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DEEP LEARNING FOR FORECASTING THE ENERGY CONSUMPTION IN PUBLIC BUILDINGS

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Agenda

- Context and Motivation
- Objectives
- Related Work
- LSTM-based Method for Forecasting Energy Consumption
- Experimental Results
- Conclusions

Context and Motivation

- An increase of 50% in energy consumption is expected worldwide between 2018-2050
  - Major source of increase: countries with strong economic growth
- The electric energy is hard to store at a large scale and expensive to store at a small scale
- The forecasting of energy demand is important for the economical running of power plants
- Non-residential buildings are on average 40% more energy intensive than residential buildings

Objectives

- Develop a method based on deep learning for forecasting the energy consumption in public buildings by using past measurements
- Evaluate the method on a data set consisting of measurements taken every half an hour from a public building in United Kingdom
  - Use the mean absolute error and the mean absolute percentage error for measuring the prediction accuracy

Related Work

Ref.	Objective	Used algorithms	Features considered
[Ahmad2017]	Predict the HVAC system hourly energy consumption in a hotel	Random Forests and Feed-Forward Back-Propagation	Past energy consumption, weather data, occupancy rate
[Berriel2017]	Forecast the monthly energy consumption of residential, business, and industrial customers in Brazil	Fully Connected Neural Network, a CNN, and a LSTM network	Energy consumption in the previous 12 months
[Mocanu2018]	Forecast the energy consumption in households	Conditional Restricted Boltzmann Machine and Factored Conditional Restricted Boltzmann Machine	Energy consumption values collected at each minute over 4 years
[Tabasi2016]	Forecast the energy consumption in the industrial, residential, and transportation sectors	Linear regression	Per year GDP, population growth and industrial growth rate
[Braun2018]	Predict the energy consumption of a supermarket	Multiple linear regression	Energy consumption values and weather data

LSTM-based Method for Forecasting the Energy Consumption

- **Data Processing Steps**
  - Parse the data set and save the energy consumption measurements into a matrix and the timestamps into an array
  - Convert the timestamps into date and time objects
  - Build two matrices, containing
    - The neural network input as multidimensional input feature vectors
    - Energy consumption measurements used for error evaluation
- **Data Processing Cases**
  1) Separate the timestamp into four values: year, month, day, and half hour
  2) Enrich case 1 with seasonal data (i.e. day of the week, day of year, week of the year)
  3) Combine a regression-based approach with a time series forecasting method, by adding predictions from previous half hours as input features for the next half hour, in a sliding window manner

LSTM-based Method for Forecasting the Energy Consumption

- **Neural Network Training**
  - The data set has been split in training and testing sub-sets
  - For a given number of epochs, the network is trained and validated
  - Steps
    - Partition the training set into batches
    - For each batch, perform a forward and a back-propagation pass through the network
    - In the backpropagation pass, the Adam optimizer algorithm adjusts the weights of the network in order to minimize the (MAE) errors.
    - Compute the average of the errors for each batch to obtain the error on the training epoch, and then the trained neural network model is saved

LSTM-based Method for Forecasting the Energy Consumption

- **Neural Network Validation**
  - Since we use a sliding window method for solving the energy forecasting as a time series forecasting problem, the data subset used for validation has to start at the end of the training subset.
  - Takes each input example in turn
  - The validation example is fed to the network to obtain a predicted value, which is then normalized and included in the input data of the next input example.
  - The Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) are computed.
  - The overall error value on the whole validation subset is computed for the two error metrics.

LSTM-based Method for Forecasting the Energy Consumption

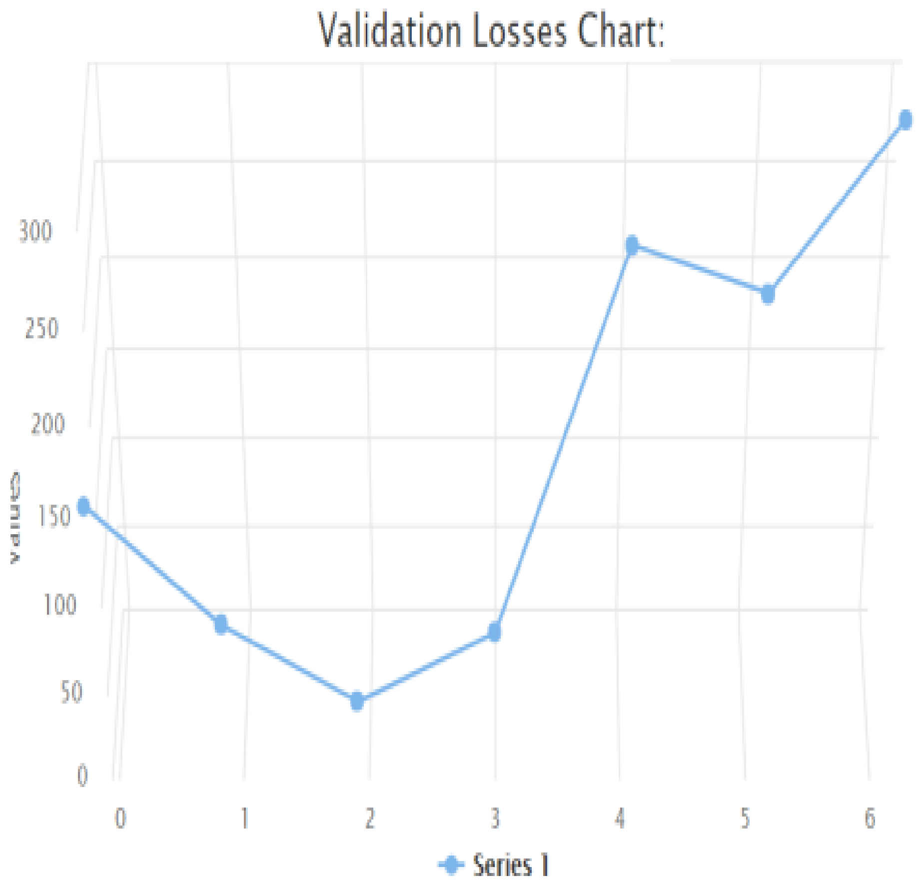
- **Forecasting the Energy Consumption**
  - Performed by using an already trained model.
  - The parameters (i.e. the weights) and the state of the network after a certain epoch are used for making predictions.
  - The forecasting can be made on a given horizon, where the starting point of the horizon must be the first validation example after the last training example.
- **Evaluating the Results**
  - Evaluation metrics considered: MAE and MAPE
  - The graphs generated during the training and validation process
    - the evolution of the MAE for the training step of each epoch
    - the evolution of the MAE and MAPE for the validation step of each epoch
    - the *actual measurements* of the energy consumption and the values of the *predicted consumption*

Experimental Results

- Evaluation dataset consisting of measurements taken every half an hour from the main building of the National Archives of the United Kingdom, in Kew
  - Each row represents a day of measurements
  - Each column represents the energy consumption for a given half an hour
- Best configuration of LSTM hyperparameters:
  - batch size = 10
  - number of layers = 3
  - sliding window size = 480
  - number of LSTM units per layer = 256

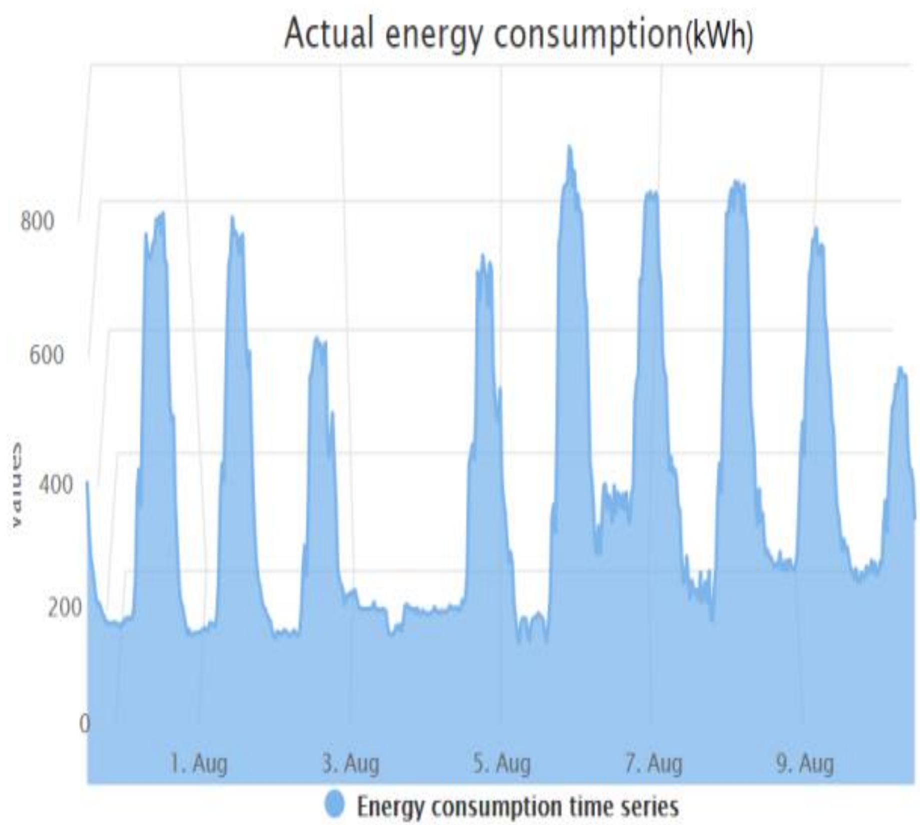
Experimental Results

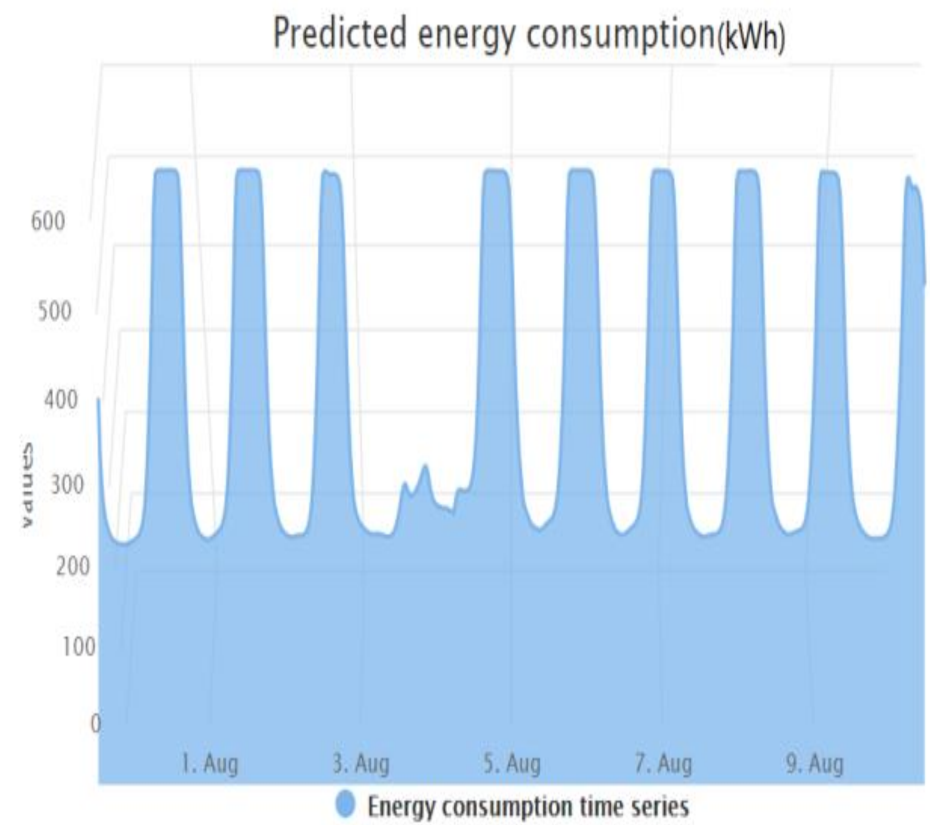
- Training and validation losses as tracked during the training process



Experimental Results

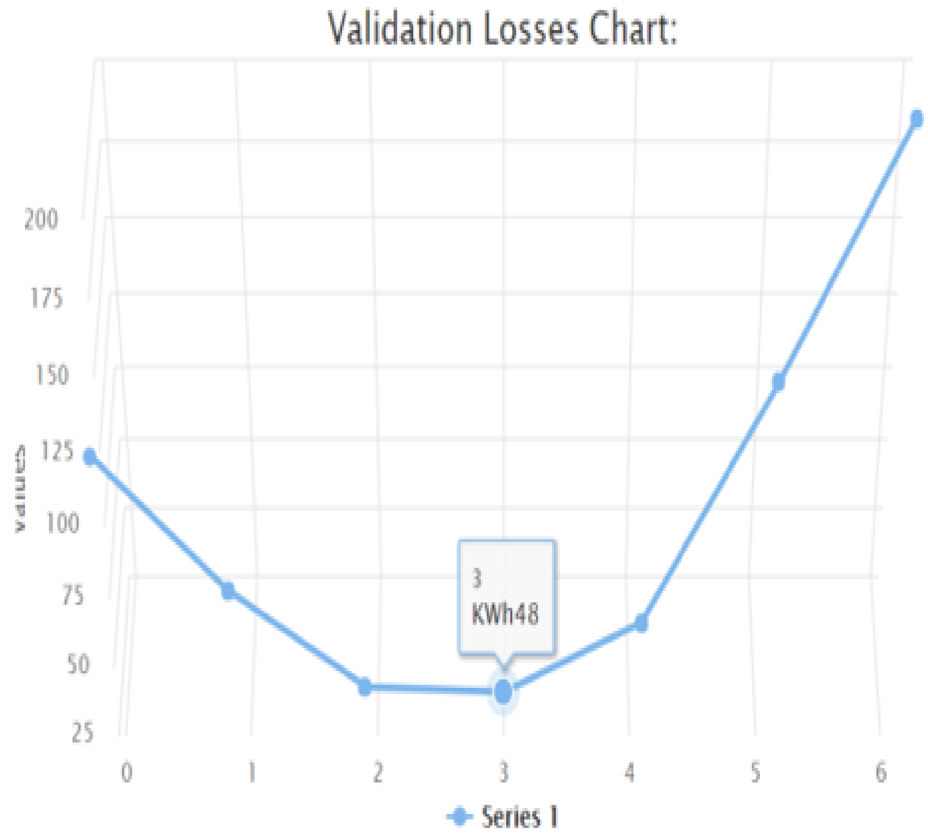
- The measured energy consumption and the predicted consumption for ten days (i.e. for 480 half hours)





Experimental Results

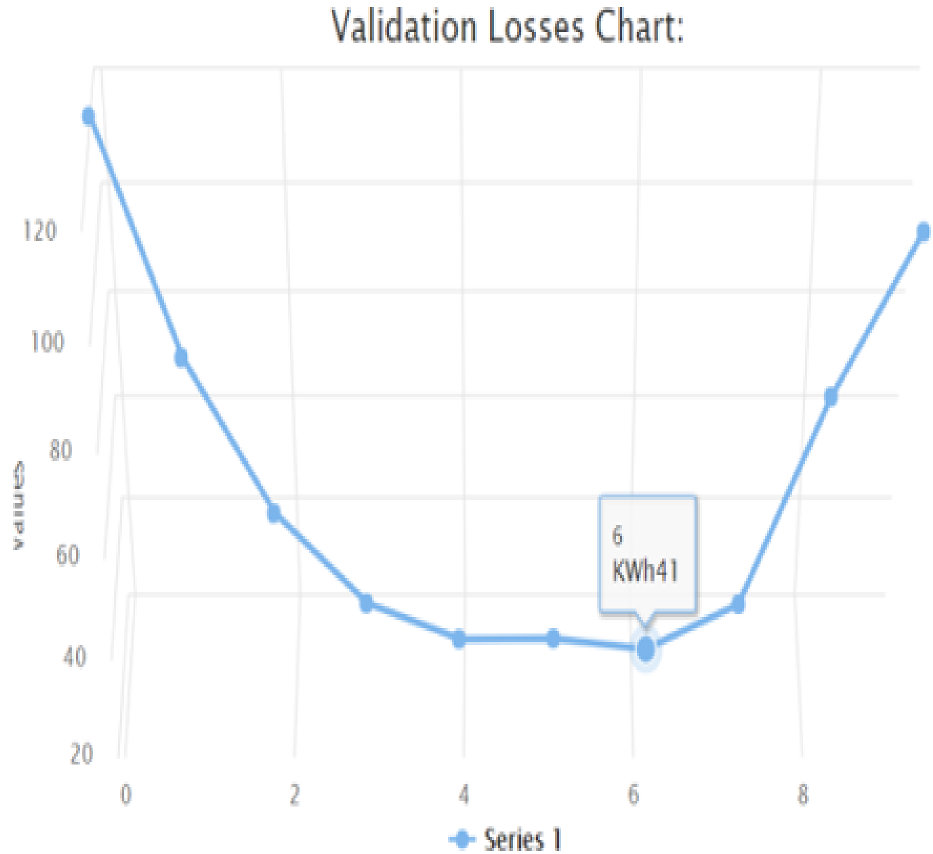
- Results obtained while increasing the sliding window size until the errors stop decreasing or even start to increase



Sliding window size of 960

Experimental Results

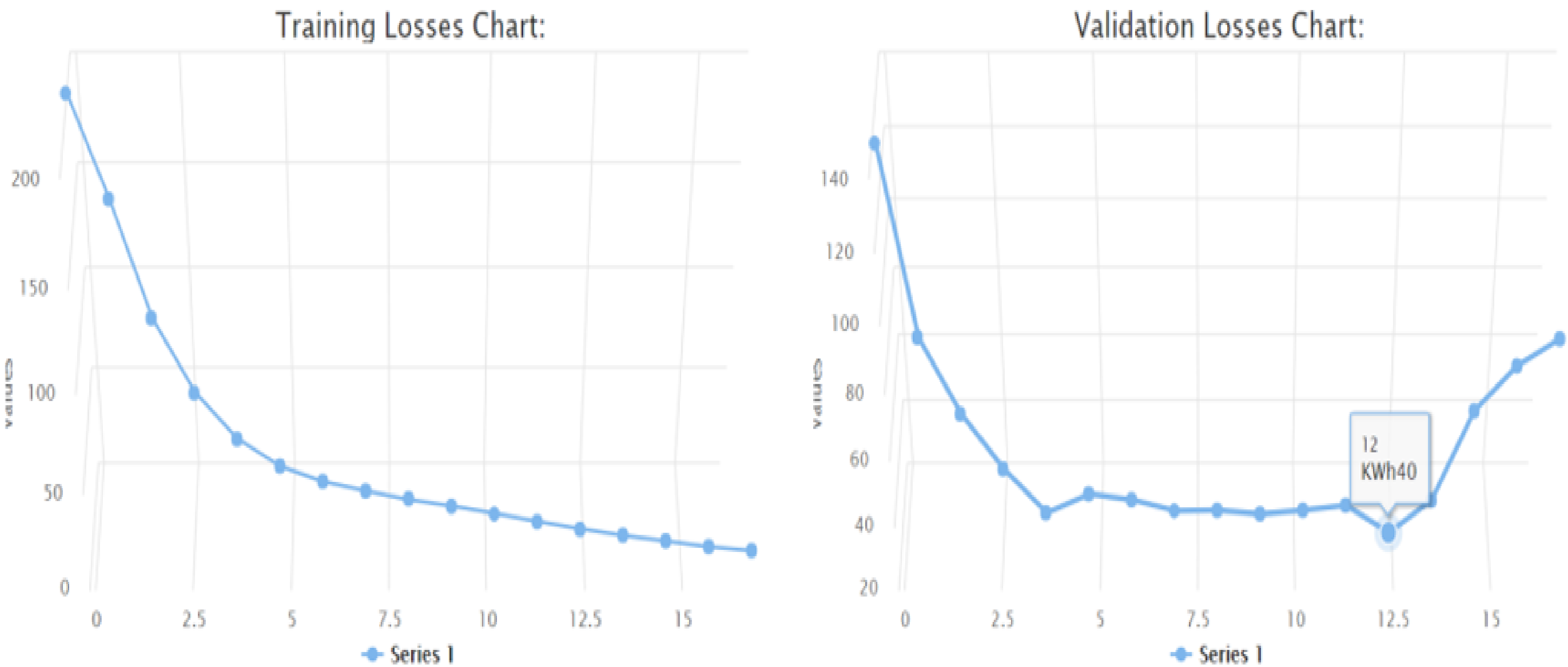
- Results obtained while increasing the sliding window size until the errors stop decreasing or even start to increase



Sliding window size of 1920

Experimental Results

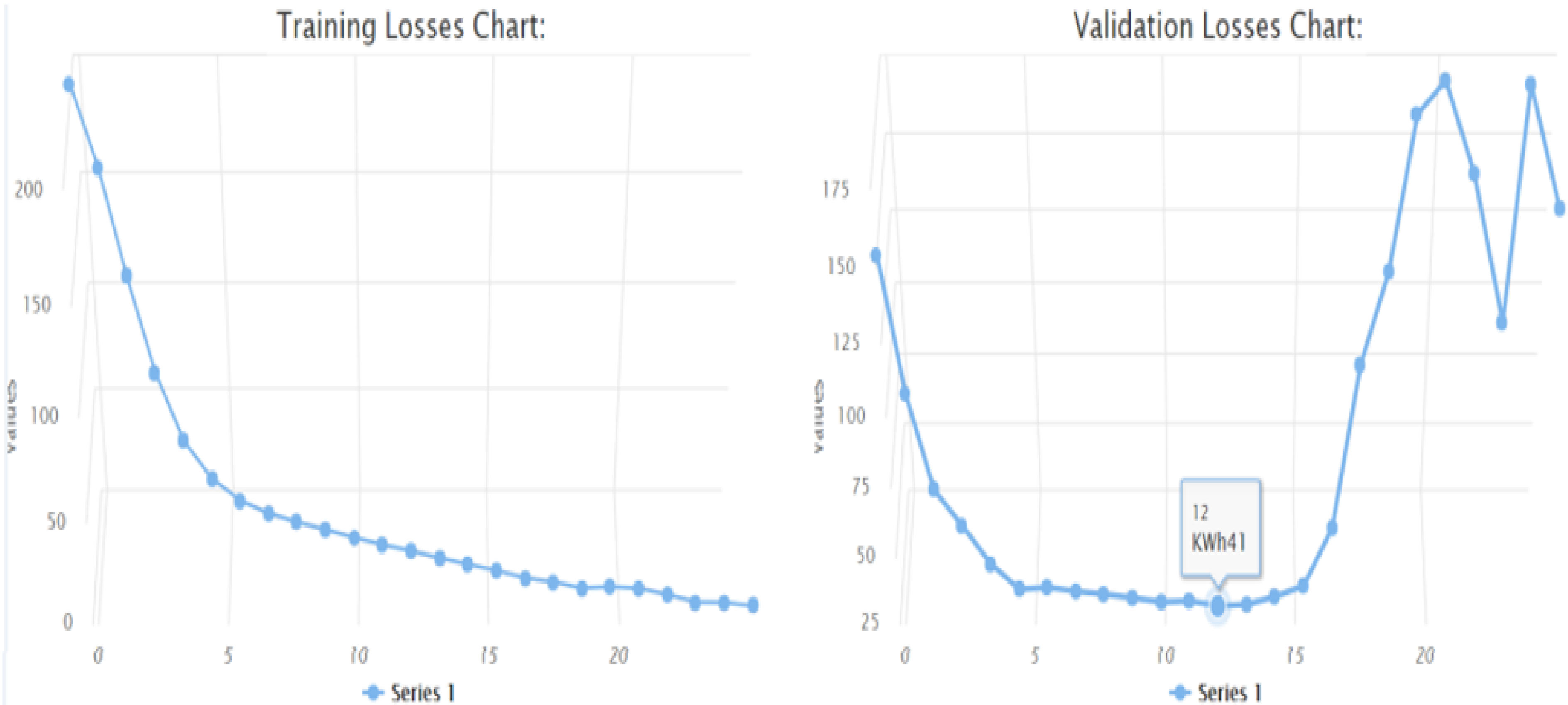
- It can be noticed that the minimal errors are obtained when using a window size of *3840 previous measurements* (on a half an hour basis)



Sliding window size of 3840

Experimental Results

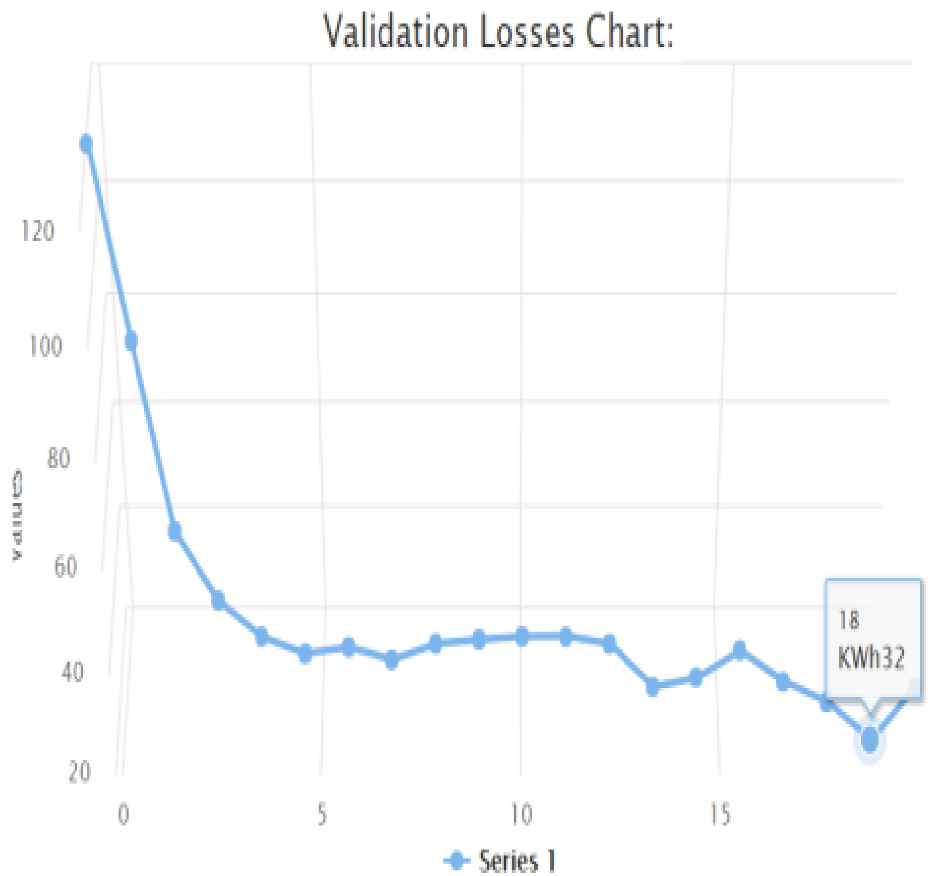
- Results obtained while increasing the sliding window size until the errors stop decreasing or even start to increase



Sliding window size of 4320

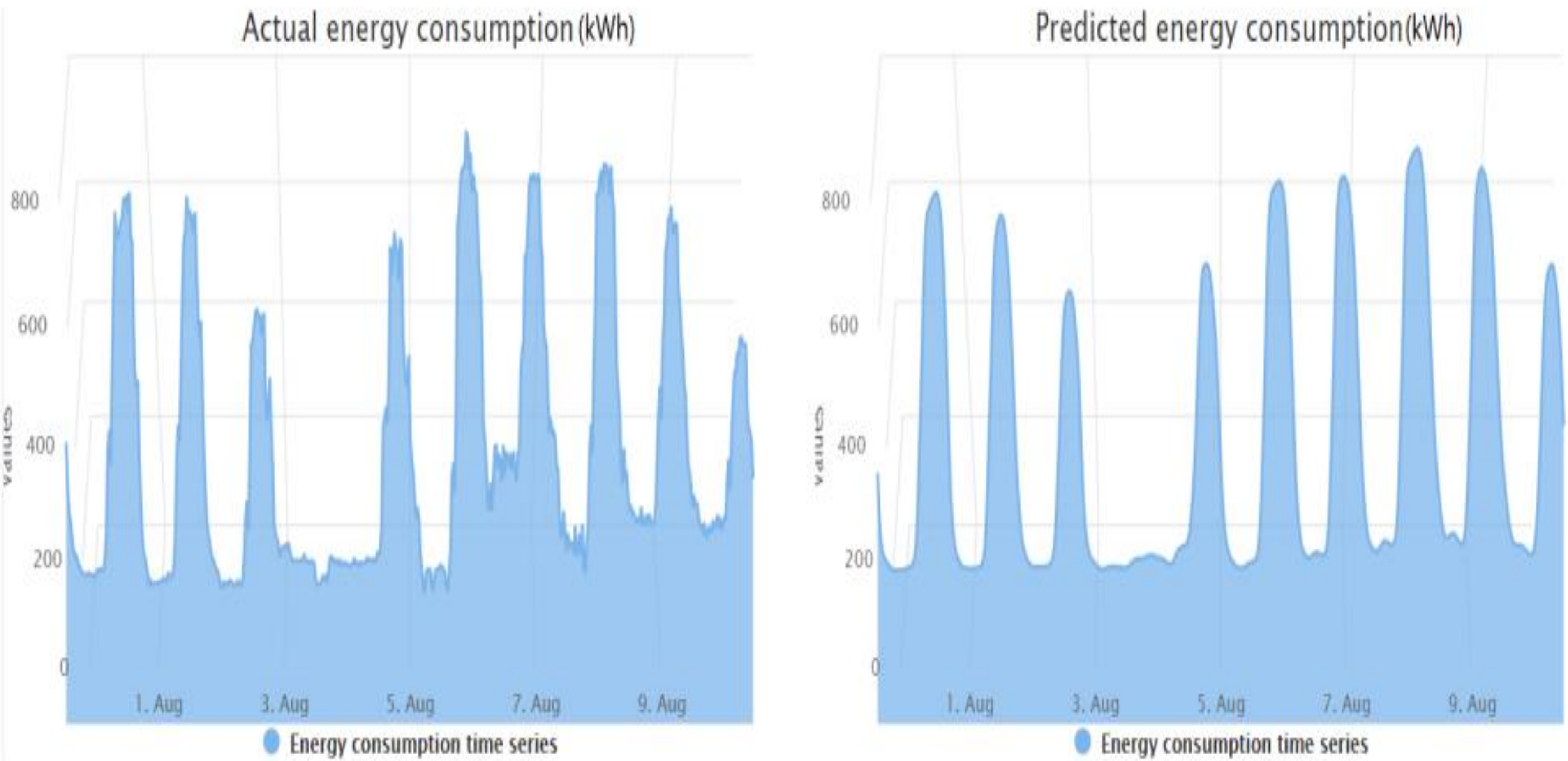
Experimental Results

- Results obtained when adding dropout layers between the LSTM layers – with *dropout keep probability* = 0.5 – a reduction of the MAE errors by about 25 percent



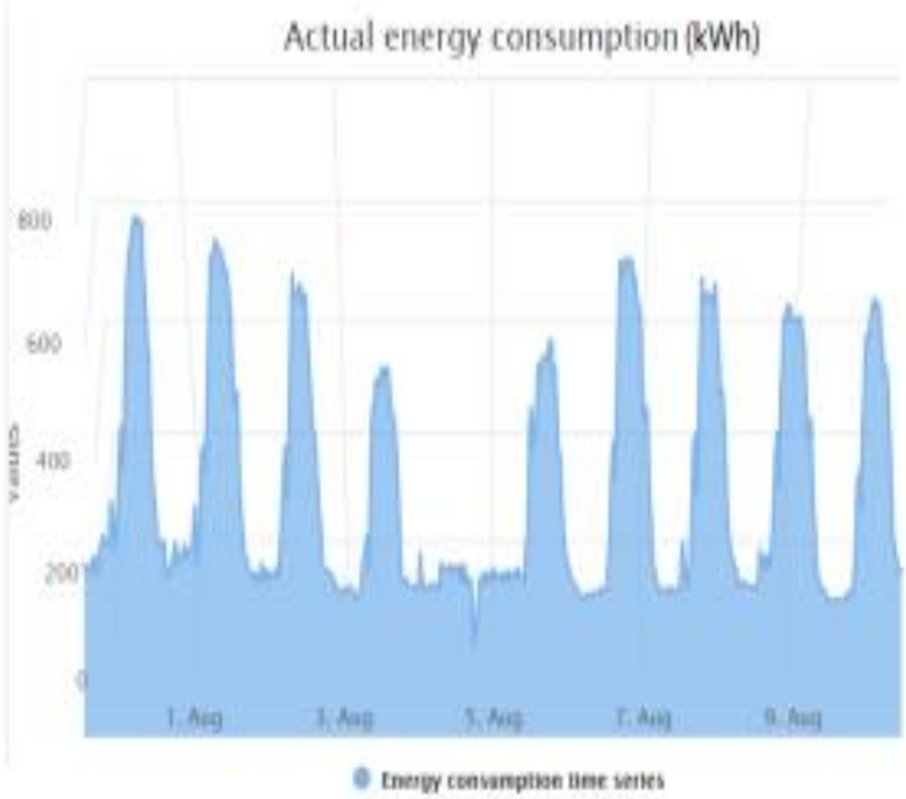
Experimental Results

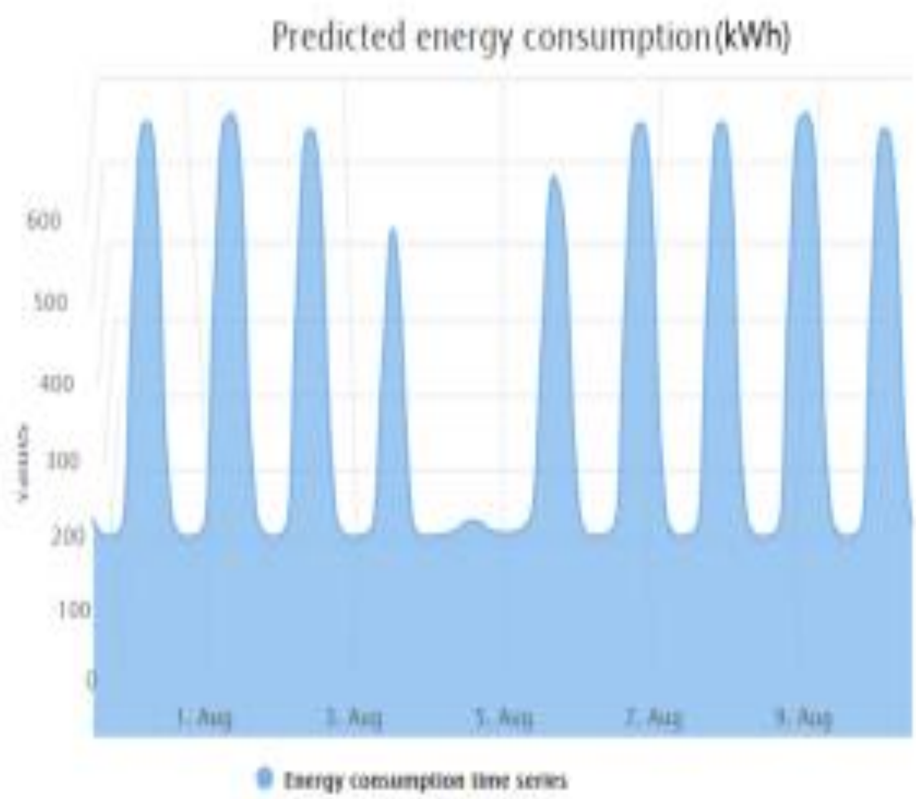
- Results obtained when adding dropout layers between the LSTM layers



Experimental Results

- Results obtained while tuning the size of the forecasting horizon

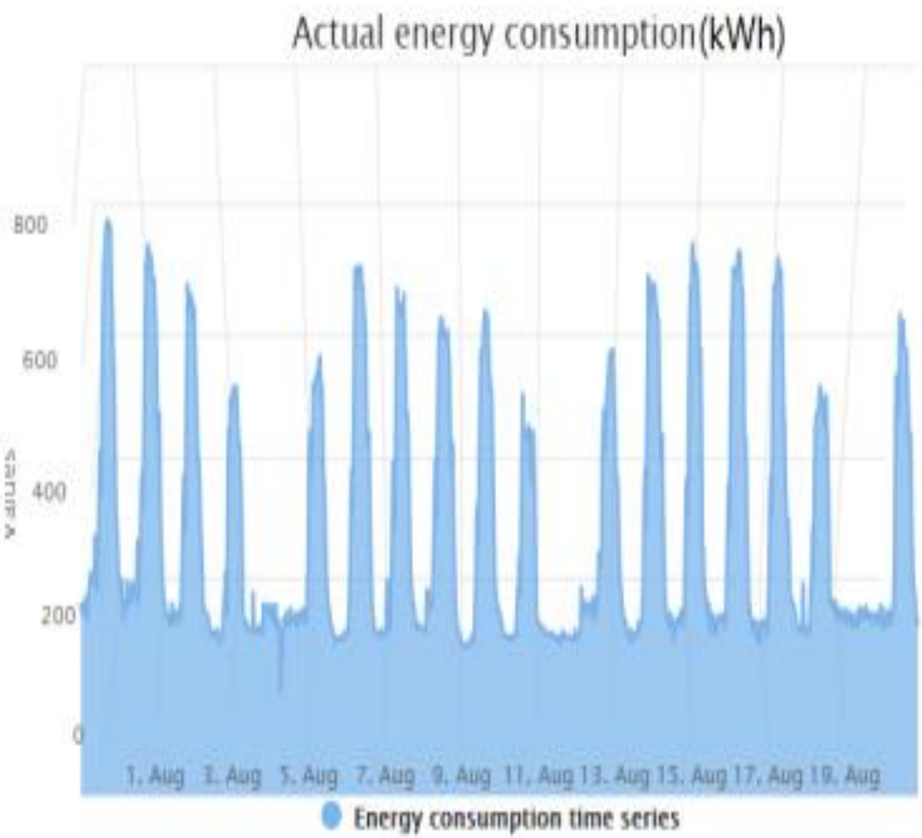


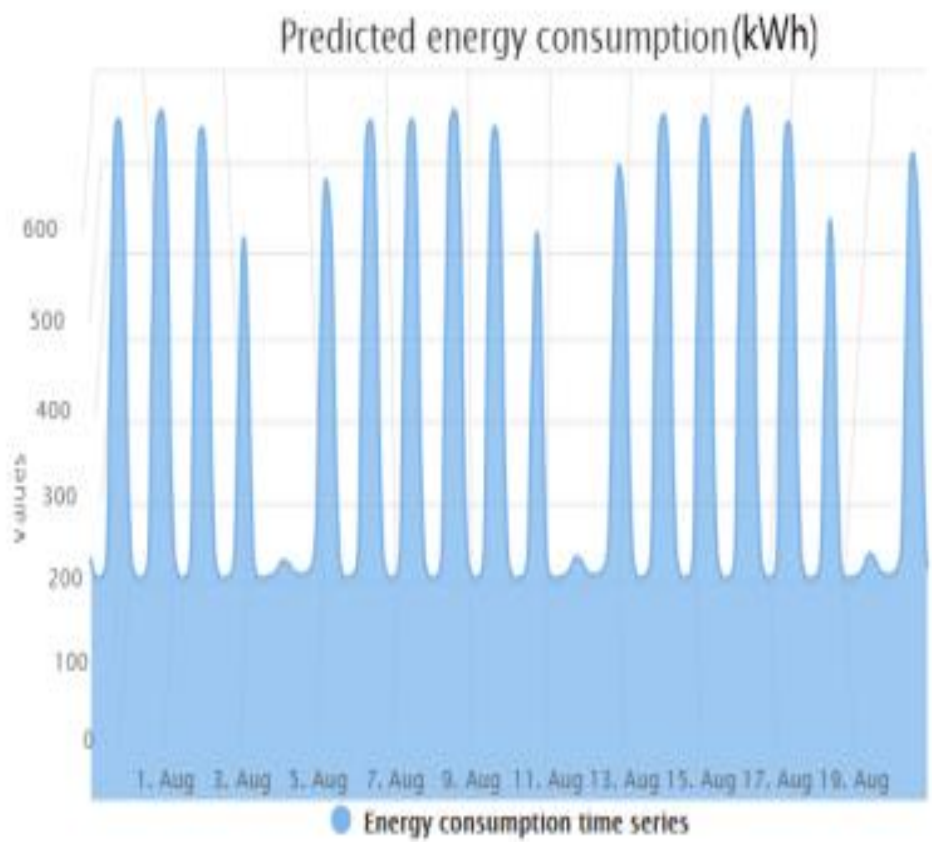


10 days forecasting horizon: MAE = 22.56; MAPE = 7.96

Experimental Results

- Results obtained while tuning the size of the forecasting horizon

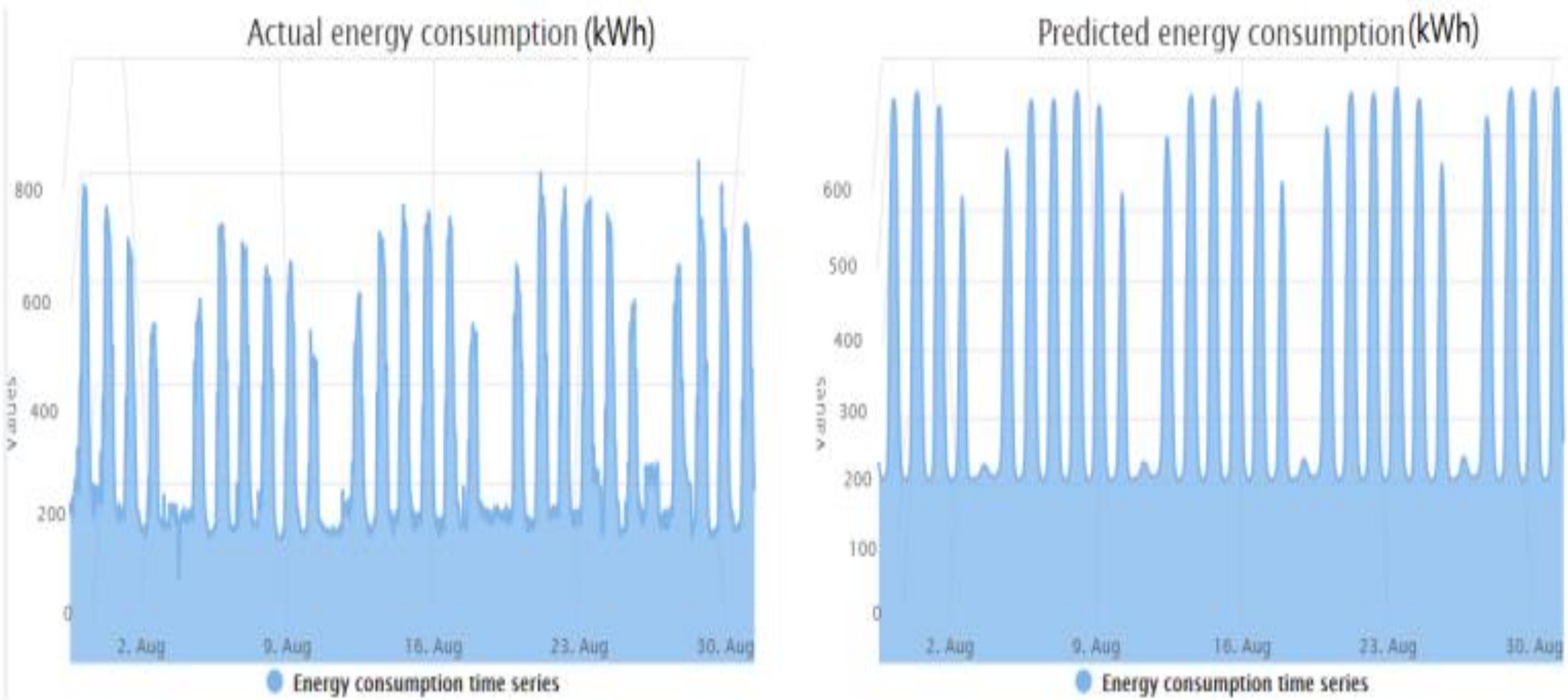




20 days forecasting horizon: MAE = 21.32; MAPE = 7.6

Experimental Results

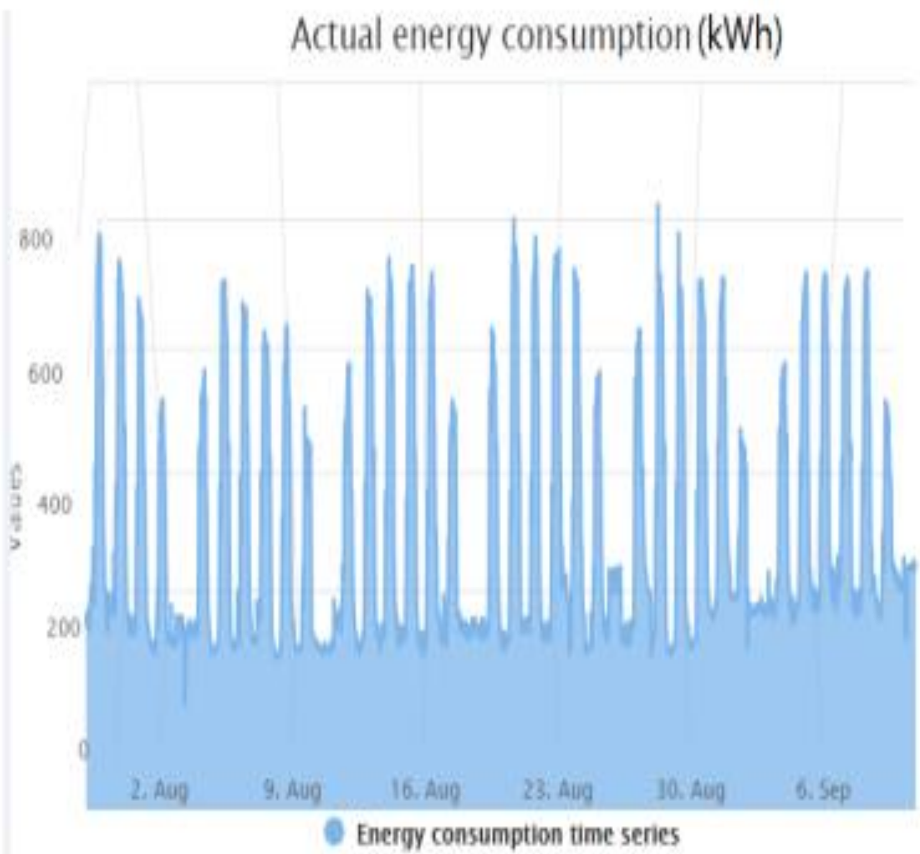
- Results obtained while tuning the size of the forecasting horizon

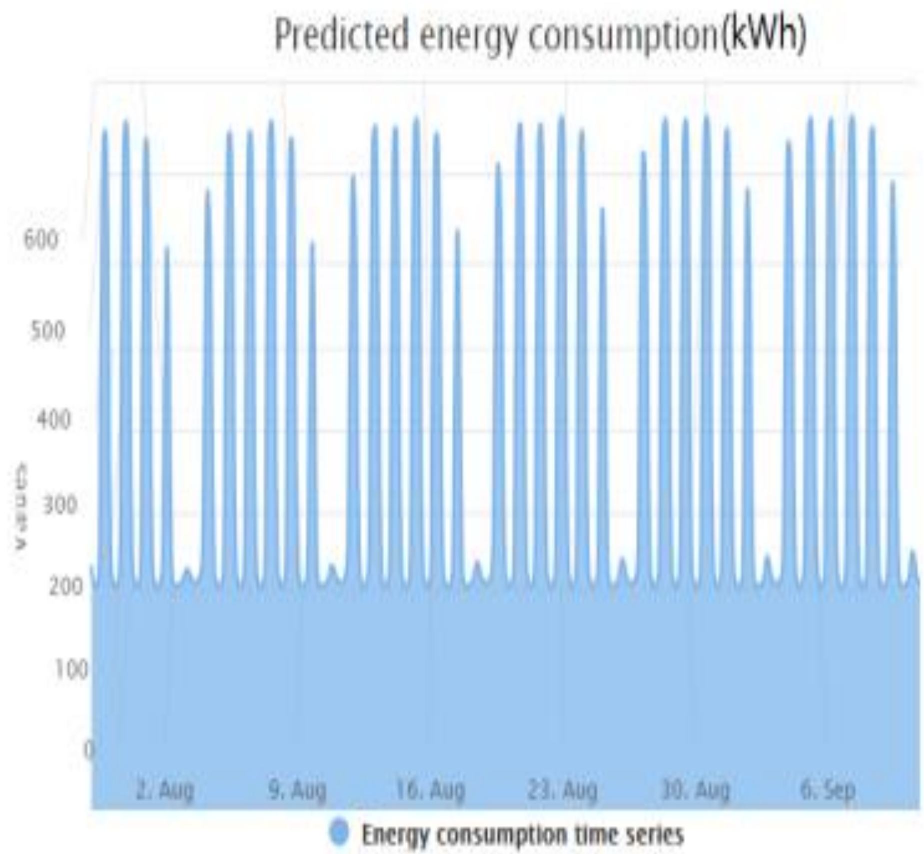


30 days forecasting horizon: MAE = 22.97; MAPE = 8.04

Experimental Results

- Results obtained while tuning the size of the forecasting horizon

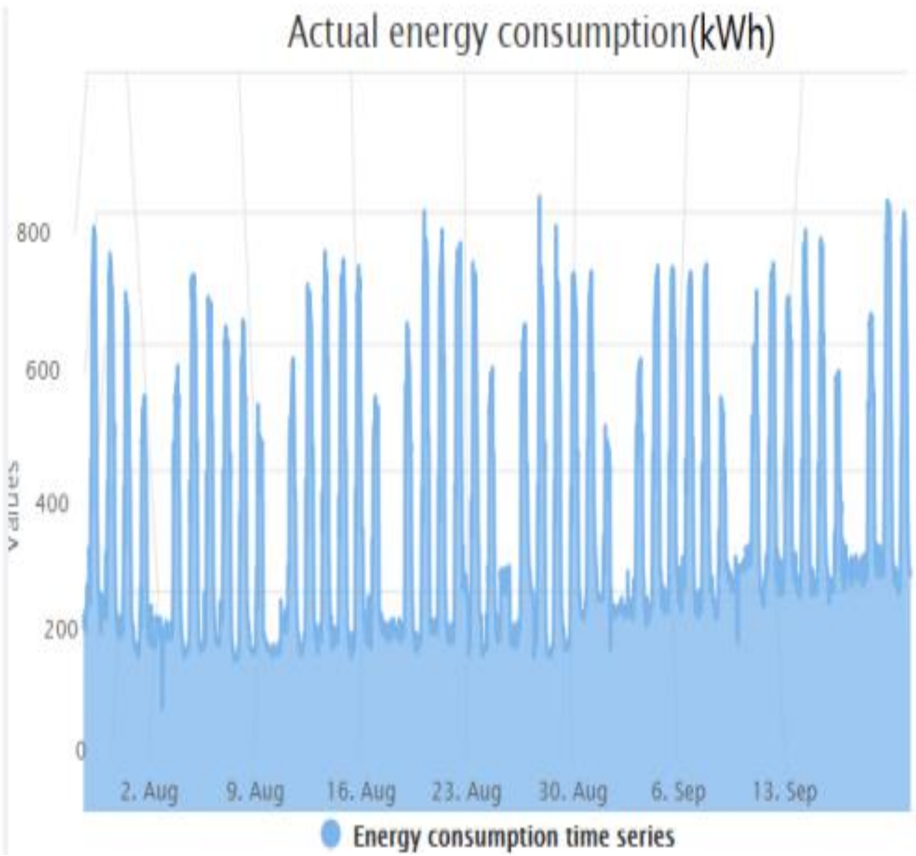


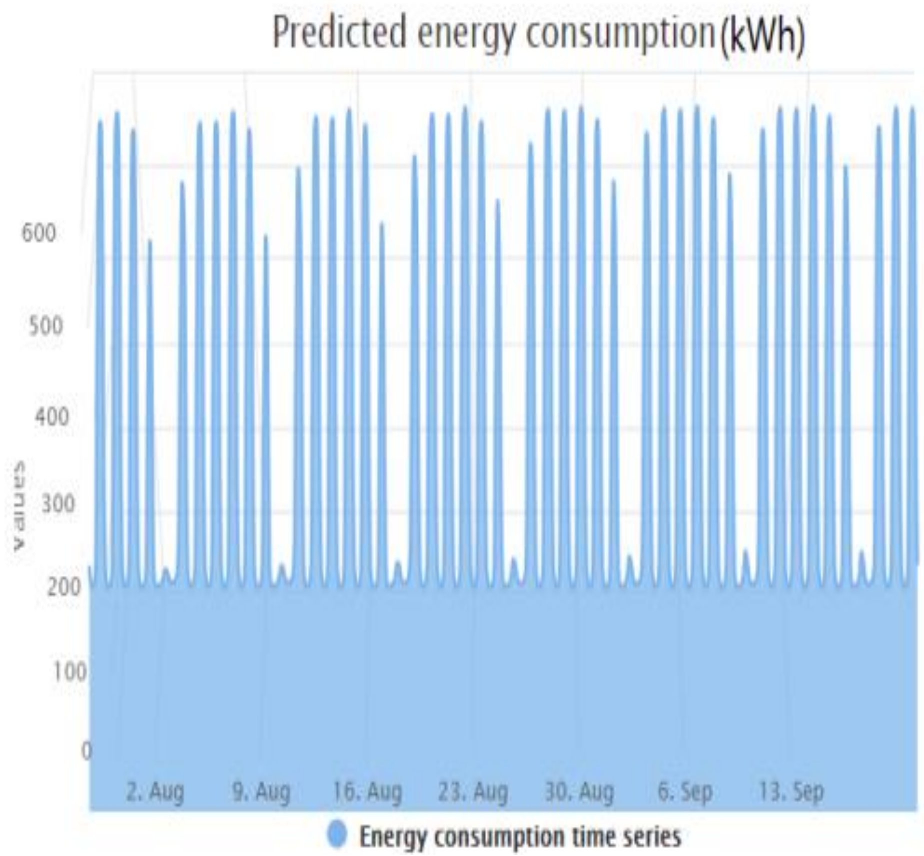


40 days forecasting horizon: MAE = 30.15; MAPE = 10.63

Experimental Results

- Results obtained while tuning the size of the forecasting horizon

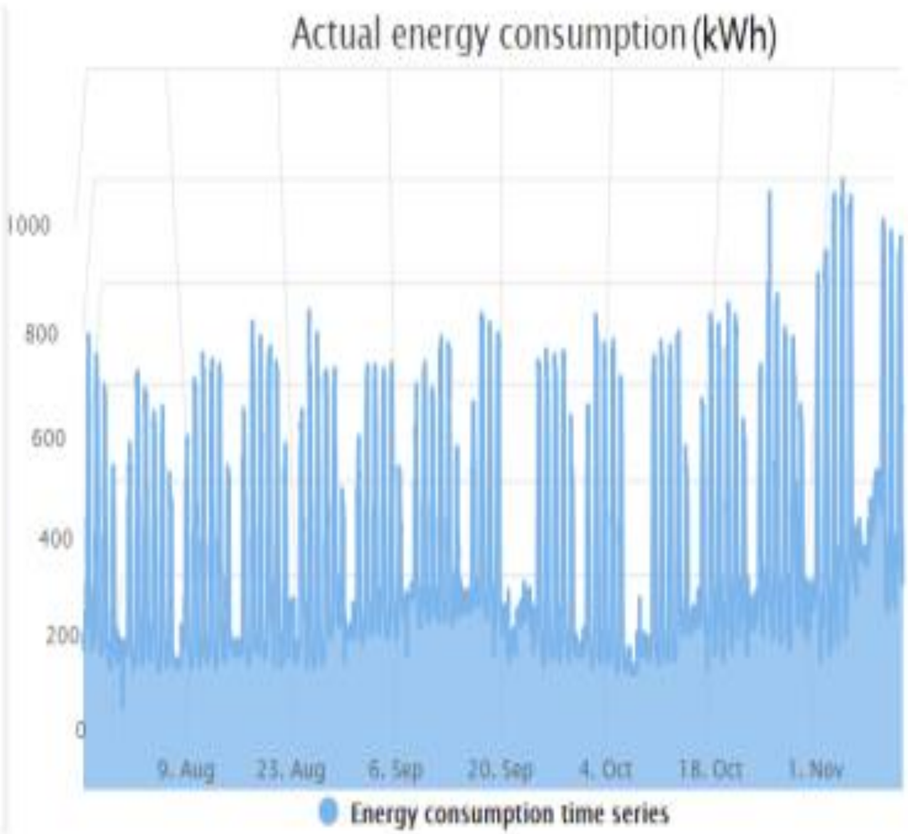


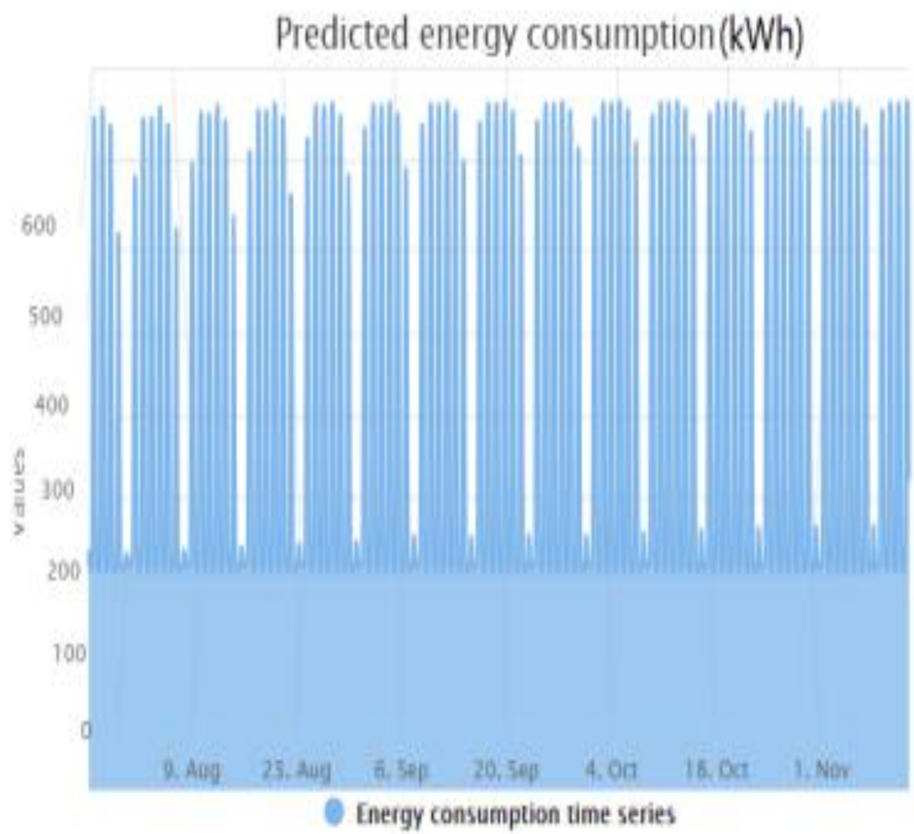


50 days forecasting horizon: MAE = 38.27; MAPE = 13.09

Experimental Results

- Results obtained while tuning the size of the forecasting horizon





100 days forecasting horizon: MAE = 64.54; MAPE = 21.05

Conclusions

- The LSTM-based method can predict the energy consumption in public buildings based on past measurements
- The LSTM-based method has been evaluated on a data set consisting of measurements taken every half an hour from the main building of the National Archives of the United Kingdom, in Kew
- The obtained results can be used to provide support in the efficient operation of the electricity grid and in the efficient management of energy consumption in public buildings.