FORECASTING POWER SYSTEM FLEXIBILITY REQUIREMENTS : A HYBRID DEEP-LEARNING APPROACH

5TH AIEE SYMPOSIUM – SESSION 8 : THE PRICE AND FORECASTING IN POWER SYSTEM

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- Variable and Renewable Energies (VRE) capacities are developing fast among power systems and the future evolution of electricity consumption is uncertain

- New flexibility mechanisms and technologies are expected for the coming decades : electricity storage, capacity markets, Power-to-X, …

- Electricity generation is more and more decentralized, consumption highly depend on local variables (weather, economy,…), and more and more energy policies are designed locally

1. Can deep-learning methods be useful to forecast a power system flexibility requirements ?

- Propose an empirical framework (CEEMDAN-ConvLSTM-2D) for power system flexibility requirements assessment and forecasting

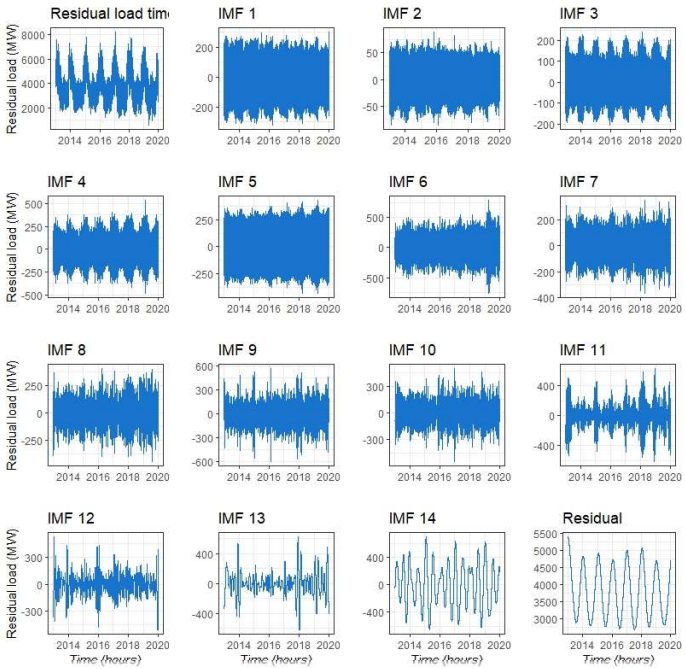
- Use this framework on a local power system, and compare the results with traditional ARIMA forecasting framework

- Build a realistic scenario for French region Occitanie power system flexibility requirements of 2020

- A widely used approximator for flexibility requirements is the Residual Load function (*Wagner A. [2012] ; Holttinen et al. [2013] ; Villar J. et al. [2018]*) :

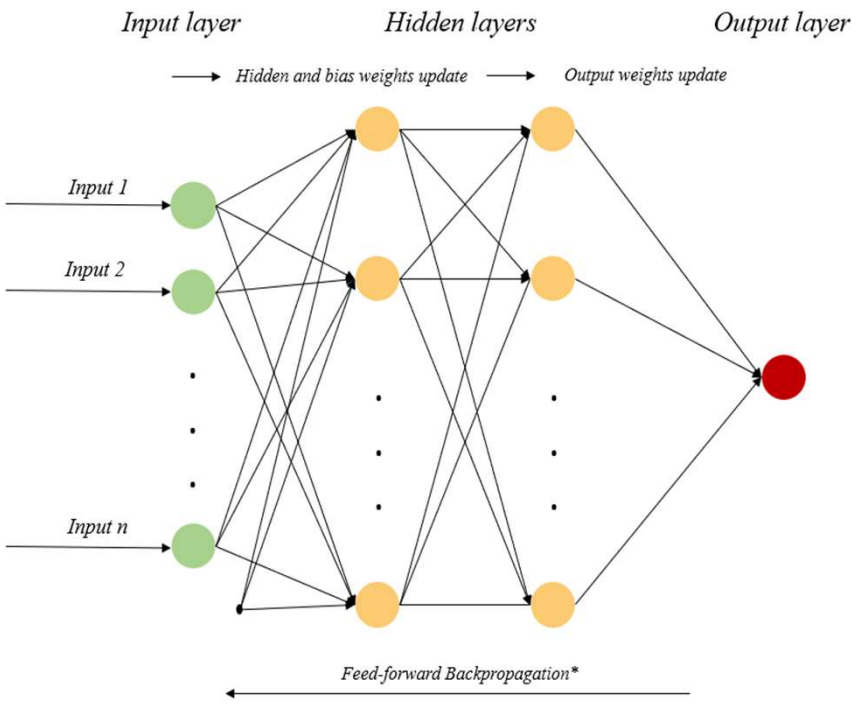
$$Residual\ load = Consumption\ - (Wind\ power\ generation + Solar\ PV\ production)$$

- Residual Load time-series can be used to investigate the different temporal aspects of flexibility requirements



2013-2019 Occitanie Residual Load and CEEMDAN-decomposed IMFs and residual

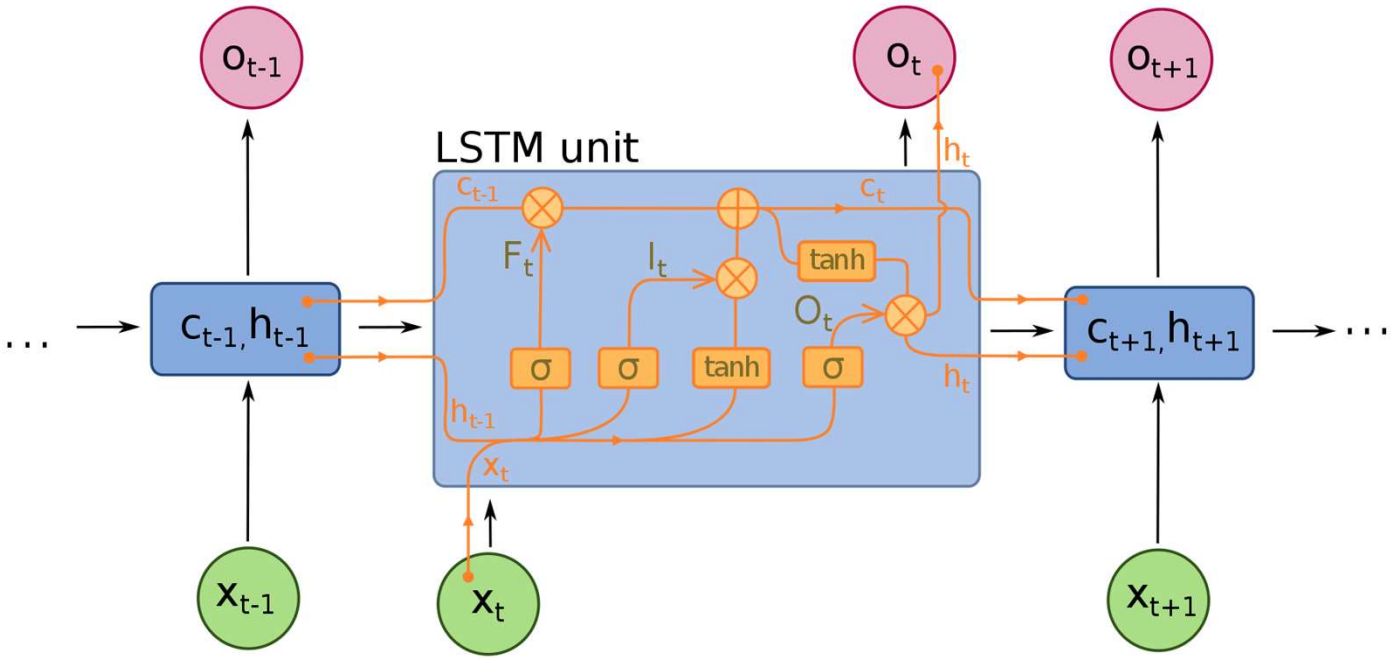
- Intrinsic Mode Functions (IMFs) extracted using a noise-augmented local extrema based-decomposition (CEEMDAN) are stationary around their mean (*Huang E. N. et al. [1998] ;Wu Z. et Huang E. N. [2009] ; Torres M. et al. [2011]*)



Typical architecture of a fully connected two hidden layered ANN.

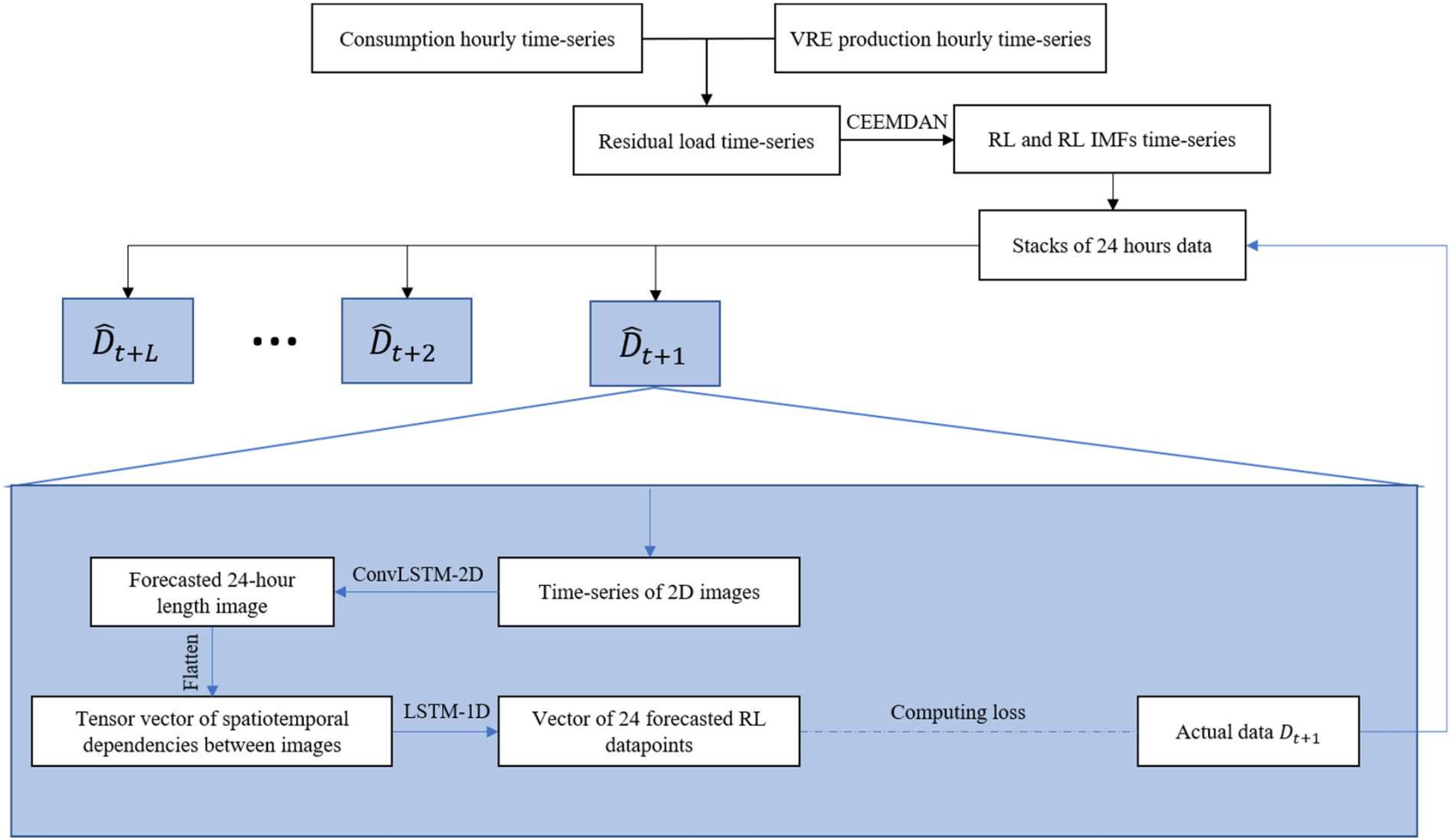
- Artificial Neural Networks (ANN) is a class of universal approximator models which architecture mimic a mammal brain (*neurons* organized in *layers* connected via *weights vectors*)

- Recurrent Neural Networks (RNN) are ANN specifically designed to handle sequential data like time-series and can perform *sequence-to-sequence* forecasting



Architecture of a LSTM unit

- LSTM units make the ANN able to « *remember* » both distant and recent past information (*Hochreither S. et Schmidhuber J. [1997]*)
- A LSTM network can also include convolution operators to *visually learn* patterns in data (ConvLSTM) (*Shi X. et al. [2015]*)


Consumption hourly time-series
VRE production hourly time-series
Residual load time-series
CEEMDAN
RL and RL IMFs time-series
Stacks of 24 hours data
$\widehat{D}_{t+L}$
$\widehat{D}_{t+2}$
$\widehat{D}_{t+1}$
Forecasted 24-hour length image
ConvLSTM-2D
Time-series of 2D images
Flatten
Tensor vector of spatiotemporal dependencies between images
LSTM-1D
Vector of 24 forecasted RL datapoints
Computing loss
Actual data D_{t+1}

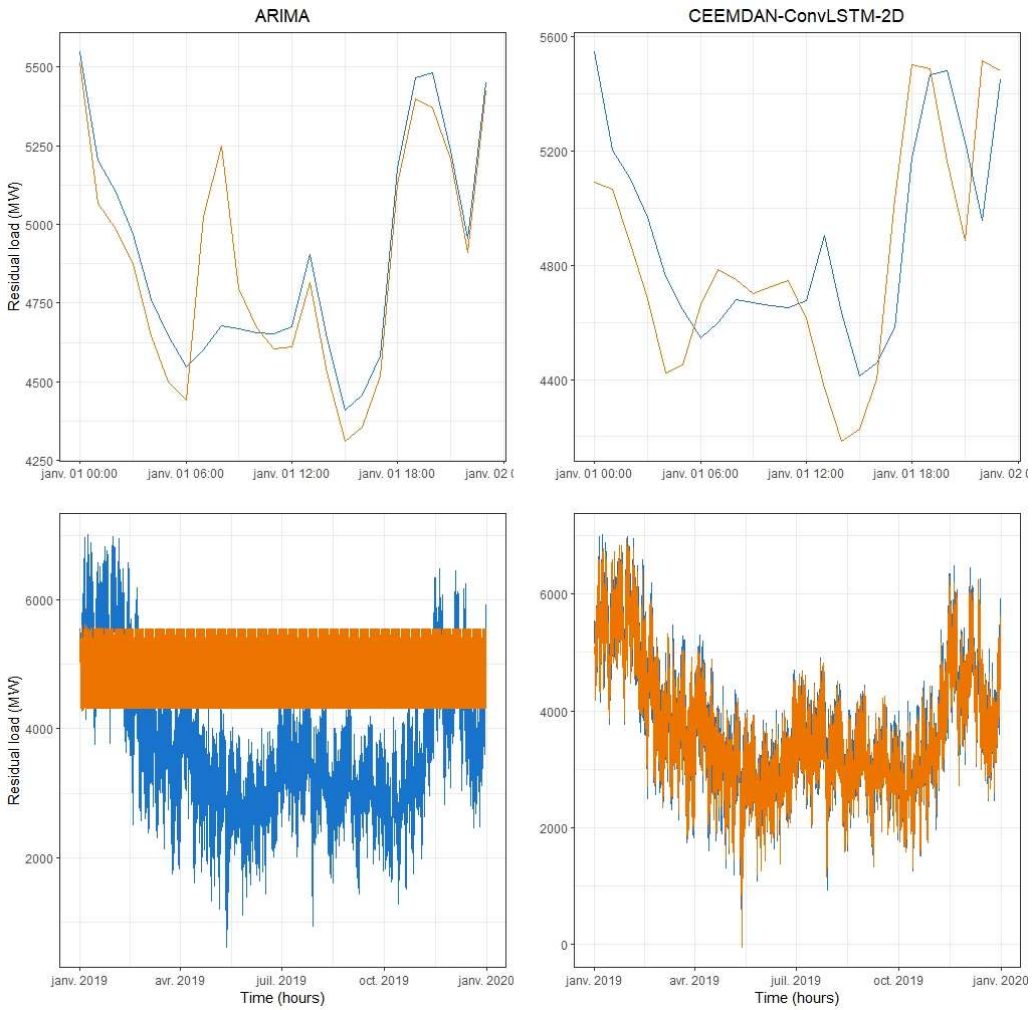
- We use data from French grid operators open-data platform : https://opendata.reseaux-energies.fr/pages/accueil/

- We selected the French region Occitanie as the geographical perimeter for our application, and use hourly consumption and VRE output time-series between 2013 and 2019

- An 85%-15% ratio is chosen to split our dataset into training and testing sets

Time-series	Unit	Length	Min.	Max.	Mean	Median	Std. Dev.
Consumption	MW	61 322	2 167	8 488	4 286.86	4 099	1 045.98
Wind production	MW	61 322	0	1 331	316.08	264	257.30
PV production	MW	61 322	0	1 568	205.86	2	314.79
Residual Load	MW	61 322	612	8 196	3 764.93	3 553	1 079.45

Descriptive statistics of Occitanie historical flexibility variables between 2013 and 2019



Forecasting results of ARIMA (left) and CEEMDAN-ConvLSTM-2D (right) frameworks for January 1rst (up), 2019 and the whole year 2019 (bottom).

	Forecasting horizon			
	01/01/2019 23 : 00		30/12/2019 23 : 00	
Framework	MAPE	RMSE (MW)	MAPE	RMSE (MW)
ARIMA	2,43%	168,81	48,34%	1 586,14
CEEMDAN-ConvLSTM-2D	3,79%	260,33	3,02%	137,12

Performance metrics of Occitanie Residual Load forecasting of ARIMA and CEEMDAN-ConvLSTM-2D frameworks for January, 1rst 2019 and for the whole year.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

- The goal of the proposed methodology is to forecast the flexibility requirements of a given power system at multiple timescales.

- Using Occitanie historical load and VRE production hourly time-series from 2013 to 2018, we train a model able to forecast the next full-day of the power system' residual load with a MAPE score of 3,79%.

- The full-year of RL forecast is given here to assess the long-term behavior of our model in terms of forecasting performances and to illustrate the use of *sequence-to-sequence* forecasting.

- In an out-of-sample forecasting context, the model undergoes the same error propagation issue as traditional statistical models.

- The sequence-to-sequence framing allows the model to use new incoming data to forecast the next days without having to be trained againg, which has a very practical value for electricity system players (TSO, DSO, producers, decision-makers…)

- As a purely empirical time-series forecasting framework, the CEEMDAN-ConvLSTM-2D methodology should be tested on other time-series data to assess its potential as universal approximator

Thank you for your attention.

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LSTM unit equations :

$$f_t = \sigma(W_{f,x}x_t + W_{f,h}h_{t-1} + W_{f,c} \circ C_{t-1} + b_f)$$

$$i_t = \sigma(W_{i,x}x + W_{i,h}h_{t-1} + W_{i,c} \circ C_{t-1} + b_i)$$

$$\tilde{C}_t = tanh(W_{c,x}x_t + W_{c,h} \circ h_{t-1} + b_i)$$

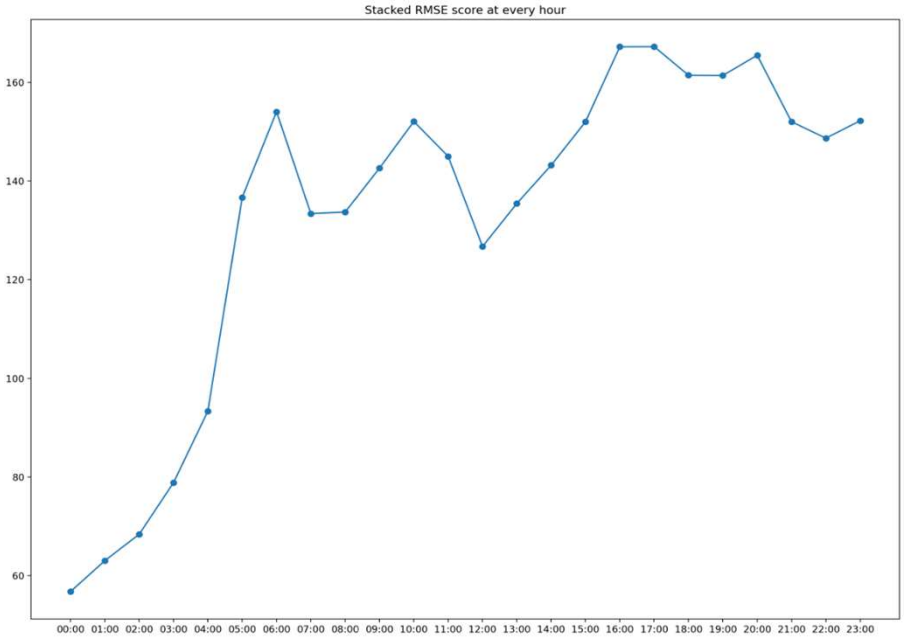
$$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t$$

$$o_t = \sigma(W_{o,x}x_t + W_{o,h}h_{t-1} + W_{o,c} \circ C_t + b_o)$$

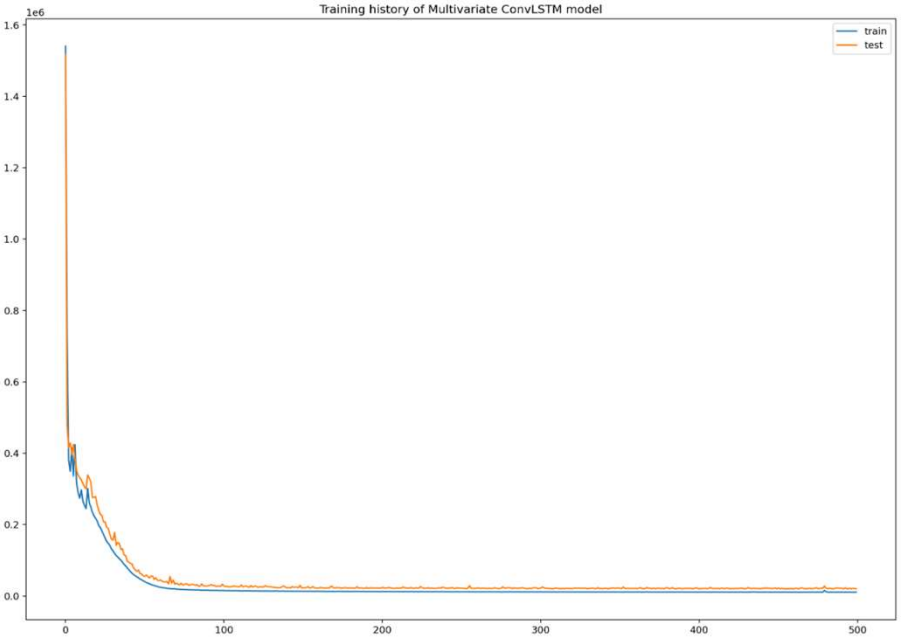
$$h_t = o_t \circ \tanh(C_t)$$

With:

- f_t the forget gate activation values
- x_t values of data at time t
- $W_{f,x}$ values of the weights vector connecting the input and the hidden layer
- h_t the output values of the hidden layer
- $W_{f,h}$ values of the weights vector connecting the hidden layers
- C_t the memory cell state
- $W_{f,c}$ the values of the weights vector connecting neurons inside the memory cell
- b_f the value of forget gate bias vector
- i_t the input gate activation values
- b_i the value of the input gate bias vector
- o_t the output gate activation values
- b_o the value of the output gate bias vector
- σ a sigmoid activation function
- $\tanh$ a hyperbolic tangent activation function



Hourly average RMSE for the whole predicted days



Learning curves (i.e. loss value with respect to training epochs) of the ConvLSTM-2D model