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Forecasting the Short-Term Energy Consumption Using Random Forests and Gradient Boosting

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AGENDA

- Introduction
- Related Work
- Forecasting the energy consumption by using Random Forests and Gradient Boosting
- Experimental Results
- Conclusions

INTRODUCTION
Context and Motivation (I)

- Electrical energy is one of the essential resources that ensures many basic human needs
- The continuous increase of demand started to raise concerns about:
  - A series of detrimental environmental and economic effects
  - The problems on the exhaustion of energy sources

INTRODUCTION
Context and Motivation (II)

- Several strategies are proposed for increasing the energy efficiency:
  - Energy retrofitting for homes and buildings
  - Reducing the cooling loads in buildings through energy-efficient design/passive cooling strategies/usage of energy-efficient cooling equipment
  - Raising the public awareness on the importance of efficient energy use
- All these can be complemented by the ability of the electricity supplies to forecast the energy demand and plan its generation accordingly

INTRODUCTION
Objectives

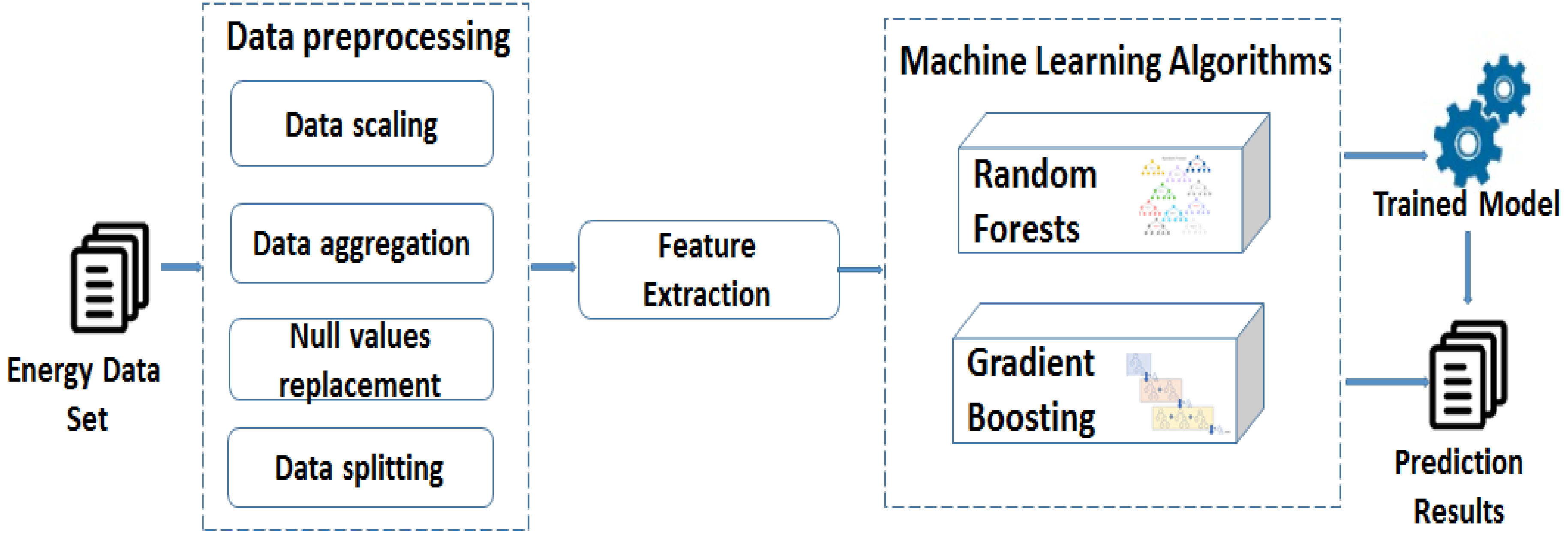
- To develop a method that integrates ML algorithms for predicting the energy consumption, based on historical data
  - The following algorithms have been integrated in our method:
    - Random Forests
    - Gradient Boosting
    - A Weighted Average Ensemble Method
- The method has been integrated into an experimental prototype and validated on a real data set

RELATED WORK

Approach	Learning algorithms used for prediction	Features	What is predicted
[Ahmad2017]	Feed-Forward Back-Propagation Decision Trees	Outdoor temperature, humidity, speed of the wind, hour of the day, day of the week, month of the year, number of guests in a day, and number of booked rooms	HVAC energy consumption in a hotel
[Chae2016]	Artificial neural networks combined with the Bayesian regularization algorithm	9 independent variables (e.g. the day type, the time of the day, the temperature schedule of the HVAC set, the outdoor air temperature, the humidity)	Energy usage in commercial buildings
[Ahmada2019]	One-Step Secant backpropagation BFGS Quasi-Newton backpropagation	Energy consumption of the previous seven days and environmental data (e.g. temperature, humidity, wind speed etc.)	Energy consumption at district-level

FORECASTING THE ENERGY CONSUMPTION BY USING RANDOM FORESTS AND GRADIENT BOOSTING

- The main steps of our method for predicting the energy consumption based on historical data:



FORECASTING THE ENERGY CONSUMPTION BY USING RANDOM FORESTS AND GRADIENT BOOSTING

- Data pre-processing step (I)
  - Involves:
    - Data normalization
    - Data aggregation
    - Replacing the null values
    - Data splitting

FORECASTING THE ENERGY CONSUMPTION BY USING RANDOM FORESTS AND GRADIENT BOOSTING

- Data pre-processing step (II)
  - Data normalization
    - Brings the values of all data to the same scale
    - For scaling the values, Min-max and MaxAbs scaler have been used
  - Data aggregation
    - For each entry in the data set an index is computed by dividing the total time that has passed in a day up until the data entry has been recorded, over the *granularity* established for the predictions
    - The *granularity of predictions* is defined as the amount of time (in minutes) within which all the energy recordings are grouped together

FORECASTING THE ENERGY CONSUMPTION BY USING RANDOM FORESTS AND GRADIENT BOOSTING

- Data pre-processing step (III)
  - Replacing the null values
    - For null values replacement, the interpolation based on neighboring values is used
  - Splitting the data set
    - We have used two methods:
      - Chronological (i.e. ordered) data splitting
      - Seasonal data splitting
        - Takes a percentage from each month for training and makes predictions on the remaining days of the month

FORECASTING THE ENERGY CONSUMPTION BY USING RANDOM FORESTS AND GRADIENT BOOSTING

- Feature extraction
  - The following features have been extracted, and different combinations of them have been considered:
    - Year, month and week of the year
    - Day of the year, day of the month and day of the week
    - Hour in the day and half hour in the day
    - Season and weekend
    - Energy consumption values

FORECASTING THE ENERGY CONSUMPTION BY USING RANDOM FORESTS AND GRADIENT BOOSTING

- Training and forecasting
  - 80% of the data are used for training, and 20% for testing
  - For evaluation, we used the following metrics:
    - Root mean square error (RMSE)
    - Mean absolute error (MAE)
    - Mean absolute deviation (MAD)
    - Mean absolute percentage error (MAPE)

EXPERIMENTAL RESULTS

- We have evaluated the following algorithms/ method
  - Random Forests algorithm
  - Gradient Boosting algorithm
  - A Weighted Average Ensemble method
    - Combines the predictions made by the two models obtained with Random Forests and Gradient Boosting
    - The contribution of each model is weighted proportionally to its quality (i.e. the accuracy of the model)
- The data set used in experiments
  - Contains information about the energy power consumption of 6 HVAC chillers installed in a building
    - The power consumption is collected at every minute during one year

EXPERIMENTAL RESULTS

- We perform a set of preliminary experiments to see how the prediction accuracy is influenced by:
  - Different *granularities of predictions*
  - Different *data splitting* approaches

EXPERIMENTAL RESULTS

- For the ***granularity of the predictions***, we have noticed that:
  - For data that describe a smaller amount of time, a smaller value (e.g. one hour) for the granularity of predictions is preferred
  - For data which cover a year, a larger value for the prediction granularity, for example one day, is more suitable

EXPERIMENTAL RESULTS

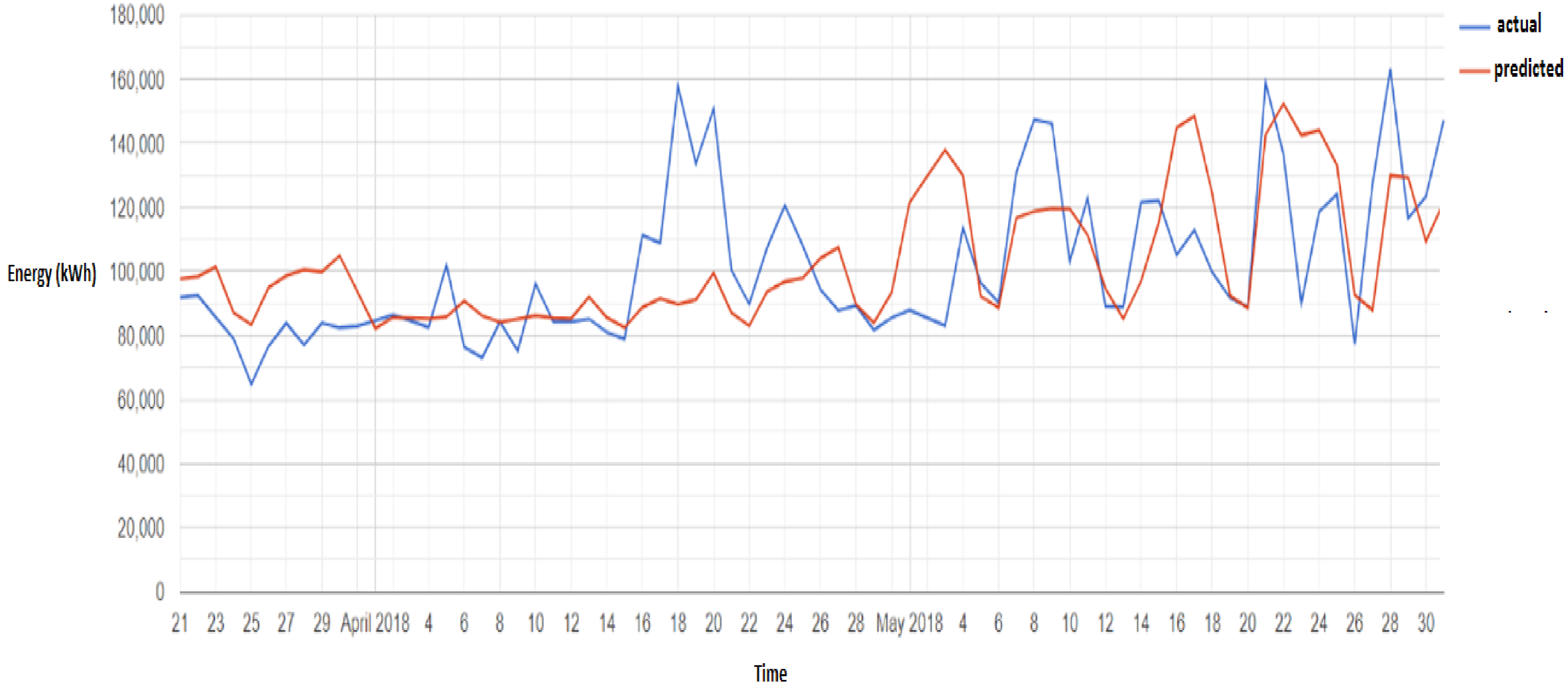
- For ***data splitting*** we have considered three methods:
  - The *first method* allows the selection of the season to which the desired forecasting interval belongs
    - Only data corresponding to that season will be used for training
  - The *second method* takes a training set percentage from each season, and not from the whole year
    - Data related to each period will be involved in the training process, which will increase the accuracy
  - The *third method* takes a certain percentage from each month for training

EXPERIMENTAL RESULTS

- The configuration (parameters) used in the experiments with Random Forests was:
  - 10 as maximum depth for trees
  - 15 trees (as number of trees)
  - 0.2 as minimum information gain threshold
- The configuration (parameters) used in the experiments with Gradient Boosted Trees was:
  - 10 as maximum depth for trees and
  - 0.2 as minimum information gain threshold
- The predictions are made with a *granularity* of one day, i.e. for an amount of time of one day

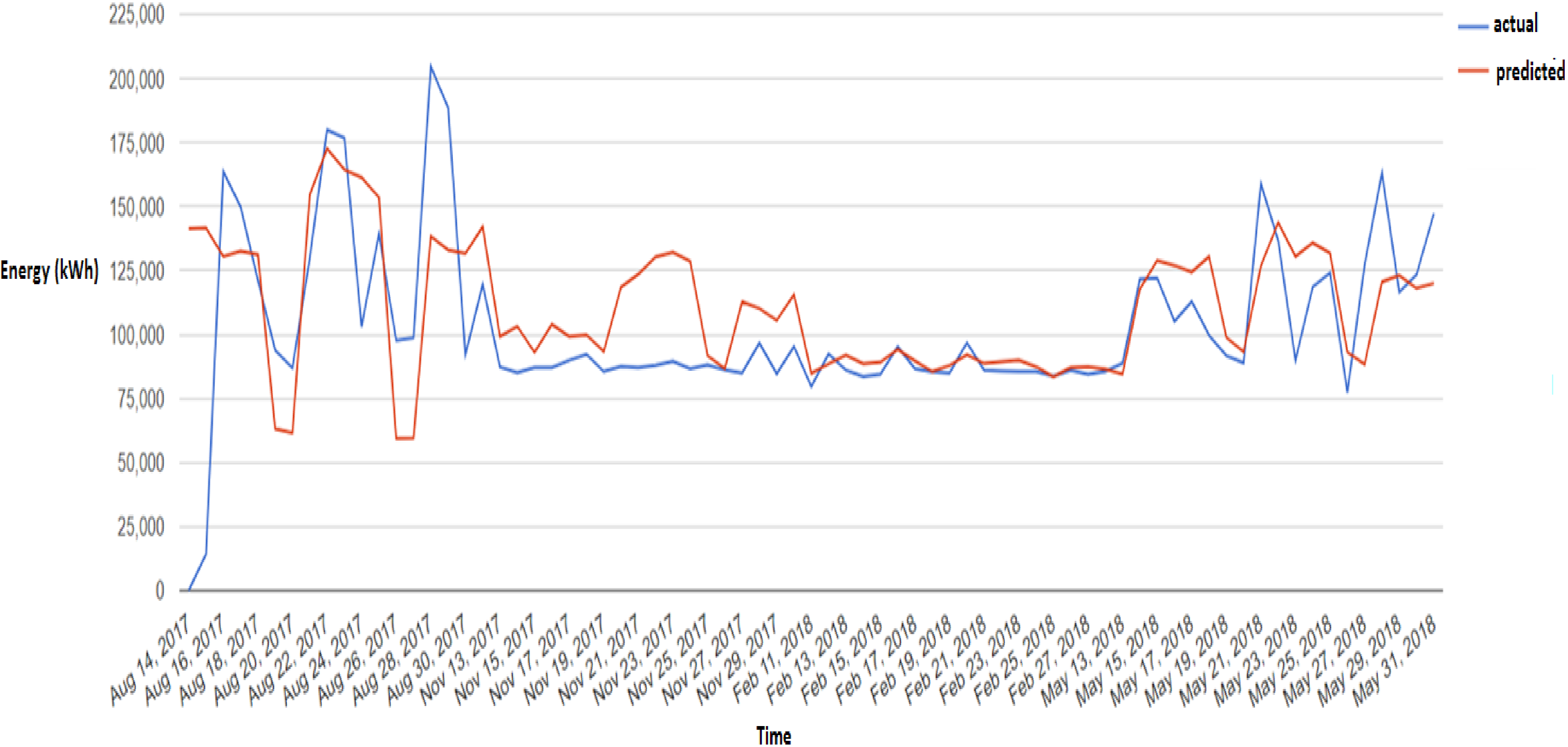
EXPERIMENTAL RESULTS

Predictions for a week using Random Forests - ordered data split



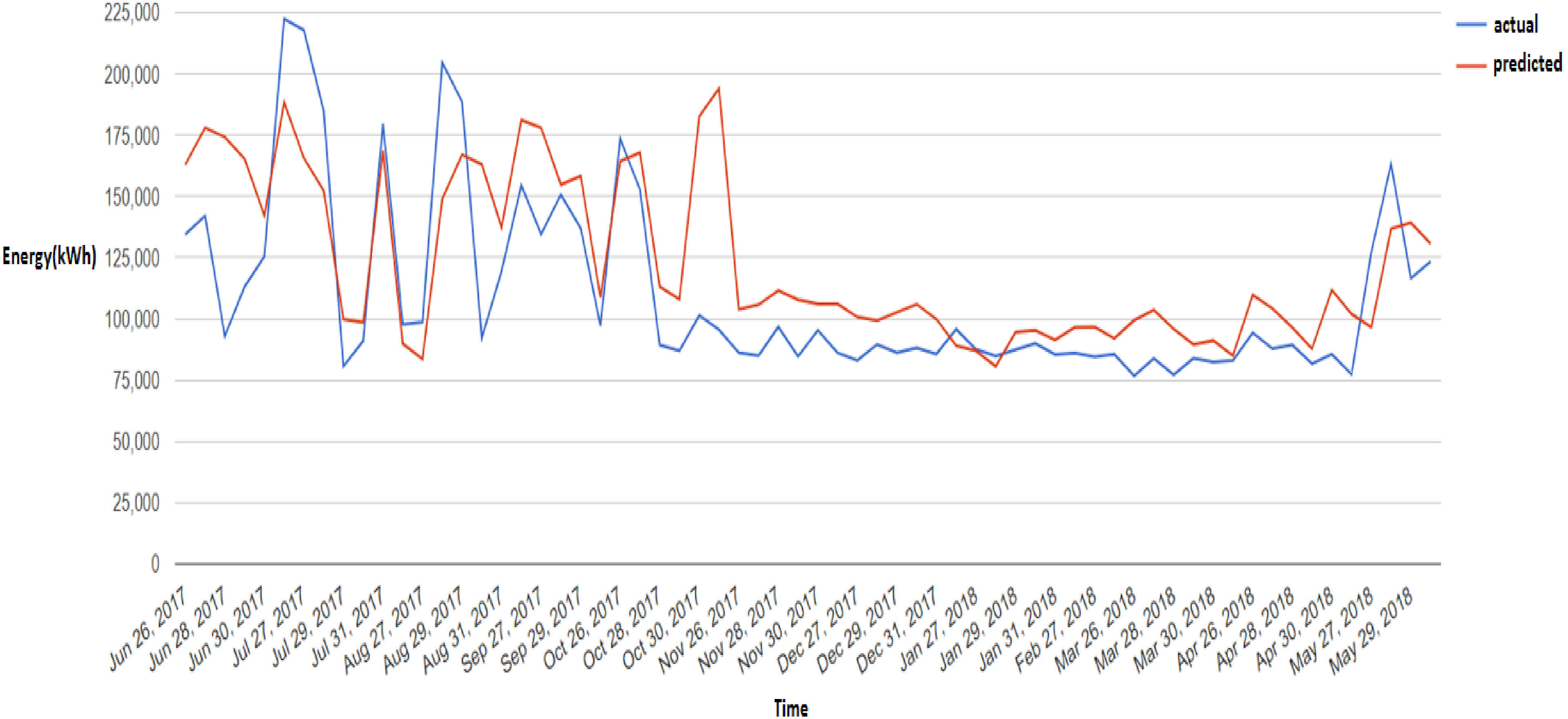
EXPERIMENTAL RESULTS

Predictions for a week Random Forests - seasonal data split



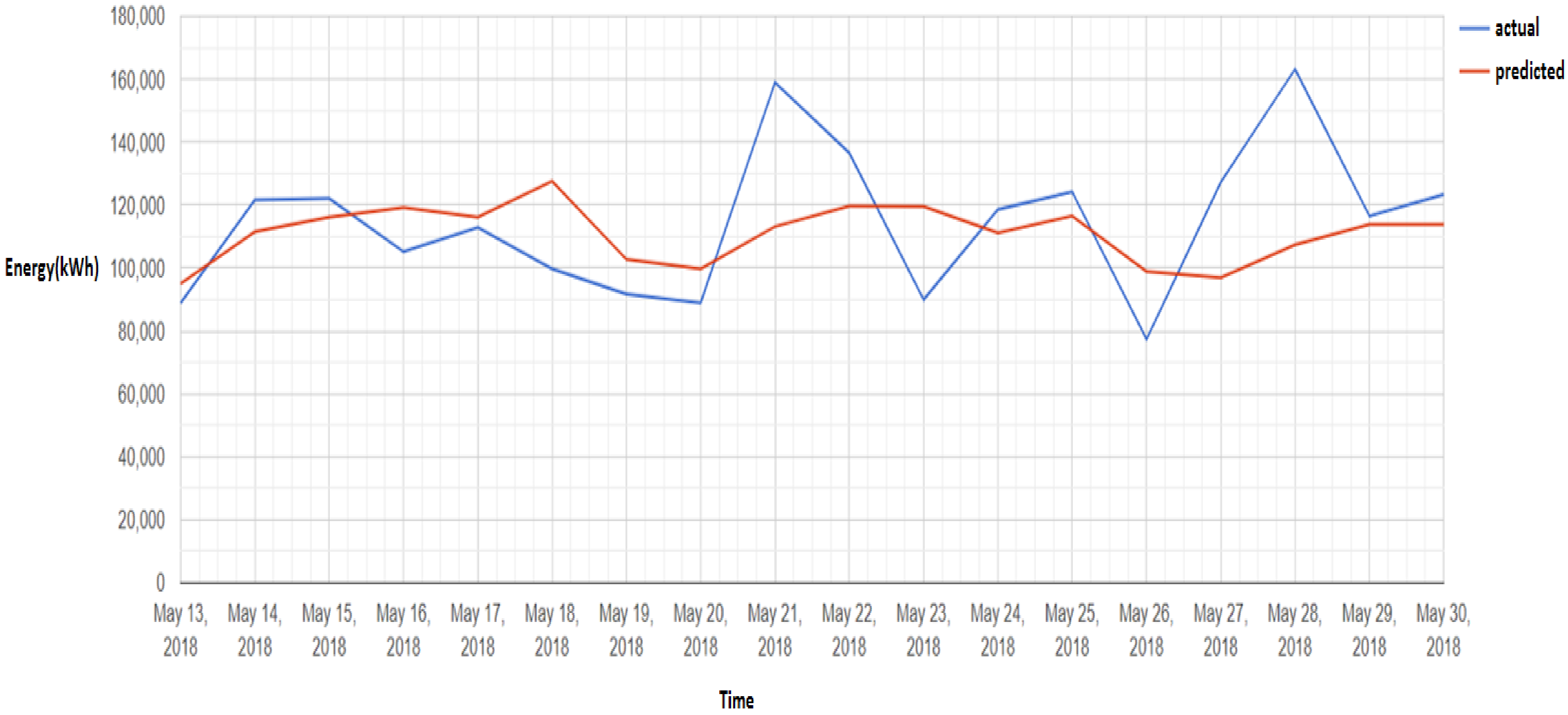
EXPERIMENTAL RESULTS

Predictions for a week using Random Forests - monthly data split



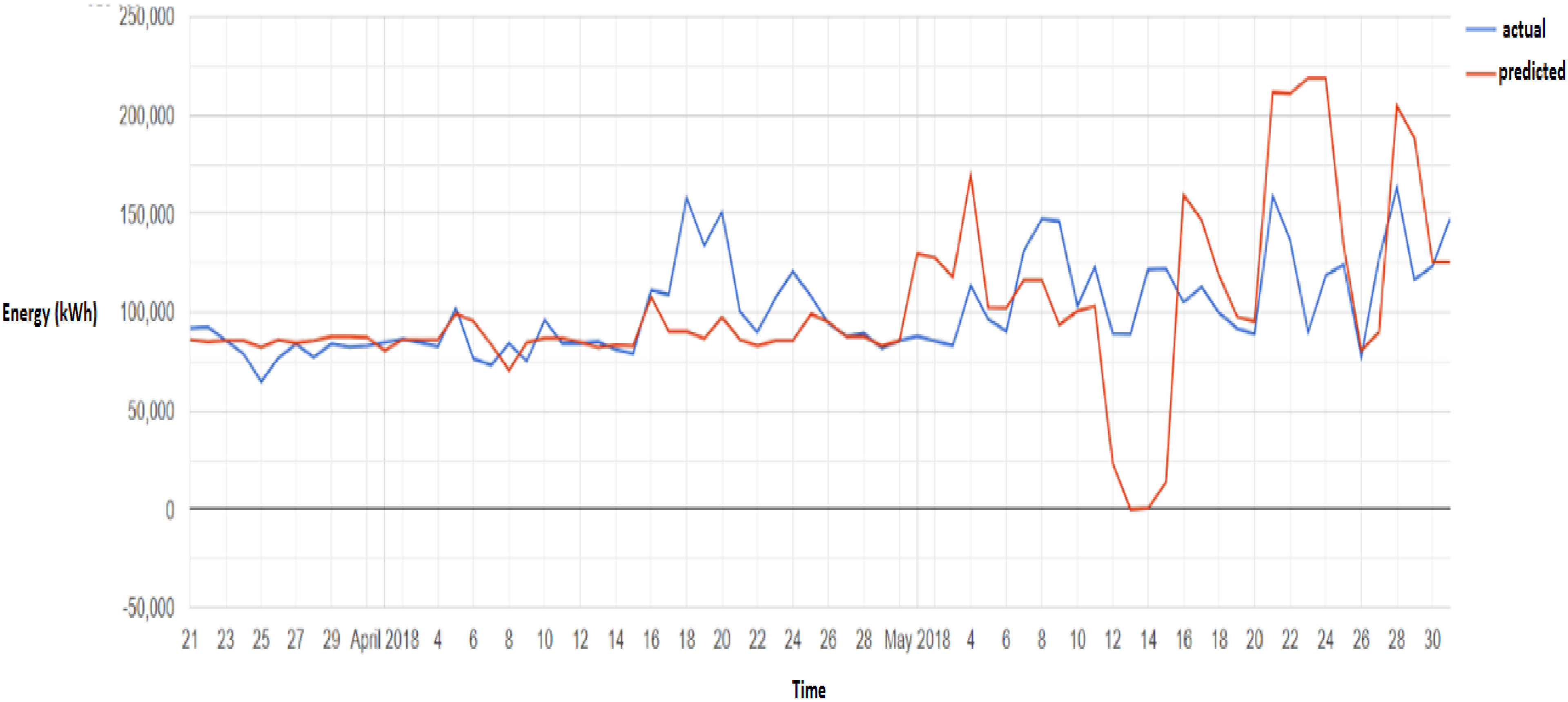
EXPERIMENTAL RESULTS

Predictions for a week using Random Forests - spring season data split



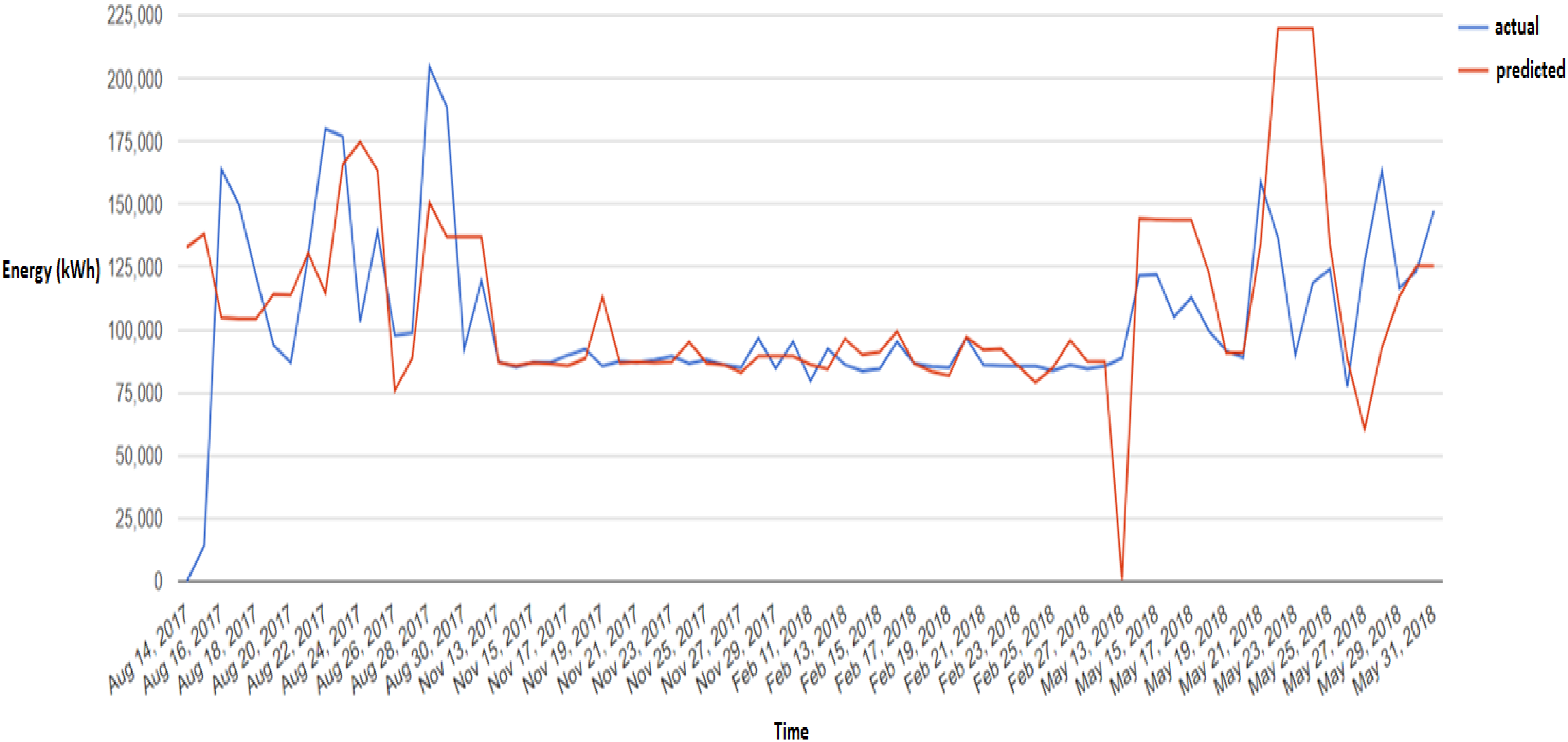
EXPERIMENTAL RESULTS

Predictions for a week using the algorithm for Gradient Boosted Trees - ordered data split



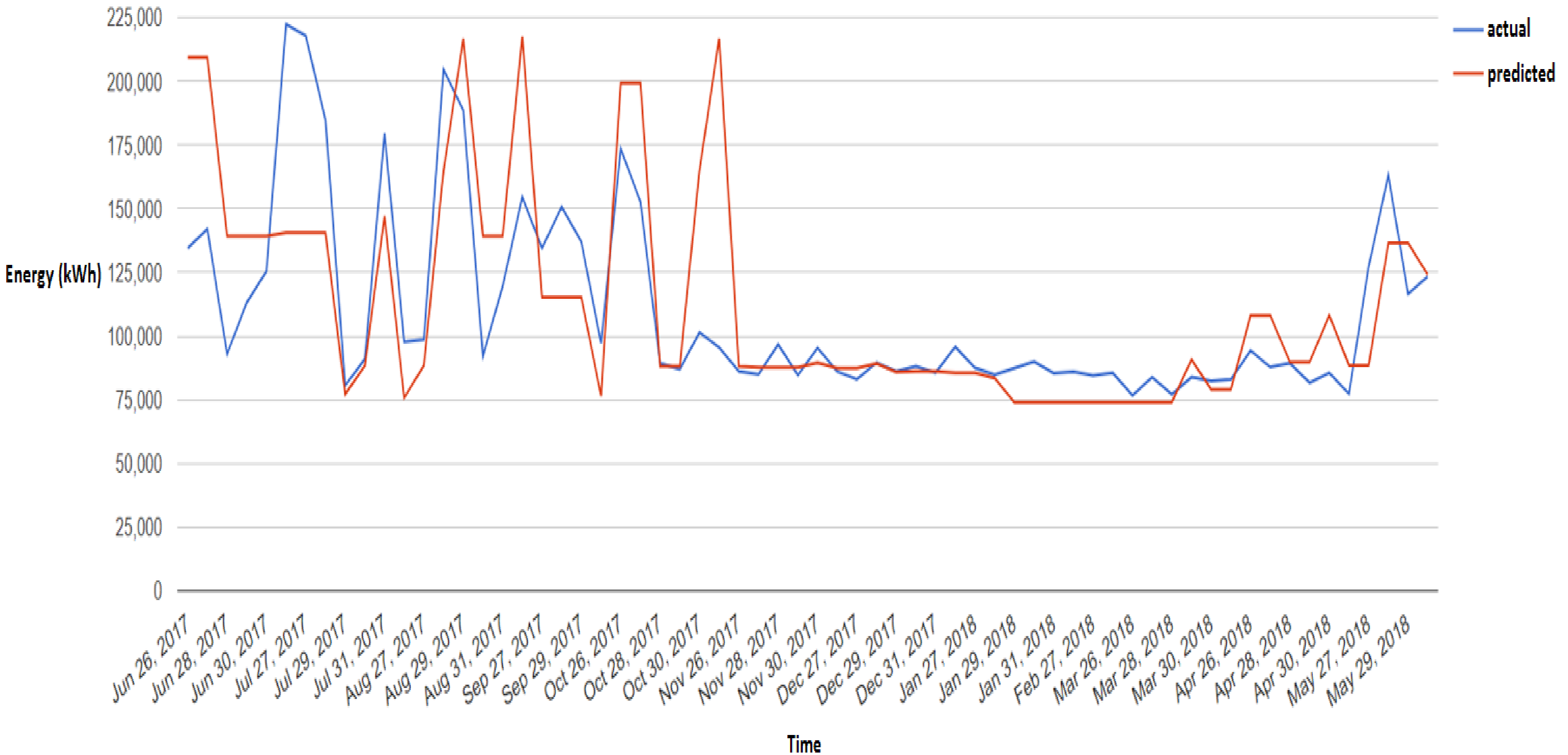
EXPERIMENTAL RESULTS

Predictions for a week using the algorithm for Gradient Boosted Trees - seasonal data split



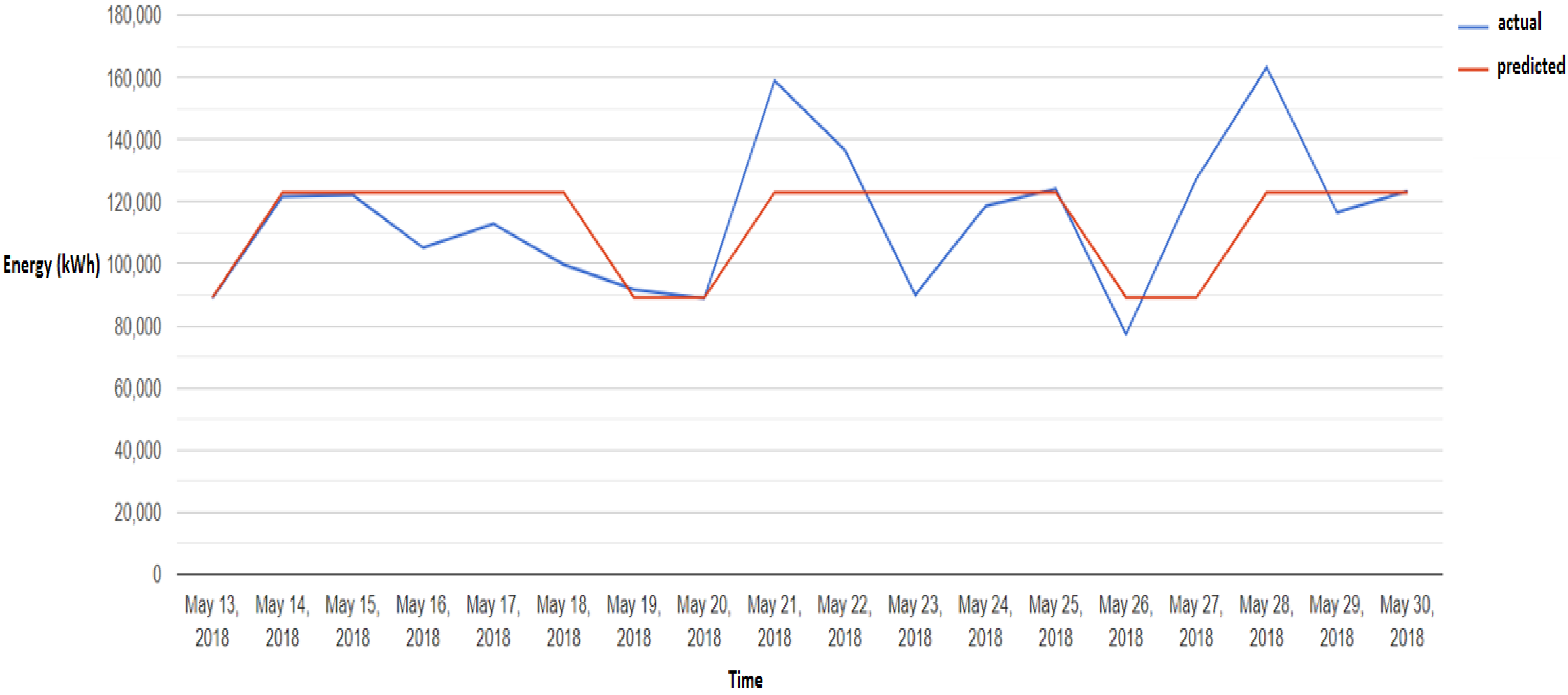
EXPERIMENTAL RESULTS

Predictions for a week using the algorithm for Gradient Boosted Trees - monthly data split



EXPERIMENTAL RESULTS

Predictions for a week using the algorithm for Gradient Boosted Trees - spring season data split



EXPERIMENTAL RESULTS

- We have also analyzed comparatively the experimental results achieved with:
  - Random Forests
  - Gradient Boosting
  - the Weighted Average Ensemble method – with the best prediction results (the lowest values for the metrics)

Metric	Random Forest	Gradient Boosting	Weighted Average Ensemble Method
RMSE	141.5	131.13	107.72
MAE	98.24	94.63	83.86
MAD	176.54	174.27	169.07
MAPE	17.06	15.89	14.27

CONCLUSIONS

- We presented a comparative analysis among two ML algorithms and a Weighted Average Ensemble method applied in forecasting the energy consumption
- We can conclude that the best results are obtained with the Weighted Average Ensemble method, followed by Gradient Boosting
  - Weighted Average Ensemble method combines the learned models with Random Forest and Gradient Boosting to get better results