Wind power forecasting: Leveraging deep learning for intra-day predictions with applications in energy trading

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Introduction

Wind energy is a growing source of renewable energy in the world. Due to the unstable nature of the wind, accurate forecasting is required. Here we address a wind power forecasting problem, namely predicting hourly power generation up to 6 hours ahead using state of the art deep learning methods based on historical measurements and additional wind forecast information from a Numerical Weather Prediction model (NWP) [2].

Short term forecasting is highly relevant to wind farm (WF) operators and energy traders for intra-day (ID) energy trading in dynamical markets such as Nord Pool's Electricity Balancing Adjustment System (Elbas). Higher quality forecasts up to 6 hours ahead can be leveraged to improve market decisions and to avoid penalization due to over- or underproduction.

Key points

- ► We combine a Long short-term memory (LSTM) model using past power measurements and a Feed-forward neural network (FFNN) mapping of NWP forecast information to a single fully connected output layer.
- ► This model outperforms a simple (effective) persistence baseline and an industry standard time series Auto-regressive (AR) model.

Data visualization

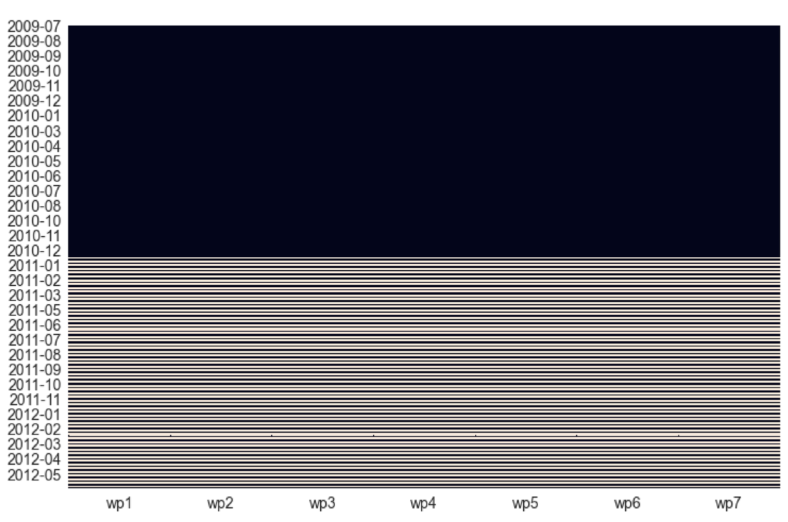

Figure 1: Data availability

► 3 yrs. of data (1.5 complete) for 7 WF's.

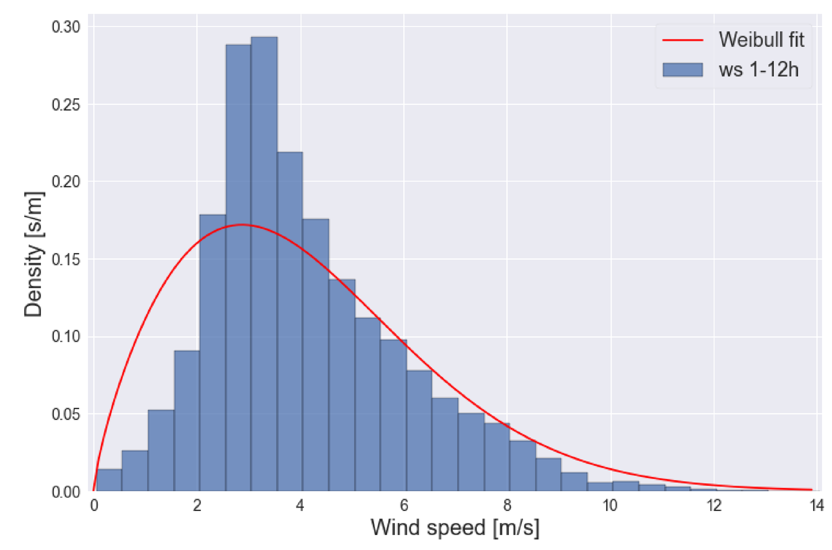

Figure 2: Distribution of NWP wind speed (ID).

► Realistic NWP output (∼Weibull dist).

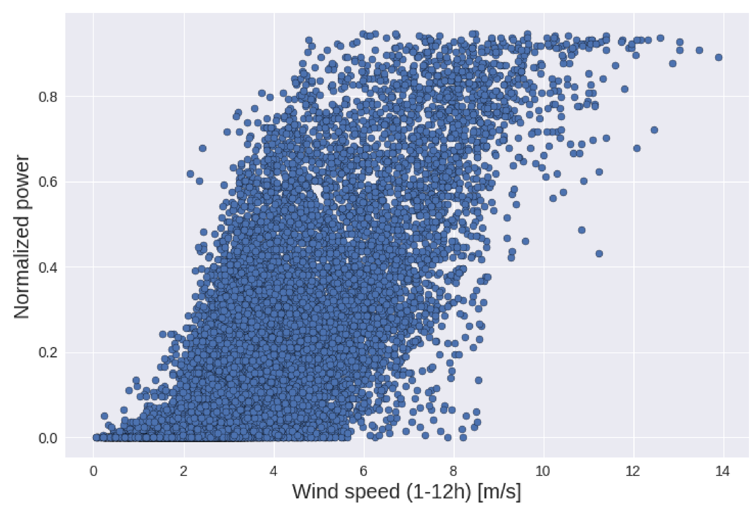

Figure 3: Relationship btw. NWP ws (ID) and power.

► Noisy mapping of power curve (WF1).

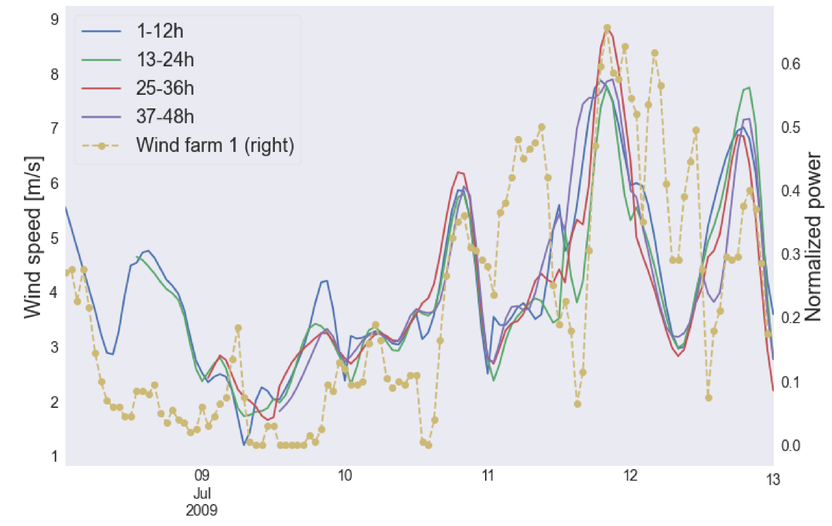

Figure 4: Window of the measured power along with ws forecasts using both NWP cycles.

► 48h NWP updated every 12h (1-12h used).

Model architectures

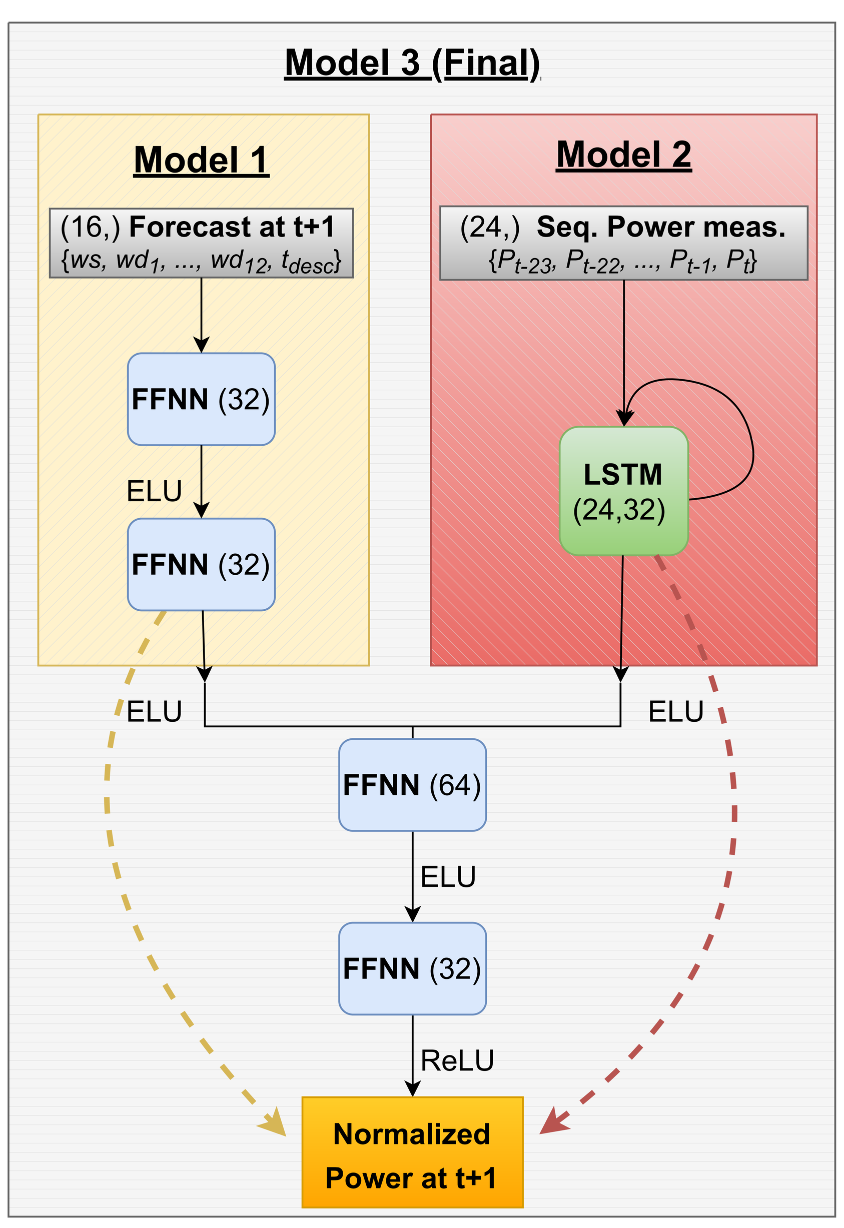

Figure 5: Model architecture representation.

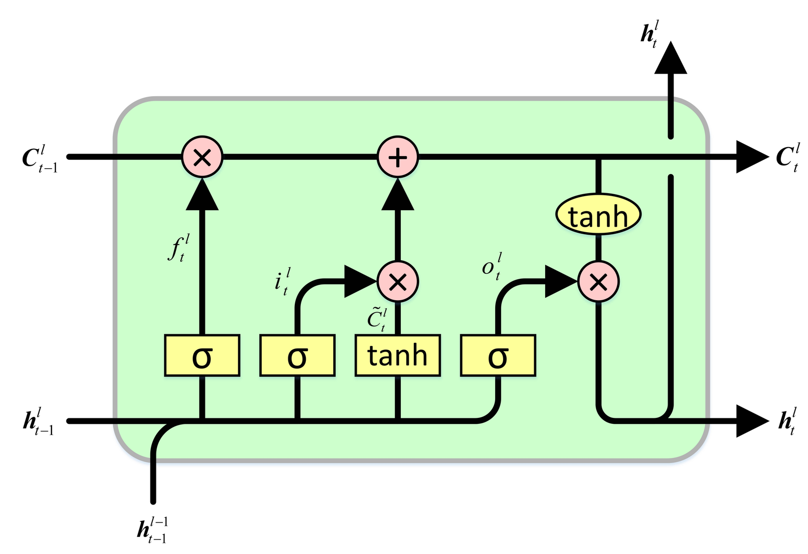

Figure 6: LSTM cell [1].

- ► Model validation using hold out:
  - ▷ 80% training.
  - ▷ 20% validation.
- ► Inputs:
  - ▷ Mapping of ws, wd (12 bins) and temporal descriptors.
  - ▷ Power history (24h sequences).
- ► Final training parameters:
  - ▷ Batch size: 128.
  - ▷ Epochs: depends on the model (based on early stopping).
  - ▷ Learning rate: 5e−6.

Model comparison

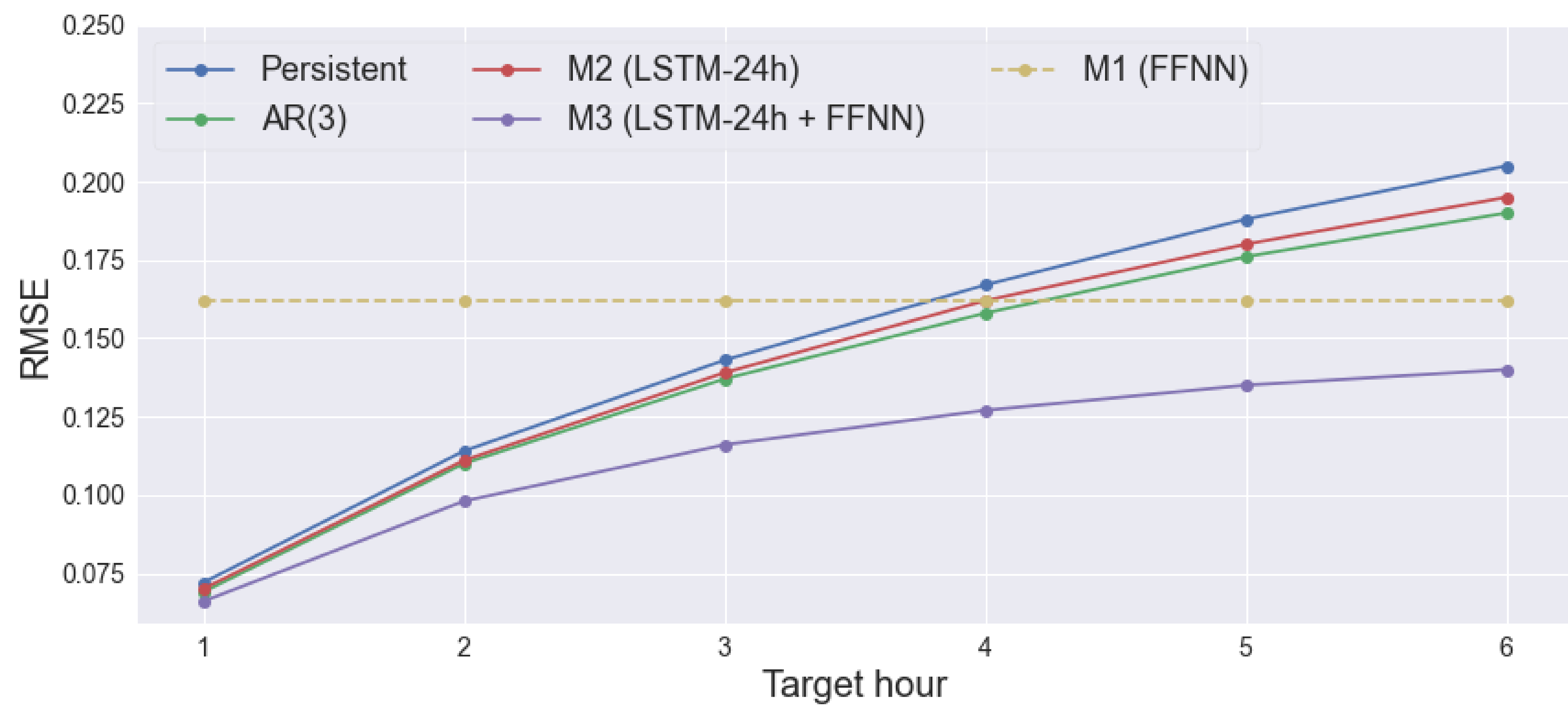

Figure 7: Comparison of models based on RMSE for different time horizons.

- ► Similar performance 1h ahead (except FFNN), due to high autocorrelation at lag 1.
- ► The performance of purely auto-regressive models degrades further ahead.
- ► Performance of LSTM + FFNN (model 3) converges to FFNN mapping (model 1).

Best model performance

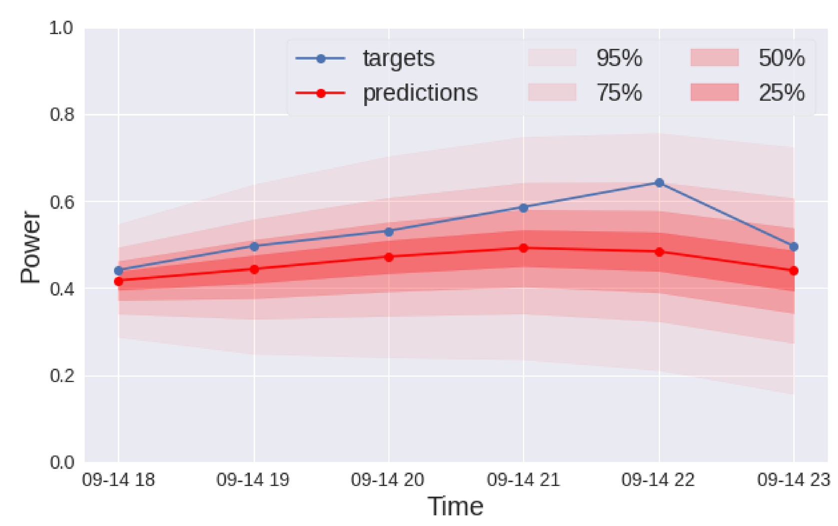

Figure 8: M3 predictions on a horizon of 6 hours with prediction intervals.

► Prediction intervals get wider with increasing horizon.

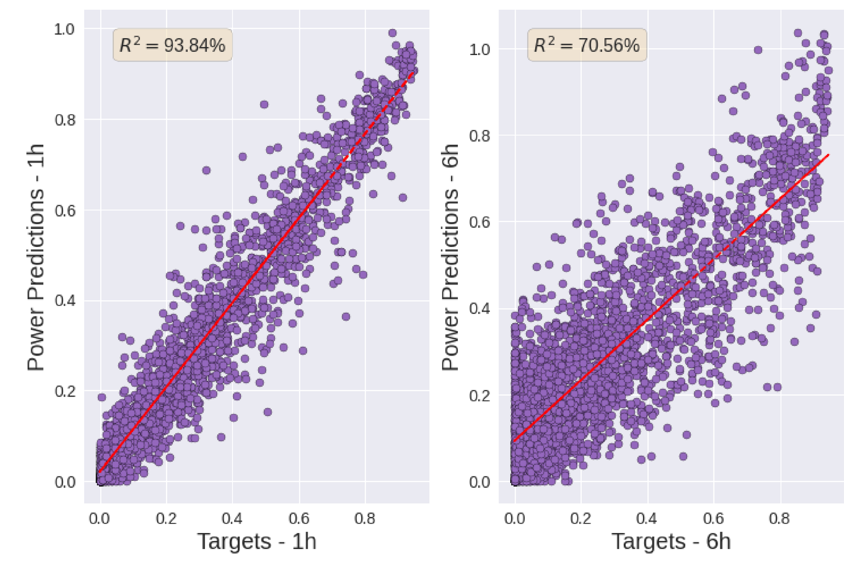

Figure 9: M3 Power predictions 1 and 6 hours ahead vs. target.

► High correlation between targets and predictions (final model).

Application for intra-day (ID) energy trading

Our ID market analysis is based on the following assumptions:

- ► 3 months operation of a 100 MW WF;
- ► an energy price of 140 $€/\mathbf{MWh}$;
- ► a simplified penalty framework [3], where mismatches due to over- and underproduction are equally penalized ($\pi_{-}=\pi_{+}=30$ $€/\mathbf{MWh}$).

The total revenue in euros is then computed as follows:

$$R_{total}\,[€] = \sum R_t = \sum E \cdot \mathbf{140} - |\hat{E} - E| \cdot \mathbf{30} \qquad (1)$$

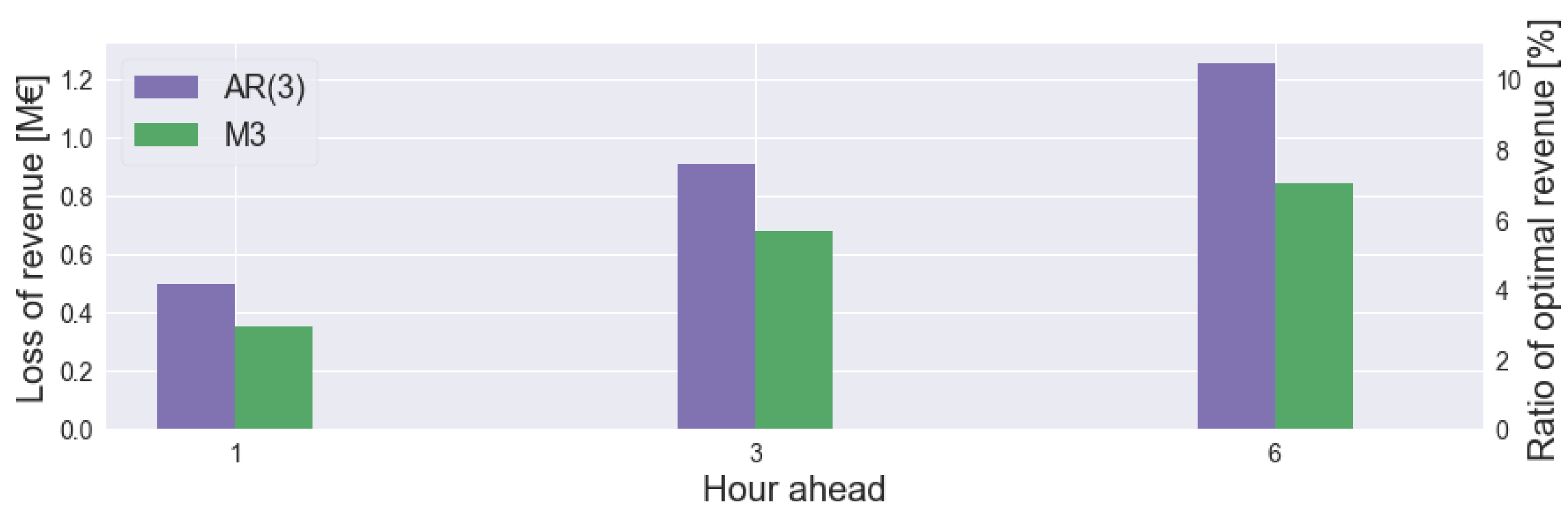

Figure 10: Revenue loss comparison between AR(3) and final model (M3).

Conclusions

- ► **The combination** of the Power history (LSTM) and NWP forecast (FFNN) consistently over-performed other models (1-6 h ahead).
- ► The final model (M3), yielded a **RMSE reduction** of 4.2% at 1 hour, 19.6% at 4 hours and 13.6% at 6 hours, in comparison with the next best model at each of those horizons.

References

[1] J. J. Gago, V. Vasco, B. Lukawski, U. Pattacini, V. Tikhanoff, J. G. Victores, and C. Balaguer. Sequence-to-sequence natural language to humanoid robot sign language. *ArXiv*, abs/1907.04198, 2019.

[2] Kaggle. Global Energy Forecasting Competition 2012 - Wind Forecasting, 2014.

[3] P. Pinson, C. Chevallier, and G. Kariniotakis. Trading wind generation from short-term probabilistic forecasts of wind power. *Power Systems, IEEE Transactions on*, 22:1148 – 1156, 09 2007. doi: 10.1109/TPWRS.2007.901117.

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