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▶ To cite this version:

Yun Bai, Simon Camal, Andrea Michiorri. Electricity Demand Forecasting through Natural Language Processing with Long Short-Term Memory Networks. 2023 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), IEEE Power & Energy Society (PES); Université Grenoble Alpes, Oct 2023, Grenoble, France. hal-04205841

HAL Id: hal-04205841 https://hal.science/hal-04205841

Submitted on 13 Sep 2023

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2023 IEEE PES ISGT-Europe October 23rd-26th, 2023, Grenoble, France

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Paper Nº: A8841YB









Introduction





Methodology



> Textual features by statistical methods

- Count features: number of news elements (words, sentences, ...)
- Word frequency: number of news containing certain words

> Textual features by semantic methods

- Sentiment scores: polarity and subjectivity by TextBlob
- Topic distribution: the probabilistic distribution of news content by Latent Dirichlet Allocation (LDA)

Textual features by represent methods

- GloVe embeddings: represent each word with a 100d vectors
- Compressed features: compress the 100d vectors into 1d by CNN autoencoder

Methodology



Granger test for feature selection

- A linear model with lag terms of two time series
- To find feature that Granger cause the electricity demand with hypothesis

> Forecasting models and evaluation

- Long Short-Term Memory (LSTM) Networks, ExtraTrees, etc
- Deterministic and Probabilistic forecasting
- Day-ahead forecasting with hourly data



Datasets and experiments

Deterministic forecasting

Probabilistic forecasting

Electric load data





News text data

Results





Experiments

- Benchmark model
 - Official benchmark ENTSO-E
 - ExtraTrees regression
 - LSTM •
- Deterministic forecasting
 - Model with separate and ٠ combination textual features

Probabilistic forecasting

- Evaluation on quantiles (Pinball loss)
- prediction intervals (Winkler score)
- forecasting distributions (CRPS)





Benchmark models

Models with textual features

Models	RMSE(MW)	MAE(MW)	SMAPE(%)
ENTSO-E	2800.50	2544.86	7.65
ExtraTrees	2800.77	2374.07	7.29
LSTM	2775.99	2333.20	7.10

ENTSO-E: official benchmark **ExtraTrees**^[1]: 1000 estimators **LSTM**^[2]:

- 1 layer with 24 neurons;
- fully-connected layer(24d 48d);
- in loss function, Mean Squared Error (MSE) for deterministic forecasting, and Pinball loss for quantile forecasting;
- batch size: 4;
- learning rate: 1e-4;
- Optimizer: Adam with an early stopping mechanism

Models	RMSE(MW)	MAE(MW)	SMAPE(%)
LSTM	2775.99	2333.20	7.10
LSTM+count features	2789.98	2348.56	7.14
LSTM+word frequencies	2915.02	2486.79	7.60
LSTM+sentiments	2834.95	2398.65	7.29
LSTM+topic distributions	2832.50	2394.67	7.26
LSTM+GloVe embeddings	2773.11	2319.20	6.99
LSTM+S+G	2732.44	2299.20	6.99
LSTM+S+G+CG	2692.33	2248.55	6.83

S: sentiments

G: GloVe embeddings **CG:** 1d CNN compressed vector of GloVe embeddings

[1] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Machine learning*, vol. 63, no. 1, pp. 3–42, 2006.
[2] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.





Deterministic forecasting

Probabilistic forecasting

LSTM results with and without textual features



- Grouped forecasting errors
- Solid lines are with textual features, dashed lines are benchmark.

Remarks:

- Higher errors in the morning are with a high level of human activity.
- The improvements in the morning are more than 5%.

Important features:

- Sentiments: the minimum subjectivity value
- GloVe embeddings: weapons, transportation, and military dimensions.
- Compressed GloVe embeddings.





> Pinball loss

Text information improves forecasts on lower quantiles, indicating the ability to extreme events.

> Winkler score

Text information narrows the 80% confidence intervals in the morning, afternoon, and evening, and brings more reliability.

> CRPS

Text information brings the forecasting distribution closer to the real one, especially in the morning.



Conclusions

• Text helps forecasting.

The textual features improve 3% from the LSTM benchmark on the average.

Text has persistent trends.

LSTM utilizes longer history of text, improving forecasting with public sentiment and more high-dimensional word representations in the news.

• Compressed textual features are with potential forecasting ability.

CNN autoencoder is used to obtain a more dense representation from word embeddings, improving the model forecasting skills.

Text enhances the forecasting reliability.

Selected textual features improve forecasting at low quantiles, narrow the confidence intervals, and bring the forecasting distribution closer to the real one.

• Future work

Text from social media, multi-lingual senarios, multiple forecasting horizons, more granular level, etc.

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