



UNIVERSITÀ DI TRENTO

Department of Information Engineering and Computer Science

Master's Degree in
Artificial Intelligence Systems

FINAL DISSERTATION

A FORECASTING SYSTEM FOR ELECTRICITY PRODUCTION AND CUSTOMER DEMAND

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Abstract

The abstract is a short summary of the work describing the target, the subject of the thesis, the methodology and the techniques, the data collection and elaboration, the explanation of the reached results and the conclusion. The abstract of the dissertation must have a maximum length of 3 pages and must include the following information:

- context and motivation
- short summary of the main problem you have dealt with
- developed and / or used techniques
- reached results, the personal contribution of the student has to be highlighted

Note: Please note that the approximate number of pages is 70. These 70 pages include:

- table of contents
- abstract
- chapters

Exclude:

- frontispiece (title page)
- acknowledgements
- bibliography
- attachments

1 Introduction

Brief introduction to the work ...

1.1 Problem statement

This is the problem ...

1.2 Approach to the problem

This is the approach ...

1.3 Outline

Here it is written how the thesis is organized ...

2 State of the Art

Literature review ...

2.1 Electricity data

Analyze the electricity data standards ... [10] [12] [59] [46]

2.2 Time series forecasting

Analyze the time series forecasting techniques ... [13] [47] [7] [60] [1] [43] [49] [28] [4] [8] [32] [17] [51] [35] [6] [44] [14] [3] [9] [58] [52] [39] [5]

Some notes about forecasting competitions ... [29] [48]

2.2.1 Transformers

Analyze the transformers ... [25] [57] [62] [55] [38] [33] [34] [45] [56] [61] [41] [42] [20] [40] [26] [50]

2.2.2 AutoML

Analyze the AutoML ... [27] [24] [22] [63] [15] [2] [31] [11] [54] [19] [23] [21] [16] [37] [18] [53] [36] [30]

2.3 Electricity demand forecasting

Analyze the electricity demand forecasting techniques ...

2.4 Consumption baseline forecasting

Analyze the consumption baseline forecasting techniques ...

2.5 Electricity production forecasting

Analyze the electricity production forecasting techniques ...

3 System Model

Write about the system model ...

3.1 System architecture

Describe the system architecture ...

3.2 Common components

Describe the common components ...

3.3 Electricity demand forecasting

Describe the electricity demand forecasting model ...

3.4 Consumption baseline forecasting

Describe the consumption baseline forecasting model ...

3.5 Electricity production forecasting

Describe the electricity production forecasting model ...

4 Implementation

Write about the implementation ...

4.1 Common components

Describe the common components implementation ...

4.2 Electricity demand forecasting

Describe the electricity demand forecasting implementation ...

4.3 Consumption baseline forecasting

Describe the consumption baseline forecasting implementation ...

4.4 Electricity production forecasting

Describe the electricity production forecasting implementation ...

5 Performance Evaluation

Write about the performance evaluation ...

5.1 Electricity demand forecasting

Analyze the results on the electricity demand forecasting task ...

5.2 Consumption baseline forecasting

Analyze the results on the consumption baseline forecasting task ...

5.3 Electricity production forecasting

Analyze the results on the electricity production forecasting task ...

6 Conclusions

This chapter reports the conclusions and summary of the work done. At the end of the thesis, some ideas for future works are suggested.

6.1 Summary

Summary of the work done ...

6.2 Future works

Ideas for future works ...

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