Performance Analysis of Single and Multi-step Short-term Load Forecasts Using Multi-layer Perceptron

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Introduction

- Load forecasting:

  Efficient monitoring, resource management, decision making.

- Need for accurate and fast electrical load predictions.
- Traditional approaches:

  Statistical methods

- Modern approaches:

  Machine learning, artificial intelligence, hybrid techniques.

- Comparative study of several structural morphologies of MLPs.
- Investigate load forecasting accuracy for:

  One, twelve and twenty-four time-steps ahead.

- Data from the Greek Power System for the years 2017- 2019.

Dataset Overview & Evaluation Metrics

- Dataset consist of:

  Hourly measurements load (MW),

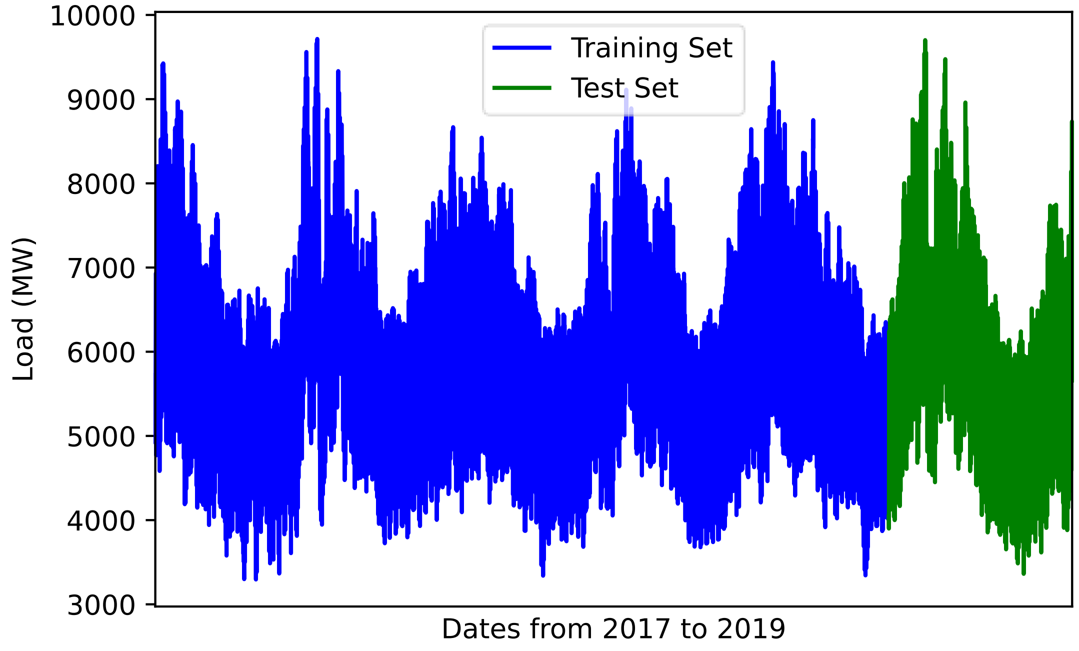
  Temperature (°C),

  Relative humidity (%)

  Temporal variables for the hour and day of the week.

- Evaluation Metrics:

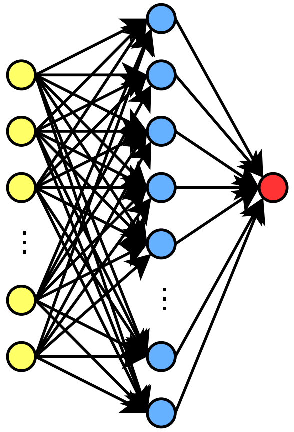
  MAE, MSE, MAPE.

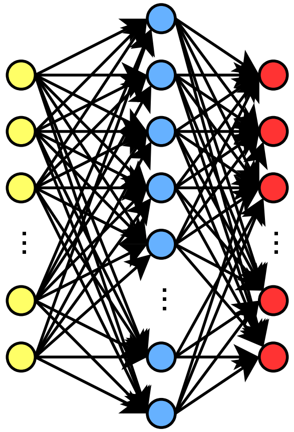


Study Case Analysis

- Univariate and multivariate load forecasting tasks.
- Number of neurons in the output layer = number of predicted output variables.
- Brute force optimization algorithm:

  Optimal hyperparameter selection on the various MLPs morphologies.





Hyperparameters

- Hyperparameters:
  number of neurons in the hidden layer,
  number of epochs throughout the training process.
- Each MLP comprises of a hidden layer.
- Minimum acceptable number of hidden neurons: half of the number of neurons in the input layer.
- Maximum number of hidden neurons can reach up to three times the number of input neurons.
- The ideal number of epochs: within the closed interval [200, 2000].

Case A: One Hour Ahead Load Forecasting

- 11 neurons in the input layer:
  - ➢ A label for the time for which the forecast is being performed.
  - ➢ A label to identify the day being predicted. Sunday is represented by the value 1, Monday by the value 2, etc.
  - ➢ Hourly temperature value.
  - ➢ Hourly humidity estimation.
  - ➢ Seven hourly load values for the period from the current time up to one week in beforehand of the prediction.

Case B: Twelve Hours Ahead Load Forecasting

- 109 neurons in the input layer:
  - An integer, serving as a label to identify the day being predicted.
  - A vector consisting of 12-hourly temperature values.
  - A vector consisted of 12-hourly humidity estimations
  - A vector of 84-hourly load values.

Case C: Twenty-Four Hours Ahead Load Forecasting

- 217 input neurons:
  - An integer acting as a label to designate the day being forecast.
  - A vector consisting of 24-hourly temperature values for the day of which the prediction is conducted.
  - A vector consisted of 24-hourly humidity values for the day of which the prediction is conducted.
  - A vector of 168-hourly load values.

Optimization Results

Results of the optimization approach for each case study.

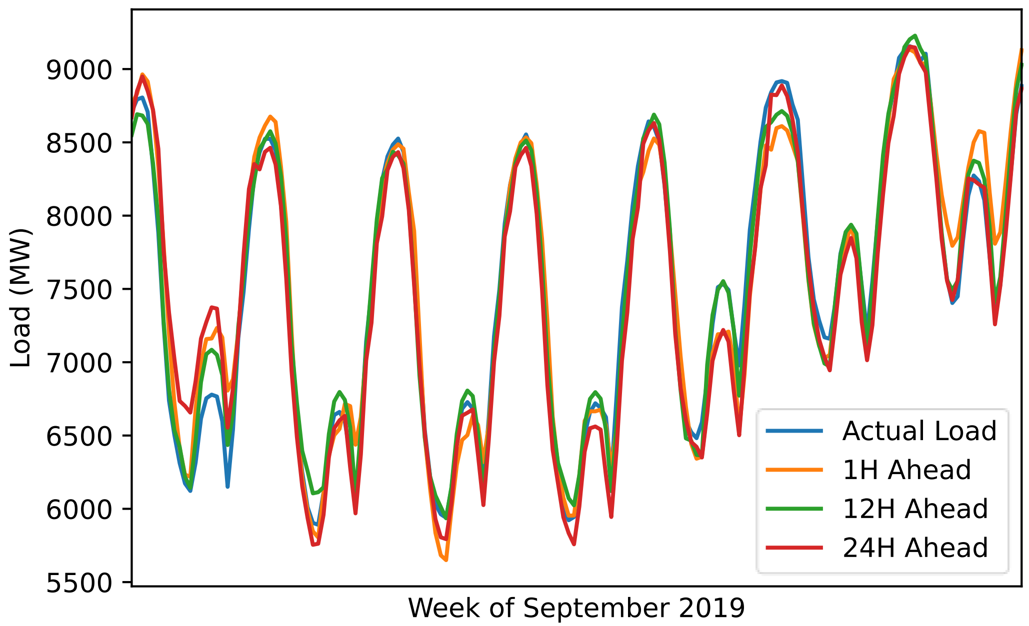
MLP	*Neurons*	*Iterations*	*Time (H:MM:SS)*
1h Ahead	33	2000	2:20:11
12h Ahead	275	1800	0:56:59
24h Ahead	436	1800	1:19:43

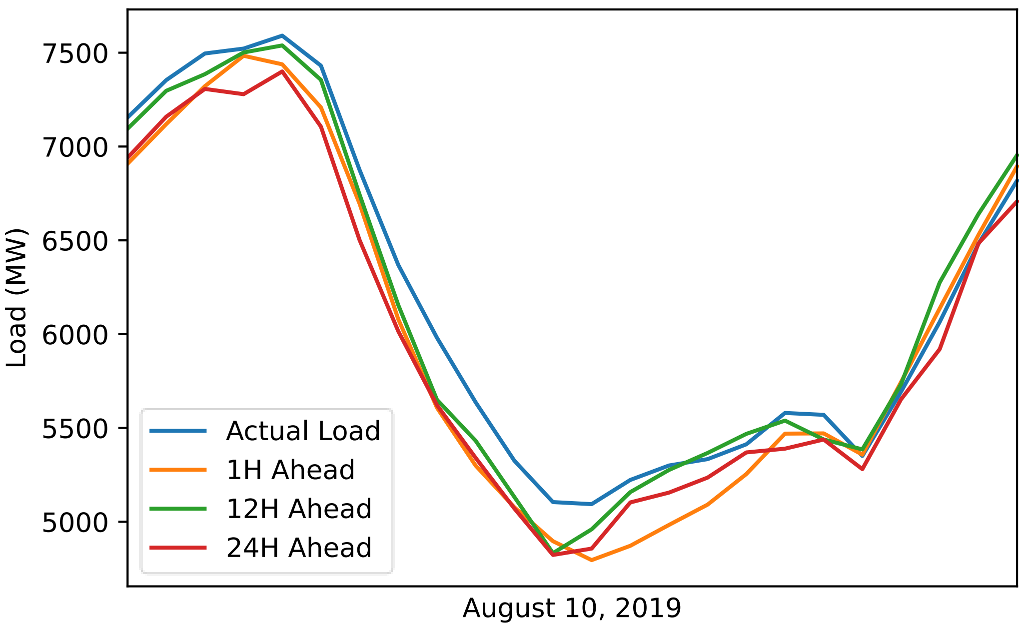
Accuracy Metrics

Forecasting results of the investigated MLPs architectures

MLP	*MAE*	*MSE*	*MAPE (%)*
1h Ahead	182.076	67603.22	2.774
12h Ahead	162.845	54383.46	2.435
24h Ahead	187.315	66564.93	2.742

Graphical Comparison of Forecasting Results





Conclusion

- The error values for the one hour ahead, and twenty-four hours ahead forecast are very similar in terms of error metrics.
- The twelve hours ahead model exhibited improved performance compared to the other forecasting horizons.
- The algorithm can adapt to multi-step ahead forecasting.
- Future work: can be implemented on Demand Side Management and Demand Response programs