Ensemble Deep Learning for Forecasting ^{222}Rn Radiation Level at Canfranc Underground Laboratory

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Introduction

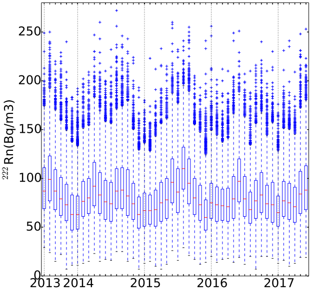
- **Ensemble Deep Learning Architectures** have demonstrated to improve the performance in comparison with the individual architectures composing the ensemble.
- In the current work, an ensemble of variants of Convolutional and Recurrent Neural Networks architectures are applied to the prediction of the ^{222}Rn **level** at the Canfranc Underground Laboratory (Spain).
- To **predict the low-level periods** allows appropriately scheduling the maintenance operations in the experiments hosted in the laboratory.

Materials and Methods

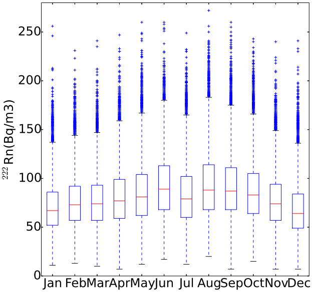
LSC

ArDM Experiment

Data



(a)



(b)

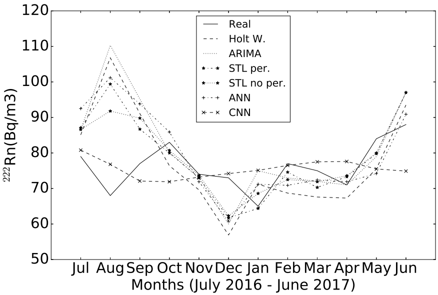
Figure: Monthly box-plots of ^{222}Rn level at Hall A of the LSC, by year (Fig. 1(a)) and gathering the months independently of the year (Fig. 1(b)). Data taking corresponds to the period from July 2013 to June 2017.

Data

- Alphaguard P30 in each hall recording the radioactivity level every 10 minutes, with an accumulated record from July 2013 to June 2017 —comparison with HAIS'18 work—.
- With regard to the measurements, few missing values are in the data set, as well as gaps of several days in some years. The larger gaps appear in July 2014 with 913 missing values, in June 2015 with 1053, and in January 2016 with 585. In the worst case, the gap spans over a week (7.3 days). However, the missing values are not representative in comparison with the total number of observations (more than 200,000), nor the number of observations per month ($\approx$ 4,000).
- ^{222}Rn time series is very noisy. Only the monthly median exhibits a certain modulation.
- Therefore, the monthly medians of the ^{222}Rn level has been selected as the monthly representative value. This critically penalizes the data volume accessible, reducing it to 48 values.

Previous effort at HAIS'18

- The training set —the three firsts years, from July 2013 to June 2016—, and the testing set the last twelve months, from July 2016 to June 2017.



Modelling and Forecasting of the ^{222}Rn Radiation Level Time Series at the LSC. *HAIS* 2018

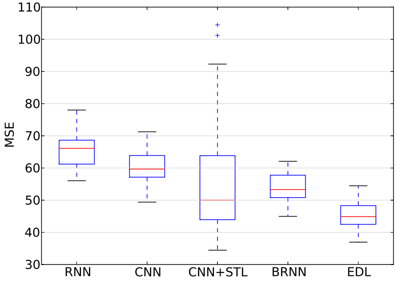
Previous and current efforts

- In *HAIS'18*, forecasting using non-stochastic methods —such as ARIMA, Holt-Winters Exponential Smoothing and Seasonal and Trend Decomposition using Loess—, plus ANN and CNN.
- In (in detail exploration) *SOCO'19*, forecasting using an ensemble deep learning with Recurrent Neural Networks, Bidirectional Recurrent Neural Networks, Convolutional Neural Networks and STL Convolutional Neural Networks.
- STL+CNN was presented in *CAEPIA'18*. STL decomposed time series is independently predicted with CNN.

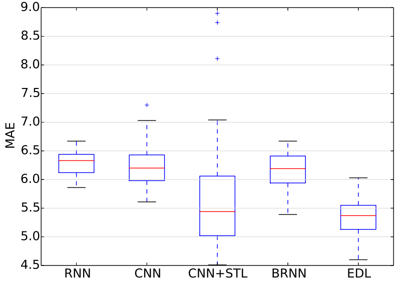
Current efforts

- CNN and CNN+STL: two layers 32 and 64 filters with `relu`, `MaxPooling1D` with size 2, and an output a dense layer with a single neuron with linear activation function, and trained with 10 epochs.
- BRNN: single hidden layer with 24 LSTM elements and trained with 100 epoch. Hyperbolic tangent as activation function, output a single dense layer of a neuron with linear activation function.
- In all the algorithms, the loop-back parameter is configured to 12 values of the time series, the Mean Squared Error has been selected as the `loss function`, and the weights are optimized by using `Adam optimizer`.

Experimental Results



(a) MSE



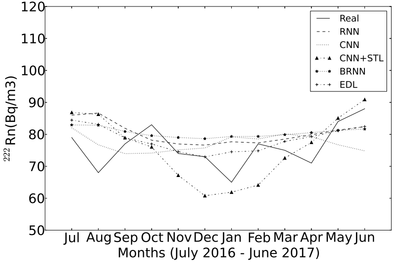
(b) MAE

Figure: Mean Squared Error (MSE) and Mean Absolute Error (MAE) for the deep architectures evaluated for 25 independent runs.

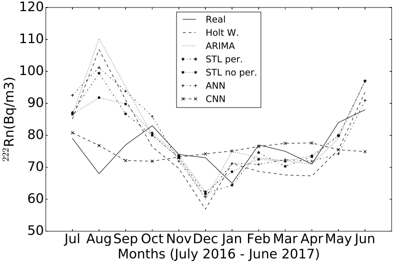
Table: Mean Squared Error (MSE) and Mean Absolute Error (MAE) for the deep architectures evaluated for 25 independent runs.

	MSE	MAE
RNN	65 ± 6	6.3 ± 0.2
CNN	60 ± 5	6.2 ± 0.4
CNN+STL	54 ± 5	5.8 ± 1.2
BRNN	54 ± 5	6.1 ± 0.3
EDL	45 ± 4	5.3 ± 0.4

The application of the Kruskal-Wallis test to the MSE and the MAE indicates that the differences between the medians are significant for a confidence level of 95% (p-value under 0.05).



(a) Forecast from SOCO'19



(b) Forecast from HAIS'18

Figure: Real values and forecasting for the test set —the fourth year, from July 2016 to June 2017— for the methods used in SOCO'19 (Fig. 3(a)), and for the methods used in HAIS'18 (Fig. 3(b)).

Conclusions and Future Work

Conclusions

- We used an Ensemble Deep Learning (CNN, RNN, BRNN, CNN+STL) to successfully improve the forecasting capacity of the ^{222}Rn level at LSC.
- It has been proved that the improvements are statistically significant.
- On-going work. Update data set, make predictions, communicate to LSC and hosted experiments, integrate in LSC communications.
- Can we manipulate the loss function for better forecasting low-activity periods?

Thanks

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Questions?

More questions?