVS-PT (b) SPS-UK



Massive penetration of Distributed Energy Resources (DERS)

1. RES such as PV, with Energy Storage System (ESS)
2. Prosumers, such as Local Energy Communities (LECs).
3. Low carbon technologies (LCTs) such Electric Vehicle (EVs), and Electric Heating Systems (EHSs)



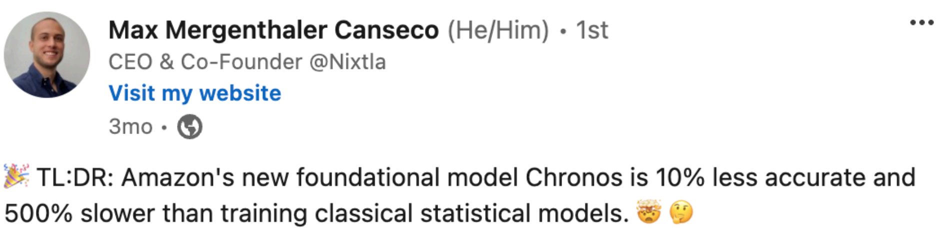


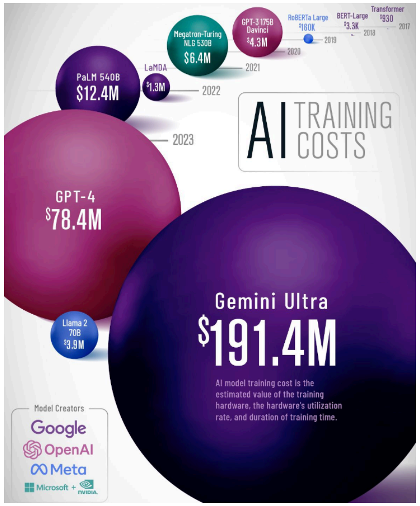
*Need for **accurate**, **reliable** and **scalable** probabilistic forecasting.*

Beyond Current Methods: The Power of DNNs in Power Load Forecasting

- DNNs excel at identifying non-linear relationships=> Crucial for accurate load forecasting with DERs.

- DNN Architectures: LSTMs, Transformers and now LLM such as Chronos, TimeGPT etc => computationally expensive to train and run, limiting scalability.





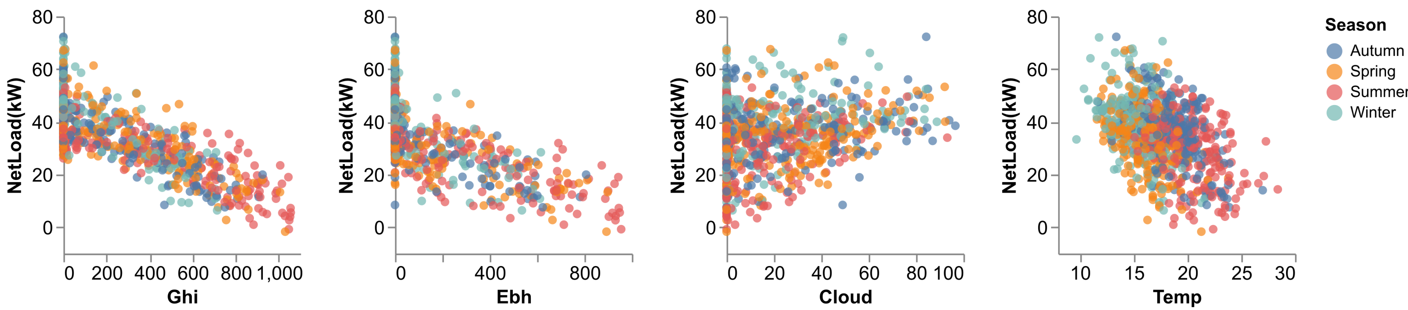
- **The Shift: Lightweight DNNs:** New architectures like D-LiNEAR, N-BEATS, and NHITS offer a balance => trade-off between accuracy and lower computional cost.

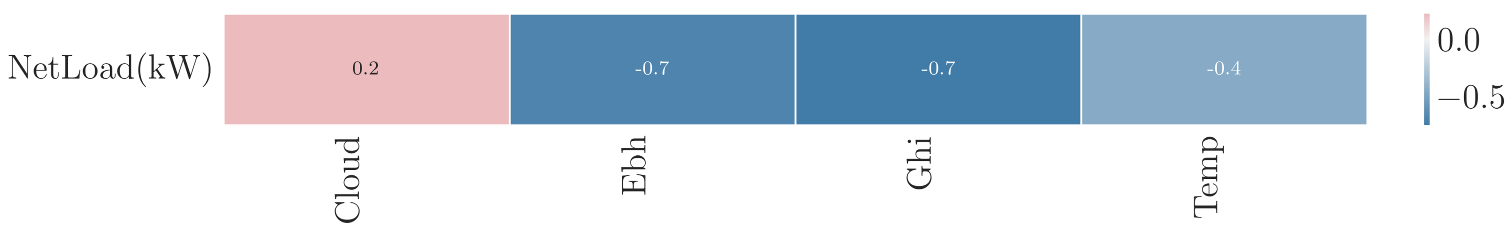
Oreshkin, Boris N., et al. "N-BEATS: Neural basis expansion analysis for interpretable time series forecasting." *arXiv preprint arXiv:1905.10437* (2019).

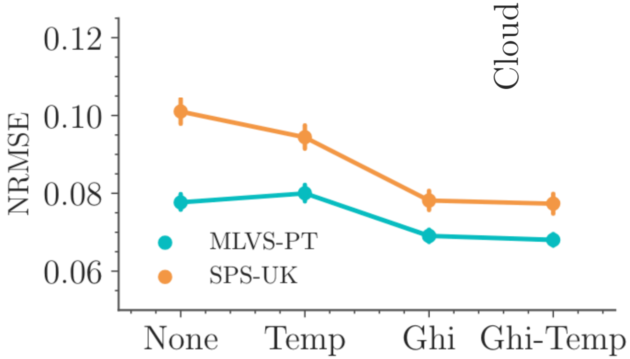
Challu, Cristian, et al. "NHITS: Neural Hierarchical Interpolation for Time Series Forecasting." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 37. No. 6. 2023.

Net Load and Weather Variables: A Statistical and Empirical Analysis

- **Weather variables significantly influence both power demands and generation. .**





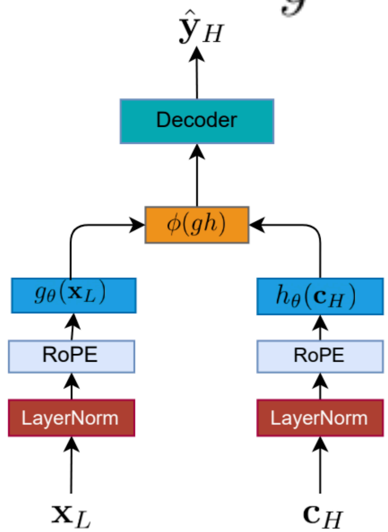


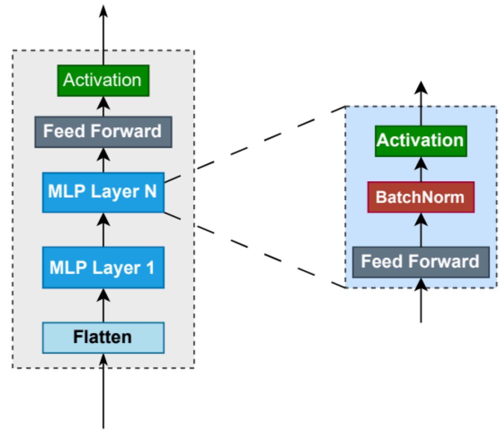
- ☑ *Solar Irradiance (Ghi & Ebh) Strongly correlates with net-Load*
- ☑ *Ghi & Temperature Impact Forecasting Accuracy*

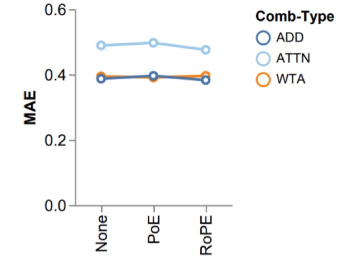
Chu Y, Pedro HTC, Kaur A, Kleissl J, Coimbra CFM. Net load forecasts for solar-integrated operational grid feeders. Solar Energy. 2017;158:236-246. doi:10.1016/j.solener.2017.09.052.

A Novel Scalable MLP Architecture For Power Forecasting (MLPF)

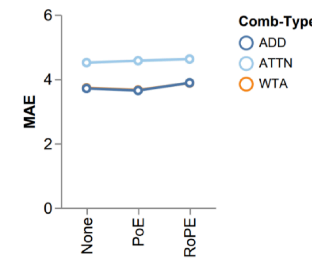
$$\hat{y} = f_\theta^1(x_1) + f_\theta^2(x_2) + \dots f_\theta^n(x_n)$$







(a) SPS-UK-MAE



(b) MLVS-PT-MAE

MLPF *effectively capture the complex relationship between historical power features and future covariates.*

$$\mathcal{L}_\theta(\mathbf{y}_H, \hat{\mathbf{y}}_H) = \frac{1}{H}\sum_{t=1}^{H} \lambda(y_t - \hat{y}_t)^2 + (1-\lambda)|y_t - \hat{y}_t|$$

- Efficiency through Simplicity: MLP-based Approach for Net-Load Forecasting with Uncertainty Estimates in Low-Voltage Distribution Networks Faustine, Anthony, Pereira, Lucas, and Nuno J Nunes. IEEE Transactions on Power Systems 2024.
- Github: https://github.com/sambaiga/mlpforecast/
- PyPi: https://pypi.org/project/mlpforecast/

MLPFQR: A Novel Approach to Probabilistic Load Forecasting

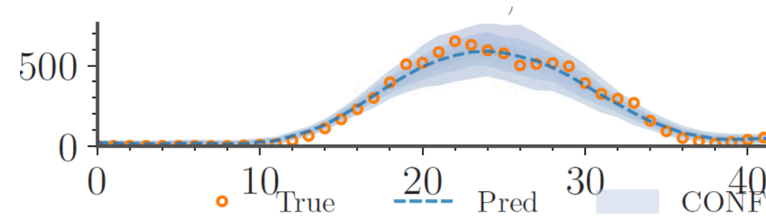
- **QR is a successful non-parametric approach for probabilistic forecast.**

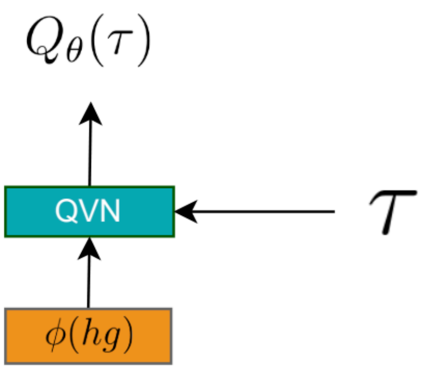
- It model complex distributions without making any apriori assumptions on the underlying distribution of the data.

$$p(y_t|\mathbf{x}_L, c_H) = \{Q_\theta(\hat{\tau}^1_{\theta H}), Q_\theta(\hat{\tau}^2_{\theta H}) \ldots Q_\theta(\hat{\tau}^N_{\theta H})\}$$

where $\tau \in [0, 1]$ is a set of $N \times H$ quantile probabilities satisfying:

$$\tau_t^1 < \tau_t^2 < \ldots \tau_t^{N-1} < \tau_t^N$$

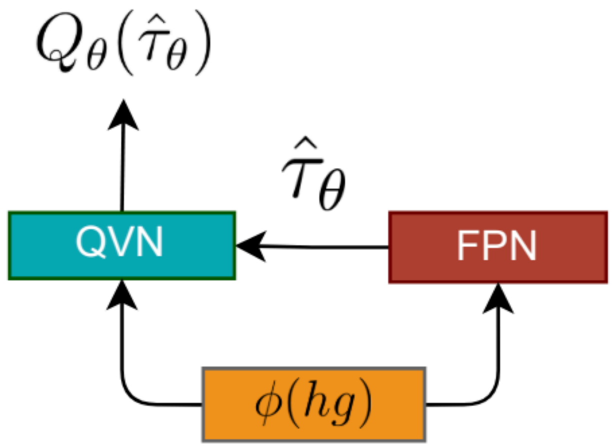


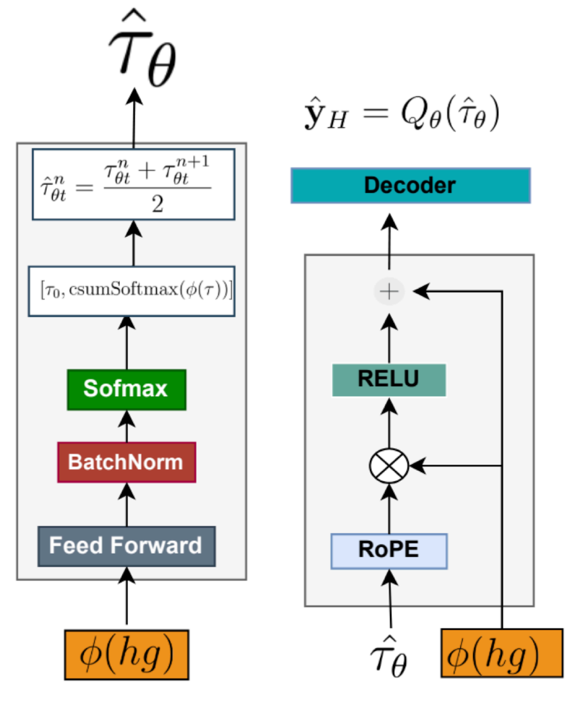


Current QR methods *often rely on heuristic approaches to select the specific quantile probabilities (τ) used in the model=> may not always capture the most relevant aspects of the forecast distribution, potentially leading to suboptimal results.*

Overcoming Heuristics: Parameterised QR with MLPF.

- **We introduce a novel architecture that learns both the quantiles fractions and quantile values directly from the data.**





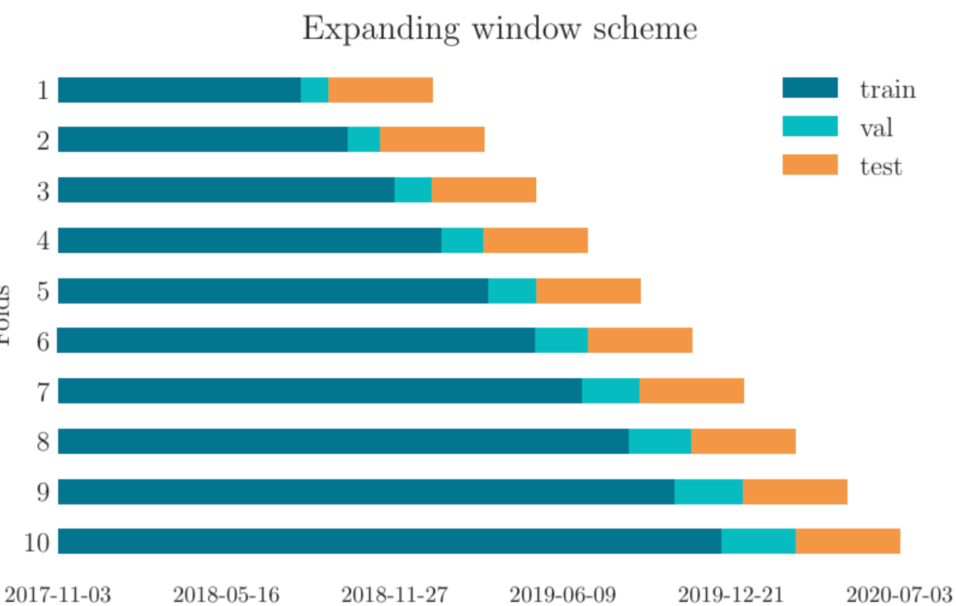
(a) FPN **(b)** QVN

$$\mathcal{L}_\tau(\rho_\kappa(\epsilon)) = \frac{1}{T}\sum_{t=1}^{T}\sum_{n=1}^{N}|\tau_t^n - \mathbb{I}\{\epsilon_{\tau_t^n} < 0\}|\frac{\rho_\kappa(\epsilon_{\tau_t^n})}{\kappa}$$

$$W_1(Q_\theta(\hat{\tau}_{\theta t}), Q_\theta(\tau)) = \sum_{t=1}^{T}\sum_{n=0}^{N-1}\int_{\tau_t^n}^{\tau_t^{n+1}}|Q_\theta(\tau_t^n) - Q_\theta(\hat{\tau}_{\theta t}^n)|d\tau$$

- A. Faustine and L. Pereira, "FPSeq2Q: Fully Parameterized Sequence to Quantile Regression for Net-Load Forecasting With Uncertainty Estimates," in *IEEE Transactions on Smart Grid*, vol. 13, no. 3, pp. 2440-2451, May 2022, doi: 10.1109/TSG.2022.3148699.
- A. Faustine, N. J. Nunes and L. Pereira, "Efficiency through Simplicity: MLP-based Approach for Net-Load Forecasting with Uncertainty Estimates in Low-Voltage Distribution Networks," in *IEEE Transactions on Power Systems*, doi: 10.1109/TPWRS.2024.3400123.

Experiment & Benchmark



Category	Model	Description
Baseline	S-Naive	Naive seasonal model [111].
Statistical	MTL	Multiple Seasonal-Trend decomposition using LOESS with ARIMA [112].
Traditional ML	CAT	CatBoost, a gradient boosting library [131].
	RF	Random Forest model [41].
DNN-based	NBEATS	Deep stack of fully connected layers with backward and forward residual links. Basis expansion for modeling non-linear relationships [60].
	NHITS	Hierarchical interpolation and multi-rate data sampling for short and long-term effects [44].
	LSTM	Long Short-Term Memory networks, excel at capturing temporal dependencies [148].
	TimesNet	CNN-based model decomposing temporal patterns into intraperiod and interperiod variations using a 1D-to-2D transformation [149].
	PatchTST	Transformer-based model for multivariate time series, using patching and channel independence [150].
	FEDformer	Transformer-based model for long-term forecasting, separating different frequency components [151].

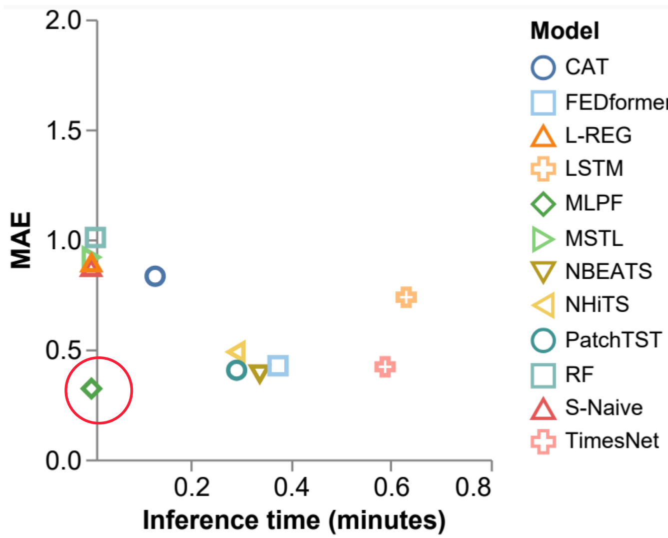
Datasets

- Madeira LowVoltage distribution substation dataset in Portugal (MLVS-PT)
- The Stentaway substation dataset in Plymouth-UK (SPS-UK)
- Albanian national electricity consumption and weather conditions for 2016-2019 (ALBANIA)
- Hybrid power plant is the aggregate solar capacity in East England (PV).

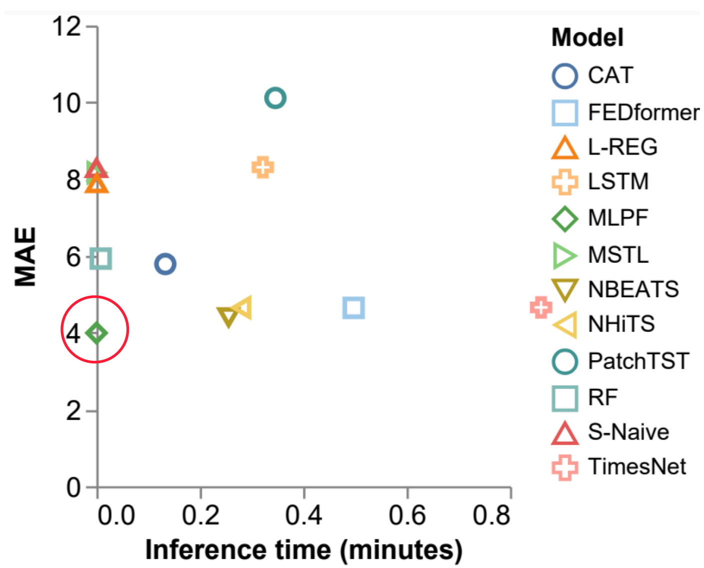
Metrics

- NMRSE:Normalized Root Mean Squared Error
- MAE:Mean Absolute Error
- PICP:Predictive Interval Coverage Probability
- NMPI:Normalized Median Prediction Interval width
- CRPS:Continuously Ranked Probability Score
- Winker Score (WS): Winkler Score
- Statistical test: Diebold–Mariano-test

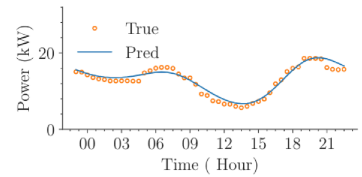
Results: Point forecast benchmark



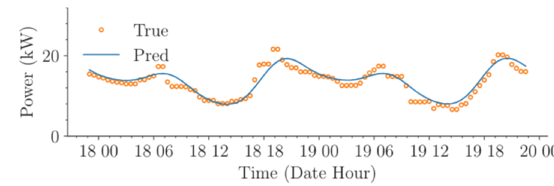
SPS-UK Dataset



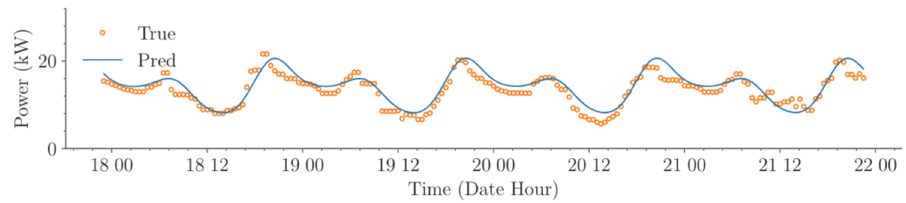
MLVS-PT Dataset



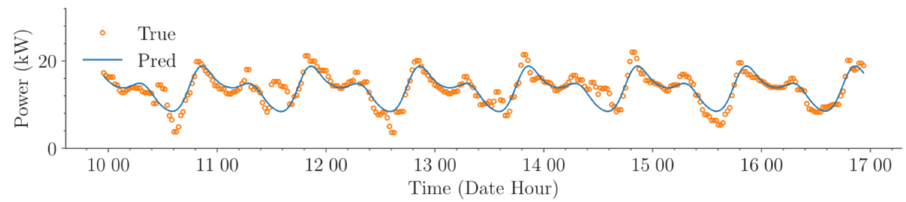
(d) 1 days



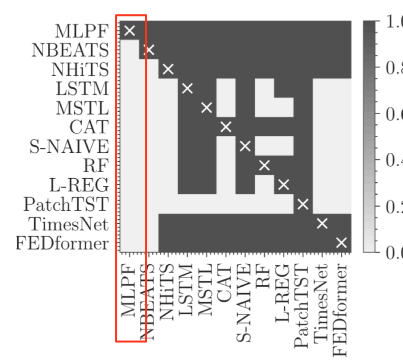
(e) 2 days



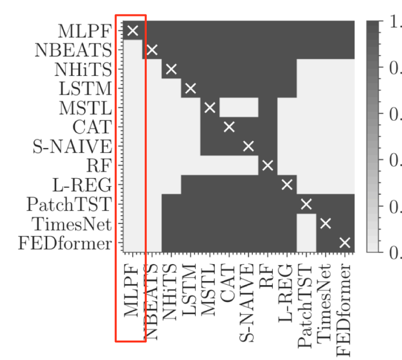
(f) 4 days



(g) 7 days



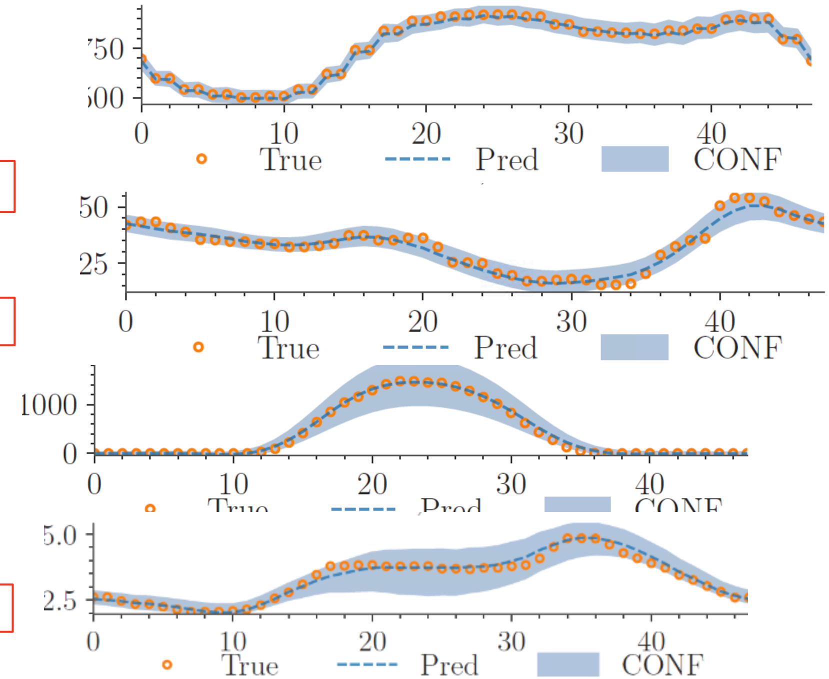
(a) MLVS-PT



(b) SPS-UK

Results: ProbForecast Benchmark

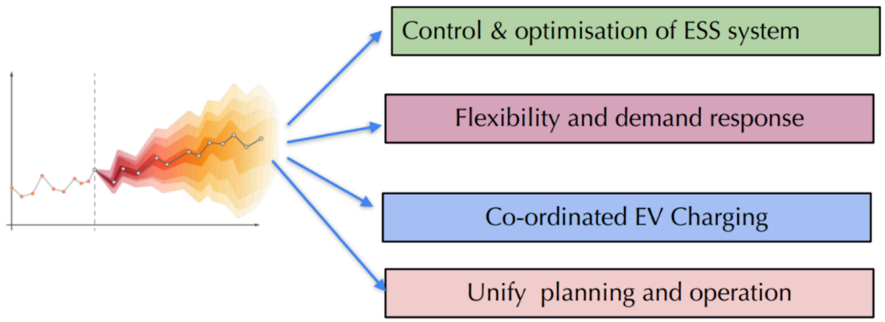
Dataset	Model	NRMSE	PICP	NMPI	NWS	NCRPS
ALBANIA	MLP-BNN	0.04	0.99	0.26	0.26	0.02
	MLP-MCD	0.08	0.97	0.46	0.46	0.03
	MLPQF	**0.03**	0.84	**0.09**	**0.10**	**0.02**
MLVS-PT	MLP-BNN	0.10	0.94	0.42	0.42	0.06
	MLP-MCD	0.12	0.93	0.42	0.42	0.06
	MLPQF	**0.09**	0.78	**0.21**	0.25	**0.04**
PV-UK	MLP-BNN	0.16	0.95	1.24	1.24	0.09
	MLP-MCD	0.26	0.95	1.43	1.43	0.10
	MLPQF	**0.14**	0.91	**0.18**	**0.20**	**0.05**
SPS-UK	MLP-BNN	0.15	0.95	0.70	0.70	0.08
	MLP-MCD	0.21	0.92	0.65	0.65	0.08
	MLPQF	**0.13**	0.84	**0.23**	**0.28**	**0.05**



- *MLPFQR produce a probabilistic forecast with a good trade-off between covearge coverage (capturing the entire range of possibilities) and sharpness (providing a precise forecast).*
- *It effectively captures the entire distribution of future outcomes while maintaining a high degree of accuracy in the predicted quantiles*

The Future is Probabilistic: A Call to Action

- DERs are transforming the grid, creating a dynamic and complex system.
- Traditional forecasting methods struggle to predict the variable nature of DERs.



The Future of Power Forecasting is Probabilistic.

- **Less is More:** Sometimes, simpler approaches can be highly effective.
- Our proposed lightweight MLPFQR architecture balances complexity with efficiency
- Delivers accurate forecasts while quantifying uncertainty and
- Achieves high performance compared to complex DNN models.

Let's embrace probabilistic forecasting and invest in developing efficient and scalable solutions.

EATON
Powering Business Worldwide

LARSyS
Laboratory of Robotics and Engineering Systems

TÉCNICO LISBOA

About Eaton

We make what matters work.

We're an intelligent power management company committed to improving the quality of life and the environment. Our products, technologies and services make a difference in the world.

$23.2B
2023 sales

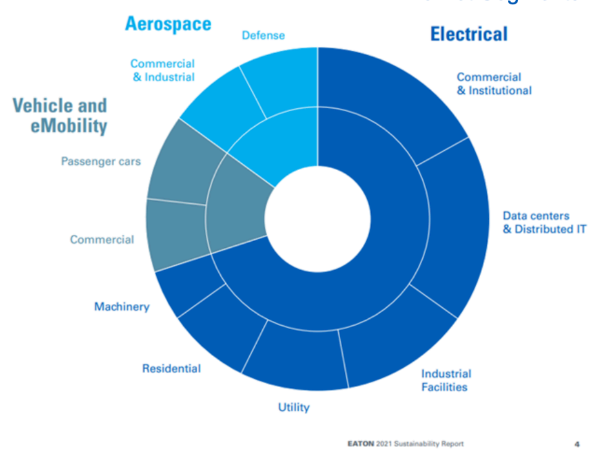
Operate in **170** countries

>92K
Employees around the world

NYSE ticker **ETN**

Established **1911**

Market Segments



44TH ISF
IIF

DIJON FRANCE
JUNE 30 - JULY 3