IA meeting 16/11/2020

Deep learning-based multi-output quantile forecasting of PV generation

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Probabilistic forecasting context

System
-> PV/wind plant -> **uncertainty** on the generation

Goal
-> The **intermittent** power from a PV/wind plant has to be **predicted** to **improve decision-making** (such as robust-optimization) on a day ahead and intraday basis

How ?
-> in contrast to point predictions, probabilistic forecasts aim at providing decision-makers with the **full information** about potential future outcomes

Paper focus
-> **quantile forecast** that provide a probabilistic information about future renewable power generation, in the **form of a threshold level associated with a probability**

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Forecasting timeline

Time resolution is **15 minutes** -> **96** time steps per day

Day ahead forecasts:
- 1 time gate 12:00, day D;
- prediction for D+1 from **00:00 to 23:45** (96 forecasting time periods)

Intraday forecasts:
- 4 time gates 00:00, 06:00, 12:00, and 18:00, day D+1
- prediction for D+1 from **00:00/06:00/12:00/18:00 to 23:45** (96/72/48/24 forecasting time periods).

Quantiles:
- 0.1, 0.2, …, 0.9

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Contributions

A tailored deep learning-based multi-output quantile PV forecaster:

- a deep learning-based **multi-output quantile** architecture;
- implement & test an **encoder-decoder** architecture;
- use the **weather forecasts** of the **MAR** regional climate model;
- a proper assessment of the quantile forecasts is conducted by using a **k-cross validation** methodology and **probabilistic metrics**

*ps: this is not rocket science … we are not machine learning experts so any feedback to **help us to improve the approach** is welcome :)*

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Summary

1. Literature review -> cf paper
2. Quantile regression -> cf paper
3. Forecasting techniques
4. Probabilistic forecasting quality assessment
5. Case study
6. Conclusions & perspectives

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Forecasting techniques

Day ahead models:

- **GBR** (scikit-learn);
- **MLP** (PyTorch) with one hidden layer -> used also for intraday forecasts;
- **LSTM** cell & a feed-forward layer, named LSTM (TensorFlow) -> used also for intraday forecasts;

Intraday models (encoder-decoder):

- **LSTM-MLP** named ED-1 (TensorFlow);
- **LSTM-LSTM** named ED-2 (TensorFlow).

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Forecasting model inputs

Day ahead models (GBR/MLP/LSTM) inputs:

- air temperature 2 m;
- solar irradiation.

Intraday models (MLP/LSTM/ED-1/ED-2) inputs:

- air temperature 2 m;
- solar irradiation;
- last 3 hours of PV generation (not for LSTM).

Weather forecasts are provided by the **MAR regional climate model** from the Climate laboratory of Liège University: link.

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Probabilistic forecasting quality assessment

Value vs quality:

- **quality**: ability of the forecasts to **genuinely inform of future events** by mimicking the characteristics of the processes involved;
- **value**: benefits from **using forecasts** in a **decision-making** process such as participation to the electricity market.

Focus on the forecast **quality assessment**:

- Continuous Rank Probability Score (**CRPS**) -> cf paper for def
- Winkler Score (**WS**) -> cf paper for def

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The Uliège case study: dataset

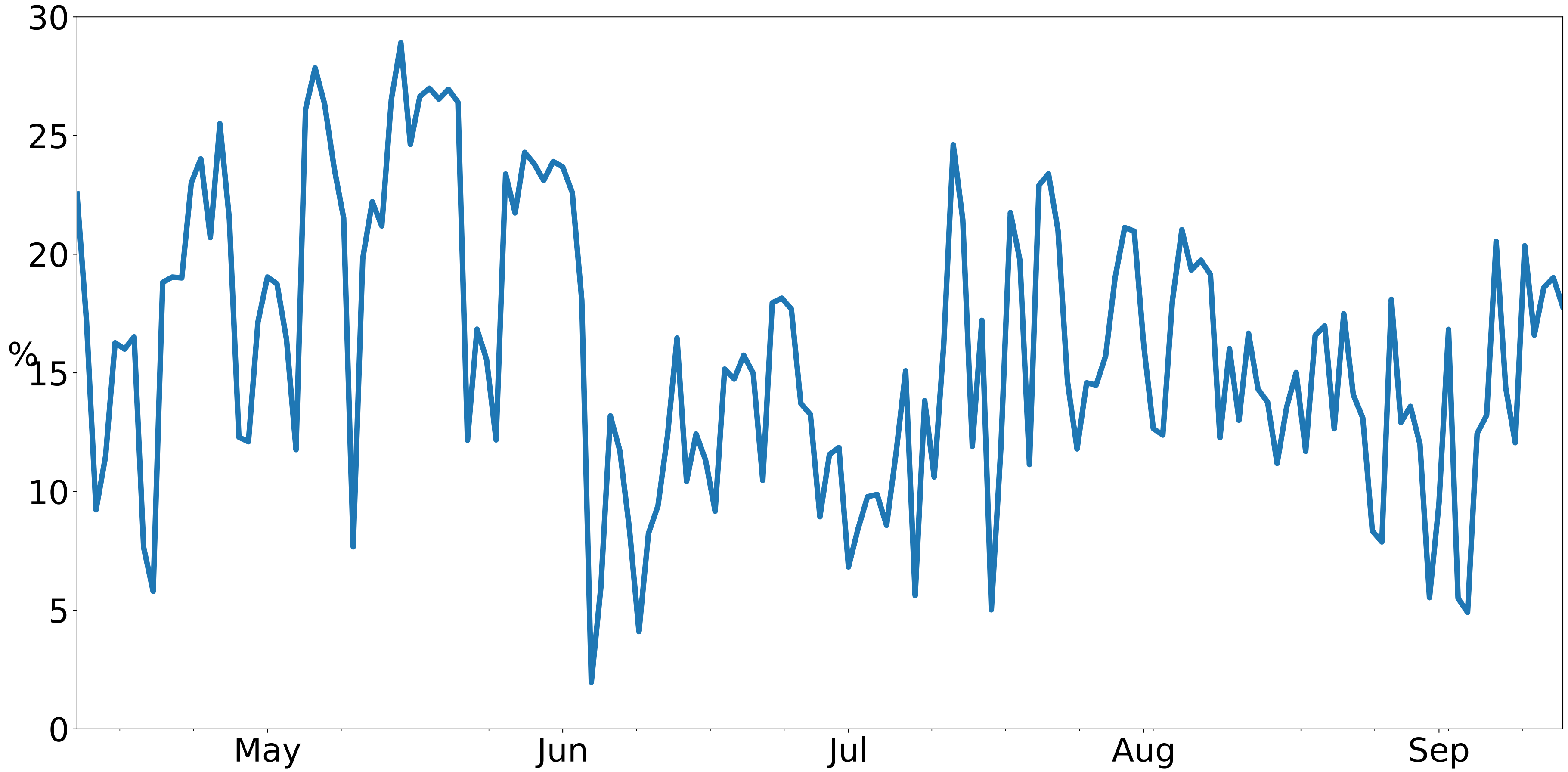

Figure 1: Daily energy PV generation normalized by the daily energy produced by the total installed capacity.

- 04/04/2020 - 14/09/2020: **157** days
- **1 min** resolution monitored on site -> **resampled to 15 min**
- Pc = **466,4** kWp

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Validation strategy

11-cross validation:

- **142/15** days per pair;
- scores (NMAE, NRMSE, CRPS, WS) are averaged over the **11 pairs**.

Forecasting time periods k:

- **11 <= k <= 80**: PV generation always 0 for 0 <= k <= 10 & 81 <= k <= 95

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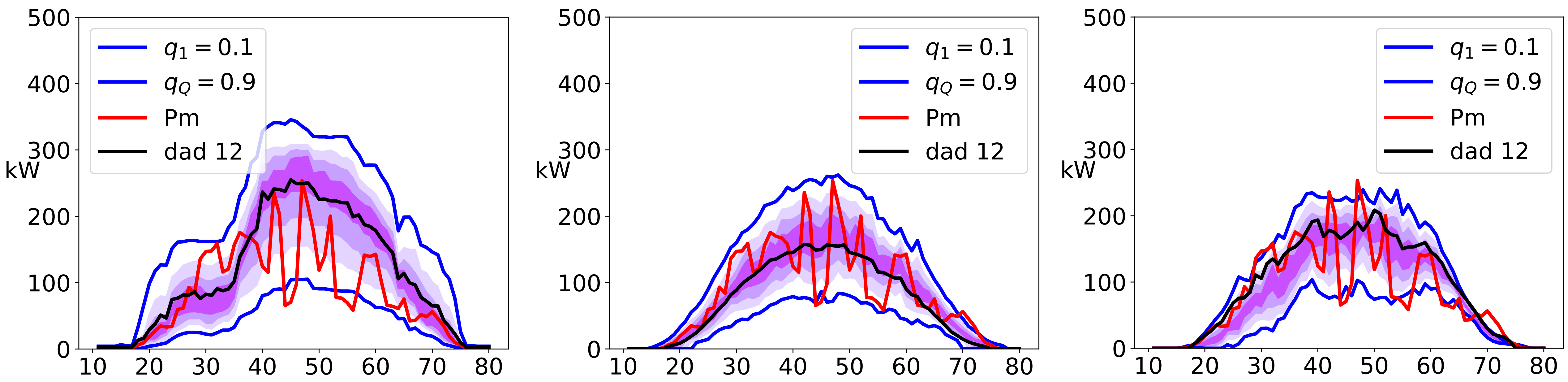
Day ahead results: point and quantile forecasts



(a) GBR *(b) LSTM* *(c) MLP*

Figure 2: Quantiles vs point forecasts of day ahead models on August 2, 2020.

Red line (Pm) = observations

Black line (dad 12) = day ahead point forecasts

Blue lines (q1, qQ) = 0.1 and 0.9 quantile forecasts

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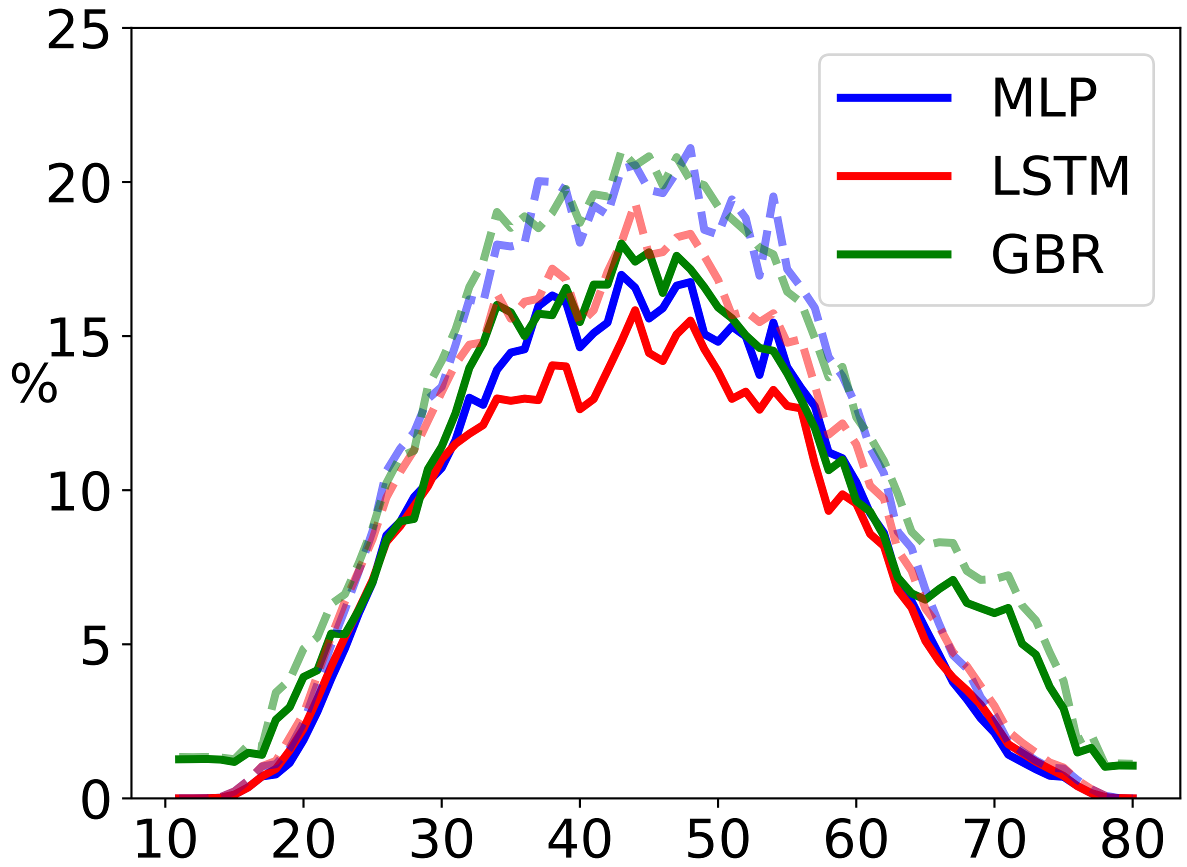
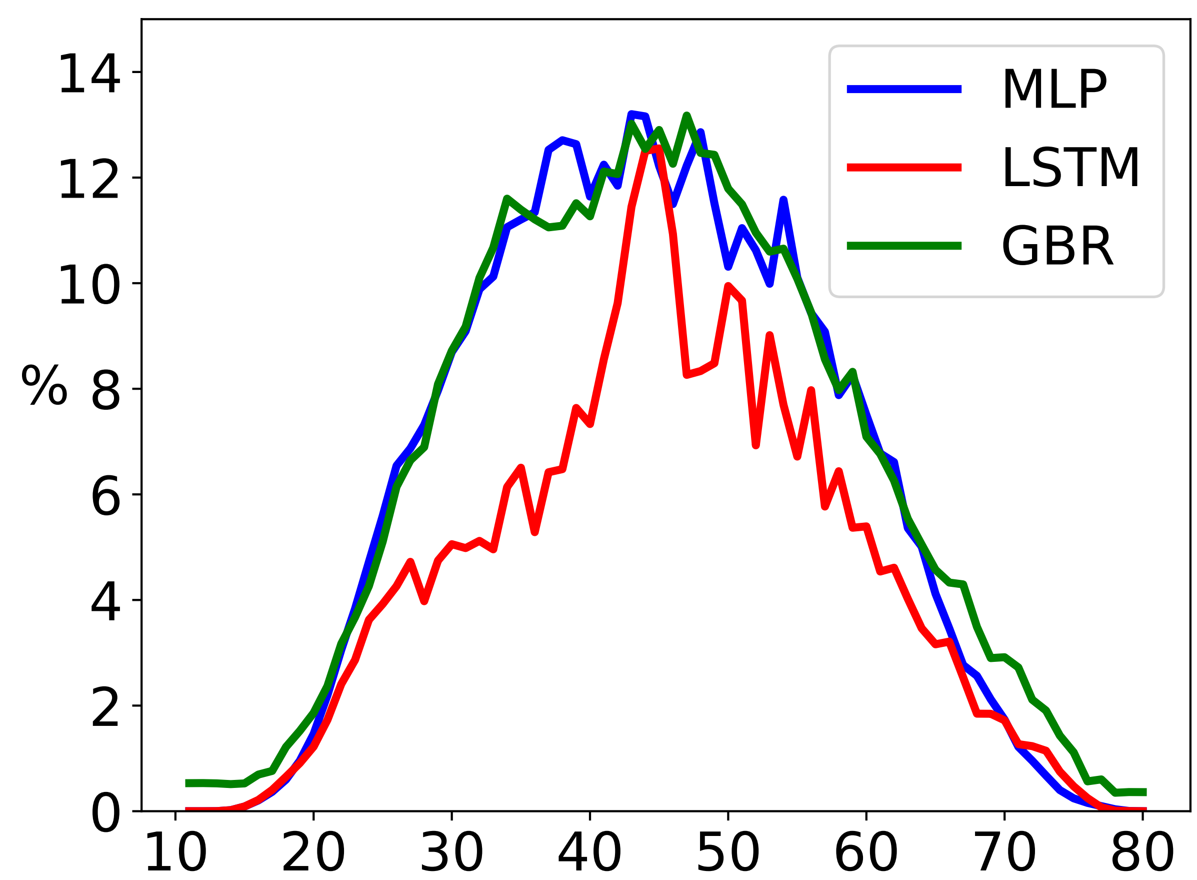
Day ahead results: point and quantile forecasts



(a) *Point forecasts: NMAE & NRMSE*



(b) *Quantile forecasts: CRPS*

Figure 3: NMAE (plain), NRMSE (dashed), and CRPS per forecasting time periods of the day ahead models (%).

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Day ahead results: point and quantile forecasts

Score	Gate	MLP	LSTM	GBR
NMAE	12	8.2 (1.2)	7.6 (1.5)	9.2 (0.9)
NMAE	24	7.9 (1.2)	7.7 (1.6)	9.0 (0.8)
NRMSE	12	10.2 (1.4)	9.2 (1.6)	11.2 (0.9)
NRMSE	24	9.7 (1.2)	9.4 (1.8)	10.9 (0.8)
CRPS	12	6.2 (1.1)	4.4 (0.2)	6.4 (0.7)
CRPS	24	6.2 (1.0)	4.4 (0.2)	6.3 (0.6)

Table 1: Averaged NMAE, NRMSE, and CRPS of the day ahead models (%).

LSTM achieved the **best results** for both point & quantile forecasts.

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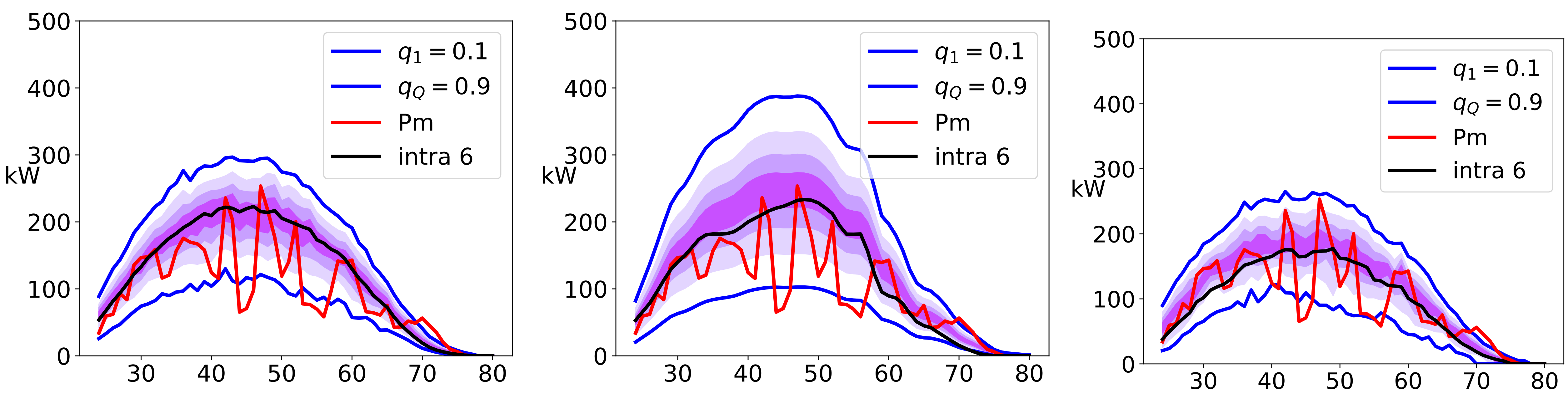
Intraday results: point and quantile forecasts



(a) ED-1 (LSTM-MLP) *(b) ED-2 (LSTM-LSTM)* *(c) LSTM*

Figure 4: Quantiles vs point forecasts of intraday models of gate 6 on August 2, 2020.

Red line (Pm) = observations

Black line (intra 6) = intraday point forecasts

Blue lines (q1, qQ) = 0.1 and 0.9 quantile forecasts

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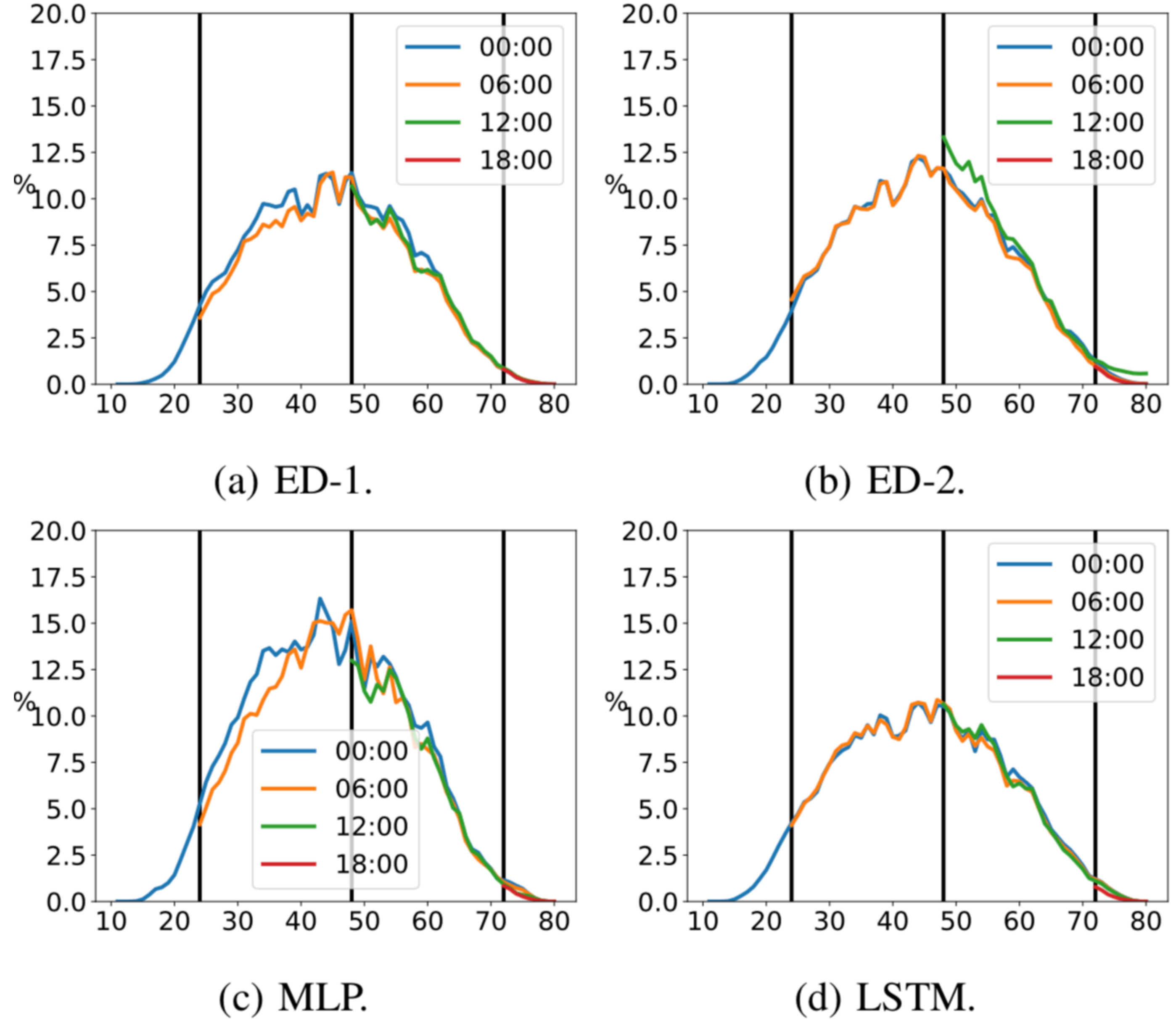
Intraday results: quantile forecasts



(a) ED-1. (b) ED-2.

(c) MLP. (d) LSTM.

Figure 5: CRPS per forecasting time periods of intraday models (%).

Intraday results: quantile forecasts

Score	Gate	MLP	ED-1	ED-2	LSTM
NMAE	6	8.9 (1.0)	8.5 (1.4)	9.4 (1.0)	7.6 (1.5)
NMAE	12	6.7 (1.4)	6.4 (1.3)	7.1 (1.1)	7.2 (1.1)
NRMSE	6	10.9 (0.9)	10.3 (1.3)	11.3 (1.1)	7.7 (1.6)
NRMSE	12	8.7 (1.3)	7.8 (1.2)	8.5 (1.2)	9.4 (1.8)
CRPS	6	8.1 (0.7)	5.9 (0.9)	6.6 (0.7)	6.2 (0.7)
CRPS	12	5.8 (1.2)	4.5 (0.7)	5.6 (1.8)	4.7 (0.5)

Table 2: Averaged NMAE, NRMSE, and CRPS of the intraday ahead models (%).

The **LSTM** achieved the best NMAE and NRMSE for the **06:00 gate** and the **ED-1** achieved the best NMAE and NRMSE for the **12:00 gate, and the best CRPS for both gates**.

Conclusions & perspectives

Results:

- best **day ahead** model for both point & quantile forecasts: **LSTM**;
- LSTM-MLP yields accurate results in comparison with the MLP & LSTM-LSTM models.;
- LSTM produced similar results than the LSTM-MLP.

Perspectives:

- consider a **larger dataset** (one full year at least);
- PV **scenarios**.