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Dynamic Line Rating Forecasting & Evaluation

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Introduction

- Interest of DLR
- Case study
- Results
- Conclusion

Outline

Introduction

- What is Dynamic Line Rating?

Interest of Dynamic Line Rating

- Why is Dynamic Line Rating interesting for system operations?
- Why are Dynamic Line Rating forecasts needed?
- Case study description

Results

- Description of the used models.
- Results obtained.
- Conclusion



Introduction

- Interest of DLR
- Case study
- Results

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Conclusion

Introduction



What are static and dynamic line rating?

- Introduction
- Interest of DLR
 - Case study
 - Results
 - Conclusion
- The sag of an overhead line depends on the temperature at its core. This temperature increases with current.
- For security purposes, the sag is limited in order to maintain a minimum clearance from objects.
- This can be achieved by limiting the maximum current of the line.





What are static and dynamic line rating?

• Static Rating (SR): This limit is fixed for each season, and is defined with restrictive weather characteristics.

 $I_{SR} = f(Low Wind Speed, High Ambient Temperature).$

- **Dynamic Line Rating (DLR):** this limit is dynamically modified depending with weather characteristics.
 - $I_{DLR} = f(Wind Speed, Ambient Temperature).$



Introduction Interest of DLR Case study

Results Conclusion



- Interest of DLR
- Case study
- Results
- Conclusion



Evolution of Dynamic Line Rating and Static Rating for an 110 kV line, for the period of the 23/10/2010 to the 12/11/2010



- Introduction
- Interest of DLR
- Case study
- Results
- Conclusion

The interest of DLR for wind power integration



Interest of DLR for wind power integration



- Real case study in the Orkney islands (UK).
- Real-time DLR permits to reduce drastically the curtailed wind generation.
 - For one year, the total curtailed energy is reduced **from 32% to 7%** of the total produced energy.



Introduction Interest of DLR Case study

Results Conclusion

Interest of DLR – Economic benefits

• Study made on a simple Canadian network:



M. Khaki, P. Muslilek, J. Heckenbergerova, and D. Koval, "Electric Power System Cost/Loss Optimization Using Dynamic Thermal Rating and Linear programming," in EPEC, Halifax, NS, 2010.



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Introduction

- Interest of <u>DLR</u>
- Case study
 - Results
- Conclusion

Interest of DLR – Economic benefits

• Implementation of the DLR on the curtailed line:



M. Khaki, P. Muslilek, J. Heckenbergerova, and D. Koval, "Electric Power System Cost/Loss Optimization Using Dynamic Thermal Rating and Linear programming," in EPEC, Halifax, NS, 2010.



Introduction Interest of DLR Case study

Results Conclusion

Interest of DLR forecasting

- Introduction Interest of DLR Case study
- Results
- Conclusion
- DLR forecasts are needed because many operations for grid management require day-ahead decisions.
- DLR forecasts can be useful for :
 - Network operators: Network reliability increase.
 - Market operators: Electricity market transmission capacity allocation improved.
 - Electricity producers: More possibility for bidding on the electricity market.



State of the Art – DLR forecasting

- Most studies focus on real-time DLR, and only few (≈5 studies) focus on DLR forecasting.
- For day-ahead forecasts, the main weather uses forecast one ensembles to get the density function of the DLR.
 - The reliability is correct for low quantile forecasts.
 - However, the model has been evaluated with reanalysis data and not with terrain data.



24 hours-ahead DLR forecasts





Introduction

- Interest of DLR
- Case study
- Results
- Conclusion

- Results
- Conclusion
- Develop a probabilistic model for day-ahead DLR forecasting taking into account:
 - Observations made at weather stations linked to the line rather than reanalysis data.
 - Numerical Weather Predictions (NWP).

• Evaluate the performance of the model through:

- Its ability to increase the exploitable rating of the line (i.e. sharpness).
- Its ability to make safe forecasts (i.e. reliability).





- Interest of DLR
- Case study
- Results
- Conclusion
- In general, we want the DLR forecast to be above the observed DLR for the 99% to 95% of time (depending on the case).

 For this, probabilistic forecasts are needed, the 1% to 5%-quantile being here taken as the DLR forecast.



- Introduction
- Interest of DLR
- Case study
- Results
- Conclusion

Case study



Case study

- Interest of DLR
- Case study
- Results
- Conclusion

- The studied case is an 110kV line located in the UK.
- Data has been collected through several weather stations located on the line, for the period of December 2008 to January 2011:
 - The wind speed (m/s).
 - The direction of the wind (°).
 - The temperature (°C).
 - The solar radiation (W/m²).
- Historic NWPs provided by ECMWF for the same weather parameters.



- Introduction
- Interest of DLR
- Case study
- Results
- Conclusion

Results



- Introduction
 Interest of DLR
- Case study
 Results
- Conclusion

$$D\widehat{LR_{t+k,\alpha}} = f(\widehat{Ws}, \widehat{S}, \widehat{T}, \widehat{Wd}, \underbrace{Ws, S, T, Wd}_{NWP}$$
 Weather station observations

- Four different probabilistic models were developped for DLR prediction:
 - A Quantile Linear Regression. (QLR)
 - A Quantile Random Forest. (QRF)
 - A Kernel Density Estimator. (KDE)
 - A Mixture Density Neural Network. (MDNN)



Quantile Linear Regression (QLR)

- For each quantile, a linear function is fitted. For 99 quantiles, 99 linear functions are then fitted.
- For each function, the following function is minimized:

$$z = \left[(1 - \tau) \sum_{y_i < q} (y_i - q) + \tau \sum_{y_i \ge q} (y_i - q) \right]$$

• τ is the studied quantile, q is the τ – quantile forecast and y_i is the observation.



Introduction Interest of DLR Case study

Results Conclusion

Quantile Random Forest (QRF)

Introduction
 Interest of DLR
 Case study
 Results
 Conclusion



- The Random Forest generates n decisional trees, with nodes randomly generated.
- Each tree gives for an input X, a set of outputs y_k .
- The α-quantile forecast is the value y_{α} such as the number of outputs inferior to this value is equal to α% of the total amount of outputs.



Kernel Density Estimation (KDE)



• The method gives an estimate of the probability density function of the predicted DLR depending on the input X.

$$\hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^n K_h(x - x_i) = \frac{1}{nh} \sum_{i=1}^n K\Big(\frac{x - x_i}{h}\Big),$$

- The Kernel function is a normal one.
 - The smoothing parameter h is selected through bandwith crossvalidation.
- The features are selected with a greedy selection using the Mutual information criterion.



Introduction Interest of DLR Case study

Results Conclusion

Mixture Density Neural Network (MDNN)

 The Mixture Density gives for the forecast a Probability Density Function (PDF) equal to the sum of a limited number of PDF, here some gaussian curves:

$$\widehat{f_h(x)} = \sum_{i=1}^p \alpha_i(x) \ast \widehat{f_{Gaussian}}(\mu_i(x), \sigma_i(x), x)$$

- μ_i are the expected values, σ_i are the variances, α_i are weights defined with the constraint their sum is equal to 1.
- The parameters depend on the input X, and are defined through a Neural network.
- The number of layers and terminal nodes is arbitrary selected, both equal to 6.



Introduction Interest of DLR Case study

Results Conclusion

- Interest of DLR
- Case study Results
- Conclusion

• The four models are compared through:

– Deterministic indices (RMSE).

- Probabilistic indices (i.e. reliability, sharpness, Continous Ranked Probability Score).



- Introduction
- Interest of DLR
- Case study
 - **Results**
- Conclusion



RMSE indexes for 24 hours-ahead forecasts made with the four different models.



- Case study
- Results
- Conclusion



Reliability of the different models for a 24-hour horizon, for the studied weather station. Difference between the nominal coverage and the observed one.



Interest of DLR

- Case study

Results

Conclusion



Sharpness of the predictive intervals of the different models for a 24-hour horizon, for the studied weather station.



Case study

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- Results
- Conclusion
- The Continuous Ranked Probabilistic Score (CRPS) is used to evaluate the models:

$$CRPS(y_i) = \int_{-\infty}^{+\infty} (F(y) - 1\{y \ge x\})^2 dy$$

• *x* is the observation, and F is the cumulative distribution of the PdF.





- Introduction
- Interest of DLR
- Case study
- Results
- Conclusion ٠

	RMSE	Reliability	Sharpness	CRPS
QLR				
KDE				
QRF				
MDNN				



- Interest of DLR
- Case study
 - Results
 - Conclusion



Day-ahead DLR forecasts made at the studied weather station, from the 28/10/2010 to the 03/11/2010. The Model is a **QRF**.





- Interest of DLR
- Case study
 - **Results**
 - Conclusion



Day-ahead DLR forecasts made at the studied weather station, from the 28/10/2010 to the 03/11/2010. The Model is a **QRF**.



Introduction

- Interest of DLR
- Case study
 - **Results**
- Conclusion



Day-ahead DLR forecasts made at the studied weather station, from the 28/10/2010 to the 03/11/2010. The Model is a **MDNN**.



Model evaluation – security aspects



Day-ahead DLR forecasts made at the studied weather station, from the 04/04/2010 to the 06/04/2010. The Model is a **MDNN**.



Introduction

- Interest of DLR
- Case study
 - Results

Conclusion

Model evaluation – security aspects



For the different models, distribution of the values of errors between the 1%-DLR forecast and the observation, if the forecast is superior to the observed DLR.



Introduction

- Interest of DLR
- Case study
 - Results

Conclusion

- Introduction
- Interest of DLR
- Case study
- Results

٠

Conclusion

Conclusions and perspectives



Conclusions and perspectives

- Introduction
 Interest of DLR
 Case study
 Results
 Conclusion
- DLR forecasts can improve greatly the ampacity of lines. This may help to avoid congestions in cases of high wind penetration.

Predicted Quantile	QRF	MDNN
1%	18,6%	37,4%
3%	34,7%	48,8%
5%	43,5%	55,6%

Amount of time where the 1%-DLR forecasts are superior to 120% of the SR

- Four models were tested. The QRF appears to be the most suitable among them for DLR forecasts, due to security purposes.
- Future work will focus on the optimization of the models and the demonstration of the value of DLR forecasts for power systems.



Thank you for your attention





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