



UNIVERSITI PUTRA MALAYSIA

***APPLIANCE LEVEL STAND-BY BURST FORECAST MODELLING
USING MACHINE LEARNING TECHNIQUES***

ABID MUSTAFA

FK 2021 98



**APPLIANCE LEVEL STAND-BY BURST FORECAST MODELLING USING
MACHINE LEARNING TECHNIQUES**

By

ABID MUSTAFA

**Thesis Submitted to the School of Graduate Studies, Universiti Putra
Malaysia, in Fulfilment of the Requirements for the Degree of
Master of Science**

November 2020

COPYRIGHT

All material contained within the thesis, including without limitation text, logos, icons, photographs, and all other artwork, is copyright material of Universiti Putra Malaysia unless otherwise stated. Use may be made of any material contained within the thesis for non-commercial purposes from the copyright holder. Commercial use of material may only be made with the express, prior, written permission of Universiti Putra Malaysia.

Copyright © Universiti Putra Malaysia



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in
fulfilment of the requirement for the degree of Master of Science

APPLIANCE LEVEL STAND-BY BURST FORECAST MODELLING USING MACHINE LEARNING TECHNIQUES

By

ABID MUSTAFA

November 2020

Chairman : Associate Professor Ir. Mohammad Lutfi bin Othman, PhD
Faculty : Engineering

Electric power is an expensive and scarce resource and the concept of modern life is not possible without the continuous uninterrupted supply of it. Therefore, a lot of efforts have been made in past to conserve and optimize the use of electric power so that it could be efficiently distributed to all consumers. The efforts to conserve the energy include government and other organizations' sponsored awareness campaign for public to encourage them to use the best practices while the efforts for optimizing its use are led by the researchers and industries. The electrical appliances and equipment are developed in a way that optimize the use of energy. In this direction, one of the important inventions was the use of standby mode for the electrical appliances which is employed when the appliance is plugged-in but not in active use. The standby mode helps optimize electric power use yet it causes some power leakage. This study strives to forecast the appliances' state (standby or running) in next minutes to prevent the power leakage during the standby mode: by accurately forecasting the standby burst the appliance could be put in off state during the forecasted burst duration. This work proposes a technique to model power consumption data and presents a comparative study of five different machine learning algorithms to study their suitability to forecast an appliance's state and standby burst. The proposed approach achieved around 90 percent accuracy and very good indications over precision, recall and F1-Score for models built using Decision Tree, Logistic Regression, Support Vector Machine (SVM), K- Nearest Neighbor (KNN), and Multilayer Perceptron (MLP).

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Master Sains

**PEMODELAN TAHAP PENGUASAAN STAND-BY BURST
MENGUNAKAN TEKNIK PEMBELAJARAN MESIN**

Oleh

ABID MUSTAFA

November 2020

Pengerusi : Profesor Madya. Ir. Mohammad Lutfi bin Othman, PhD
Fakulti : Kejuruteraan

Tenaga elektrik adalah sumber yang mahal dan langka dan konsep kehidupan moden tidak mungkin berlaku tanpa bekalan berterusan tanpa gangguan. Oleh itu, banyak usaha telah dilakukan di masa lalu untuk menjimatkan dan mengoptimumkan penggunaan tenaga elektrik sehingga dapat diedarkan secara efisien kepada semua pengguna. Usaha untuk menjimatkan tenaga termasuk kempen kesedaran yang ditaja oleh kerajaan dan organisasi lain untuk orang ramai untuk mendorong mereka menggunakan amalan terbaik sementara usaha untuk mengoptimumkan penggunaannya dipimpin oleh para penyelidik dan industri. Peralatan dan peralatan elektrik dikembangkan dengan cara yang mengoptimumkan penggunaan tenaga. Ke arah ini, salah satu penemuan penting adalah penggunaan mod siaga untuk peralatan elektrik yang digunakan semasa alat dipasang tetapi tidak digunakan secara aktif. Mod siap sedia membantu mengoptimumkan penggunaan kuasa elektrik namun ia menyebabkan kebocoran kuasa. Dalam kajian ini, kami berusaha untuk meramalkan keadaan perkakas (siaga atau berjalan) dalam beberapa minit berikutnya untuk mengelakkan kebocoran daya semasa mod siap sedia: dengan meramalkan secara tepat letusan siap sedia, kita dapat meletakkan alat dalam keadaan mati selama jangka waktu letupan yang diramalkan. Karya ini mencadangkan teknik untuk memodelkan data penggunaan tenaga dan menyajikan kajian perbandingan lima algoritma pembelajaran mesin yang berbeza untuk mengkaji kesesuaian mereka untuk meramalkan keadaan dan letupan siap sedia alat. Pendekatan yang dicadangkan kami mencapai sekitar 90 peratus ketepatan dan petunjuk yang sangat baik mengenai ketepatan, penarikan balik dan Skor F1 untuk model yang dibina menggunakan

Keputusan Pohon, Regresi Logistik, Mesin Vektor Sokongan (SVM), K Nearest Neighbor (KNN), dan Multilayer Perceptron (MLP).



ACKNOWLEDGEMENTS

On the completing masters research effectively, I would like to acknowledge and deliver a high appreciation to my research supervisor, Assoc. Prof. Ir. Dr. Mohammad Lutfi Bin Othman, who introduced me in Home Energy Management System and Machine Learning Algorithms. His supervision and constructive suggestions have been the source of inspiration to make this project successful and open new windows of knowledge.

Secondly, it is an honor for me to have Assoc. Prof Ir. Dr.Noor Izzri Bin Abdul Wahab as the members of my supervisory committee for my master degree research. He has to spend his valuable time and given me kind suggestions and guidance which added more worth to the research. In addition, great appreciation is also expressed to all the technicians and staff of Department of Electrical and Electronic Engineering for their assistance.

Furthermore, I would like to express my gratefulness to Dr. Usman Ahmed and Engr. Waqar look for their generous help and support throughout the whole research. They spent their valuable time on helping and supporting me in study and way to research.

Last but not lease, I am grateful to my family, who has been replenishing moral support every time I faced a problem. Besides that, I would like to thank my friends and course mates for spending their time and efforts when I am in need.

This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

Mohammad Lutfi bin Othman, PhD

Associate Professor Ts. Ir.
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Noor Izzri bin Abdul Wahab, PhD

Associate Professor Ir.
Faculty of Engineering
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD

Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 10 June 2021

Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) were adhered to.

Signature: _____

Name of Chairman
of Supervisory
Committee:

Associate Professor, Ir
Dr. Mohammad Lutfi bin Othman

Signature: _____

Name of Member
of Supervisory
Committee:

Associate Professor
Dr. Noor Izzri bin Abd Wahab

TABLE OF CONTENTS

	Page
ABSTRACT	i
ABSTRAK	ii
ACKNOWLEDGEMENTS	iv
APPROVAL	v
DECLARATION	vii
LIST OF TABLES	xii
LIST OF FIGURES	xiii
LIST OF ABBREVIATIONS	xviii
CHAPTER	
1 INTRODUCTION	1
1.1 Background	1
1.2 Problem Statement	1
1.3 Objectives of the Study	2
1.4 Hypothesis of the Research	2
1.5 Scope of the Study	2
1.6 Research Contribution	2
1.7 Thesis Layouts	3
2 LITERATURE REVIEW	4
2.1 Standby Power	4
2.2 Standby Power Policies and Regulations	5
2.3 Energy management	6
2.4 Algorithms Used in Standby Energy Management	7
2.4.1 Optimal Scheduling Algorithms	7
2.4.2 Genetic-Algorithms	8
2.4.3 Machine Learning Algorithms	9
2.5 Importance of Power Conservation	9
2.6 Power Consumption in Non-Trivial Sources	9
2.7 Power Conservation And Public Behavior	10
2.8 Power Consumption and Environment	10
2.9 Factors Affecting the Power Consumption	11
2.10 Power Leakage and Standby Power Consumption	11
2.11 Machine Learning and Power Management	12
2.12 Research Gap	17
2.13 Summary	18

3	RESEARCH METHODOLOGY	19
3.1	Data Collection	22
3.1.1	UK Domestic Appliance-Level Electricity Dataset	22
3.1.2	REFIT Electrical Load Measurements	22
3.2	Exploratory Data Analysis and Preparation	23
3.2.1	Statistical Indicators:	24
3.2.2	Visualizations:	24
3.3	Data Modeling	29
3.4	Building Forecast Model	30
3.4.1	Logistic Regression	31
3.4.2	Decision Tree	31
3.4.3	Support Vector Machine	31
3.4.4	K Nearest Neighbor Classifier	31
3.4.5	Multilayer Perceptron	32
3.5	Evaluation of Forecast Model	32
3.5.1	Accuracy	32
3.5.2	Confusion Matrix	33
3.5.3	Precision	33
3.5.4	Recall	34
3.5.5	F1-Score	34
3.6	System Configuration	35
4	RESULTS AND DISCUSSION	36
4.1	Confusion Matrix	36
4.1.1	10 minutes of past data to predict next 10 minutes	36
4.1.2	30 minutes of past data to predict next 30 minutes	39
4.1.3	60 minutes of past data to predict next 60 minutes	42
4.1.4	2 hours of past data to predict next 2 hours	45
4.1.5	4 hours of past data to predict next 4 hours	48
4.1.6	6 hours of past data to predict next 6 hours	51
4.2	Accuracy	54
4.2.1	10 minutes of past data to predict next 10 minutes	54
4.2.2	30 minutes of past data to predict next 30 minutes	55
4.2.3	60 minutes of past data to predict next 60 minutes	56
4.2.4	2 Hours of past data to predict next 2 Hours	56
4.2.5	4 Hours of past data to predict next 4 Hours	57
4.2.6	6 Hours of past data to predict next 6 Hours	57
4.3	Precision	58

4.3.1	10 minutes of past data to predict next 10 minutes	58
4.3.2	30 minutes of past data to predict next 30 minutes	58
4.3.3	60 minutes of past data to predict next 60 minutes	59
4.3.4	2 Hours of past data to predict next 2 Hours	59
4.3.5	4 Hours of past data to predict next 4 Hours	60
4.3.6	6 Hours of past data to predict next 6 Hours	60
4.4	Recall	61
4.4.1	10 minutes of past data to predict next 10 minutes	61
4.4.2	30 minutes of past data to predict next 30 minutes	61
4.4.3	60 minutes of past data to predict next 60 minutes	62
4.4.4	2 Hours of past data to predict next 2 Hours	62
4.4.5	4 Hours of past data to predict next 4 Hours	63
4.4.6	6 Hours of past data to predict next 6 Hours	63
4.5	F1-Score	64
4.5.1	10 minutes of past data to predict next 10 minutes	64
4.5.2	30 minutes of past data to predict next 30 minutes	64
4.5.3	60 minutes of past data to predict next 60 minutes	65
4.5.4	2 Hours of past data to predict next 2 Hours	65
4.5.5	4 Hours of past data to predict next 4 Hours	66
4.5.6	6 Hours of past data to predict next 6 Hours	66
4.6	Effect of Variation of Input Features' Length	68
4.6.1	Logistic Regression	69
4.6.2	Decision Tree	70
4.6.3	Support Vector Machines	70
4.6.4	K-Nearest Neighbors	71
4.6.5	Multilayer Perceptron	72
4.7	Summary	74
5	CONCLUSION AND FUTURE WORK	75
5.1	Conclusion	75
5.2	Future Works	76
	REFERENCES	77
	APPENDICES	83
	BIODATA OF STUDENT	97
	LIST OF PUBLICATIONS	98

LIST OF TABLES

Table		Page
2.1	Summary of low power mode requirements by country	5
2.2	Tabular summary of the performance, strength and weakness of previous researchers	16
3.1	Modeling example of time series data into tabular form	30
3.2	A confusion matrix	33
4.1	Performance Comparison of LR, DT, MLP, SVM, and KNN in different scenario	68

LIST OF FIGURES

Figure		Page
3.1	The methodology workflow summary	20
3.2	Flow chart for programming	21
3.3	Sample dataset from REFIT	23
3.4	Snapshot of data set (power usage of appliances in watts)	24
3.5	Boxplot for all devices using complete data set	25
3.6	Boxplot for all devices after removing outliers	25
3.7	Power consumption of chest freezer	26
3.8	Line plot for chest freezer power consumption in a 12-hour window	27
3.9	Power consumption of chest freezer over 12 hours window with stand-by cutoff	27
3.10	Power consumption of chest freezer in different ranges	28
3.11	Ratio of stand-by and running state readings for chest freezer	29
4.1	Confusion Matrix for Logistic Regression, predicting next 10 minutes (constructed over a subset of test set)	37
4.2	Confusion matrix for Decision Tree, predicting next 10 minutes (constructed over a subset of test set)	38
4.3	Confusion Matrix for SVM, predicting next 10 minutes (constructed over a subset of test set)	38
4.4	Confusion matrix for KNN, predicting next 4 minutes (constructed over a subset of test set)	39
4.5	Confusion Matrix for Logistic Regression, predicting next 12 minutes (constructed over a subset of test set)	40
4.6	Confusion matrix for Decision Tree, predicting next 12 minutes (constructed over a subset of test set)	40

4.7	Confusion Matrix for SVM, predicting next 12 minutes (constructed over a subset of test set)	41
4.8	Confusion matrix for KNN, predicting next 12 minutes (constructed over a subset of test set)	41
4.9	Confusion Matrix for Multilayer Perceptron, predicting next 12 minutes (constructed over a subset of test set)	42
4.10	Confusion Matrix for Logistic Regression, predicting next 12 minutes (constructed over a subset of test set)	43
4.11	Confusion matrix for Decision Tree, predicting next 12 minutes (constructed over a subset of test set)	43
4.12	Confusion Matrix for SVM, predicting next 12 minutes (constructed over a subset of test set)	44
4.13	Confusion matrix for KNN, predicting next 12 minutes (constructed over a subset of test set)	44
4.14	Confusion Matrix for Multilayer Perceptron, predicting next 12 minutes (constructed over a subset of test set)	45
4.15	Confusion Matrix for Logistic Regression, predicting next 12 minutes (constructed over a subset of test set)	46
4.16	Confusion matrix for Decision Tree, predicting next 12 minutes (constructed over a subset of test set)	46
4.17	Confusion Matrix for SVM, predicting next 12 minutes (constructed over a subset of test set)	47
4.18	Confusion matrix for KNN, predicting next 12 minutes (constructed over a subset of test set)	47
4.19	Confusion Matrix for Multilayer Perceptron, predicting next 12 minutes (constructed over a subset of test set)	48
4.20	Confusion Matrix for Logistic Regression, predicting next 12 minutes (constructed over a subset of test set)	49
4.21	Confusion matrix for Decision Tree, predicting next 12 minutes (constructed over a subset of test set)	49

4.22	Confusion Matrix for SVM, predicting next 12 minutes (constructed over a subset of test set)	50
4.23	Confusion matrix for KNN, predicting next 12 minutes (constructed over a subset of test set)	50
4.24	Confusion Matrix for Multilayer Perceptron, predicting next 12 minutes (constructed over a subset of test set)	51
4.25	Confusion Matrix for Logistic Regression, predicting next 12 minutes (constructed over a subset of test set)	52
4.26	Confusion matrix for Decision Tree, predicting next 12 minutes (constructed over a subset of test set)	52
4.27	Confusion Matrix for SVM, predicting next 12 minutes (constructed over a subset of test set)	53
4.28	Confusion matrix for KNN, predicting next 12 minutes (constructed over a subset of test set)	53
4.29	Confusion Matrix for Multilayer Perceptron, predicting next 12 minutes (constructed over a subset of test set)	54
4.30	Prediction accuracy of next 10 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	55
4.31	Prediction accuracy of next 30 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	55
4.32	Prediction accuracy of next 60 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	56
4.33	Prediction accuracy of next 2 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	56
4.34	Prediction accuracy of next 4 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	57

4.35	Prediction accuracy of next 6 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	57
4.36	Prediction precision of next 10 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	58
4.37	Prediction precision of next 30 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	59
4.38	Prediction precision of next 60 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	59
4.39	Prediction precision of next 2 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	60
4.40	Prediction precision of next 4 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	60
4.41	Prediction precision of next 6 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	61
4.42	Prediction recall of next 10 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	61
4.43	Prediction recall of next 30 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	62
4.44	Prediction recall of next 60 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	62
4.45	Prediction recall of next 2 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	63

4.46	Prediction recall of next 4 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	63
4.47	Prediction recall of next 6 hours using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	64
4.48	F1-Score of next 10 minutes prediction using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	64
4.49	Prediction F1-Score of next 30 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	65
4.50	Prediction F1-Score of next 60 minutes using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	65
4.51	F1-Score of next 2 hours prediction using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	66
4.52	F1-Score of next 4 hours prediction using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	66
4.53	F1-Score of next 6 hours prediction using MLP, Decision Tree, Logistic Regression, Support Vector Machine and K Nearest Neighbors algorithm	67
4.54	Evaluation metrics for different prediction length (10, 30, 60, 120, 240 and 360 minutes) using Logistic Regression	69
4.55	Evaluation metrics for different prediction length (10, 30, 60, 120, 240 and 360 minutes) using Decision Tree	70
4.56	Evaluation metrics for different prediction length (10, 30, 60, 120, 240 and 360 minutes) using SVM	71
4.57	Evaluation metrics for different prediction length (10, 30, 60, 120, 240 and 360 minutes) using KNN	72
4.58	Evaluation metrics for different prediction length (10, 30, 60, 120, 240 and 360 minutes) using MLP	73

LIST OF ABBREVIATIONS

MLA	Machine learning algorithm
DT	Decision tree
KNN	K- Nearest neighbor
SVM	Support vector machine
MLP	Multilayer perceptron
IEA	International energy agency
PV	Photovoltaic
SEMS	Smart energy management system
EMS	Energy management system
HEMS	Home energy management system
DR	Demand response
PAR	Peak to average
MILP	mixed-integer linear programming
DG	Distributed generation
ESS	Energy storage systems
HVAC	Heating, ventilation and air conditioning
GA	Generic algorithms
GDP	Gross domestic products
IT	Information technology
CFL	Compact fluorescent lamp
LED	Light emitting diode

AC	Air condition
TV	Television
ERM	Energy resource management
SRAM	Static Random access memory
DRV	Data retention voltage
SB	Static blockade
ARIMA	Auto-regressive integrated moving average
DLB	Dynamic Load Balancing
CMOS	Complementary metal-oxide-semiconductor
LP	Linear programming
MLP	Mixed linear programming
BMS	Battery management system
FES	Fuzzy expert system
WSN	Wireless sensor network
ANN	Artificial neural network
UK	united Kingdom
CSV	comma separated value

CHAPTER 1

INTRODUCTION

1.1 Background

Energy is one of the most scarce and expensive resource. The cheapest and cleanest energy is that which is not used. Using energy efficiently, conserving energy and materials will reduce energy usage, greenhouse gas emissions and is the focus of Energy Management (Susanne & Hiroshi, 2007).

Recent environmental problems as a global issue has attracted great attention for energy saving. As a result efforts are being made for energy saving and governments are devising policies that encourage the distribution of energy saving systems, including individual households who voluntarily install energy saving systems to reduce electric power consumption (Jinsung et al., 2013). For the last few decades, various alternatives to conventional sources of energy like solar, wind, hydrokinetic and biomass energy have been explored. However, attention must also be given to the best utilization of energy, improvement in energy efficiency and optimum management of energy resources. In-fact, energy management deals with already existing sources and actual consumption. It includes planning and operation of energy related production and consumption units (M. Reyasudin et al., 2016). Energy management is the best solution for direct and immediate reduction of energy consumption.

An energy saving system refers to a system that saves energy consumed by cutting off wasted electric power such as standby power (Jinsoo et al., 2009). Factors that are involved in the wastage of energy include consumer carelessness, line and supply losses, distribution and standby mode loss.

1.2 Problem Statement

Many works have been carried out to forecast the power consumption in various settings, such as household, commercial building, city, etc., as well. However, to the best of our knowledge, no work has been carried out to forecast the standby mode switching time and burst at an appliance level with a fine temporal granularity such as minute. In this work, the problem to predict the state of an appliance and determine the suitability of various machine learning algorithms, namely Decision Tree, Logistic Regression, KNN classifier, MLP, and SVM, for predicting the state of an appliance at a given instance of time is addressed.

1.3 Objectives of the Study

This work aims to achieve the following objectives.

1. To propose an appliance state (standby or running) forecast model, and
2. Study the suitability of Decision Tree, Logistic Regression, KNN classifier, MLP, and SVM to predict the burst.

1.4 Hypothesis of the Research

Using machine learning algorithms (e.g. Decision Tree, Logistic Regression, KNN classifier, MLP, SVM, etc.), the standby mode switching time and the burst (interval an appliance would remain in this mode) could be forecasted and hence used in power conservation.

1.5 Scope of the Study

This research work is limited to study existing machine learning algorithms to effectively forecast the standby switching time and burst. The study uses published online datasets (<https://www.refitsmarthomes.org/datasets/>) of household power consumption, as detailed in Chapter 3, and does not use on purpose collected data. In this work, only cooling devices (fridge, refrigerator, freezer, fridge-freezer, etc.) are used as these are the ones which are continuously plugged in and need to be automatically switched on-off, rather than going to standby mode, after a certain period of time. This fact makes these devices an interesting case of study for stand-by burst forecast, unlike other electric/electronic devices such as computer, kettle, microwave, etc. which are switched on/off or put on stand-by mode as per the need of the user.

1.6 Research Contribution

This work comprises of all the steps as mentioned above, in Section 1.4. However, it's main contributions are:

- i. Data preparation to remove the consistencies in the data sets such as, irregular peaks, null values, and missing data. The appliance profiling was also performed to categorize the power consumption is running and standby mode.
- ii. The primary contribution of this work resides at the data modelling stage. It proposes to model the available time series data in a tabular

form as past events representing the independent variables while the current event is the dependent variable. The problem is modeled as a classification problem and it is shown that such modeling technique gives very accurate results with accuracy of machine learning algorithms reaching close to 100 percent.

- iii. This work uses the most suitable machine learning algorithms (Decision Tree, Logistic Regression, KNN classifier, MLP, and SVM) to build the forecast models and evaluated them using the most appropriate evaluation metrics (accuracy, precision, recall, F1 score). Findings of the chosen algorithms are documented that produce very promising results.

1.7 Thesis Layouts

Chapter 1 discusses the background and motivation for this study. This chapter also provides the hypothesis and formally state study problem. The objectives, scope and contributions of the study are also outlined here.

Chapter 2 analyzes the related work and discusses the state-of-the-art standby power consumption management.

Chapter 3 details the methodology and procedures of the study including the data sets and the analysis performed. Rationale to choose the selected machine learning methods is also detailed in the same chapter.

In Chapter 4, results obtained from the analysis are presented and it is discussed that how useful could they be in standby power management.

Chapter 5 summarizes the work and puts whole of this study into a nutshell. It also discusses the important future directions that can lead from this work.

REFERENCES

- Alawadi, S., Mera, D., Fernández-Delgado, M., Alkhabbas, F., Olsson, C. M., & Davidsson, P. (2020). A comparison of machine learning algorithms for forecasting indoor temperature in smart buildings. *Energy Systems*. <https://doi.org/10.1007/s12667-020-00376-x>
- Alizamir, M., Kim, S., Kisi, O., & Zounemat-Kermani, M. (2020). A comparative study of several machine learning based non-linear regression methods in estimating solar radiation: Case studies of the USA and Turkey regions. *Energy*, 197, 117239. <https://doi.org/https://doi.org/10.1016/j.energy.2020.117239>
- Arabali, A., Ghofrani, M., Etezadi-Amoli, M., Fadali, A., & Baghzouz, A. (2013). Genetic-Algorithm-Based Optimization Approach for Energy Management. *IEEE Transactions on Power Delivery*, 28(1), 162-170.
- Bhatnagar, R., & Rao, C. (2005). Energy resource management based on data mining and artificial intelligence. In *Proceedings ACEEE Summer Study on Energy Efficiency in Industry* (pp. 6-14 - 6-23).
- Bianchini, R., & Rajamony, R. (2004). Power and energy management for server systems. In *Computer* (Vol. 37, Issue 11, pp. 68-76).
- Billinton, R. (2005). Evaluation of Different Operating Strategies in Small Stand-Alone Power Systems. *IEEE Transactions on Energy Conversion*, 20(3), 654-660.
- Bourhnane, S., Abid, M. R., Lghoul, R., Zine-Dine, K., Elkamoun, N., & Benhaddou, D. (2020). Machine learning for energy consumption prediction and scheduling in smart buildings. *SN Applied Sciences*, 2(2), 297. <https://doi.org/10.1007/s42452-020-2024-9>
- Chen, C., Duan, S., Cai, T., Liu, B., & Hu, G. (2011). Smart energy management system for optimal microgrid economic operation. *IET Renewable Power Generation*, 5(3).
- Cover, T. M., & Hart, P. E. (1967). Nearest Neighbor Pattern Classification. In *IEEE Transactions on Information Theory* (Vol. 13, Issue 1, pp. 21-27). <https://doi.org/10.1109/TIT.1967.1053964>
- David, M., Lina, S., & Vladimir, S. (2017). An electrical load measurements dataset of United Kingdom households from a two-year longitudinal study. *Scientific Data*, 4.

- Eric, H., Kimberley A., M., & Inês L., A. (2012). Electricity consumption and energy savings potential of video game consoles in the United States. *Energy Efficiency*, 5(4), 531–545.
- Evangelos I., V., & Stavros A., P. (2011). Operating Policy and Optimal Sizing of a High Penetration RES-BESS System for Small Isolated Grids. *IEEE Transactions on Energy Conversion*, 26(3), 744–756.
- Fallah, F., & Pedram, M. (2005). Standby and active leakage current control and minimization in CMOS VLSI circuits. In *IEICE Transactions on Electronics* (Vols. E88-C, Issue 4, pp. 509–519). <https://doi.org/10.1093/ietele/e88-c.4.509>
- Fan, F., Zhengwei, L., Yingjun, R., & Peng, X. (2016). An Empirical Study of Influencing Factors on Residential Building Energy Consumption in Qingdao City, China. In *Energy Procedia* (Vol. 104, pp. 245–250).
- Fernandes, S., Antunes, M., Santiago, A. R., Barraca, J. P., Gomes, D., & Aguiar, R. L. (2020). Forecasting appliances failures: A machine-learning approach to predictive maintenance. *Information (Switzerland)*, 11(4), 208. <https://doi.org/10.3390/INFO11040208>
- Frank, S., Gentile Polese, L., Rader, E., Sheppy, M., & Smith, J. (2011). Extracting operating modes from building electrical load data. *2011 IEEE Green Technologies Conference, Green 2011*, 15,. <https://doi.org/10.1109/GREEN.2011.5754872>
- Haykin, S. (1998). *Neural Networks: A Comprehensive Foundation* (2nd ed.). Prentice Hall.
- Hossin, M., & Sulaiman, M. N. (2015). A Review on Evaluation Metrics for Data Classification Evaluations. In *International Journal of Data Mining & Knowledge Management Process* (Vol. 5, Issue 2, pp. 1–11).
- Huang, M., Renau, J., Yoo, S. M., & Torrellas, J. (2000). Framework for dynamic energy efficiency and temperature management. *Proceedings of the Annual International Symposium on Microarchitecture*, 202–213. <https://doi.org/10.1145/360128.360149>
- Jayakumar, N., & Khatri, S. P. (2007). An algorithm to minimize leakage through simultaneous input vector control and circuit modification. *Proceedings -Design, Automation and Test in Europe, DATE*, 618–623. <https://doi.org/10.1109/DATE.2007.364662>

- Jinsoo, H., Haeryong, L., & Kwang-Roh, P. (2009). Remote-controllable and energy-saving room architecture based on ZigBee communication. *IEEE Transactions on Consumer Electronics*, 55(1), 264–268.
- Jinsung, B., Sunghoi, P., Byeongkwan, K., Insung, H., & Sehyun, P. (2013). Design and implementation of an intelligent energy saving system based on standby power reduction for a future zero-energy home environment. *IEEE Transactions on Consumer Electronics*, 59(3), 507–514.
- Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255 LP – 260. <https://doi.org/10.1126/science.aaa8415>
- Kavitha, S., & Anandam, K. (2018). Distributed Data Mining and Dynamic Load Balancing Algorithms in Cluster of Novel Mobile Agent Frameworks Using TCP". *Middle-East Journal of Scientific Research Journal*, 23(9), 2135–2144.
- Keerthi, S. S., & Gilbert, E. G. (n.d.). Convergence of a generalized SMO algorithm for SVM classifier design. *Machine Learning*, 46(1–3), 351–360.
- Kelly, J., & Knottenbelt, W. (2015). The {UK-DALE} dataset, domestic appliance-level electricity demand and whole-house demand from five {UK} homes. *Scientific Data*, 2(150007). <https://doi.org/10.1038/sdata.2015.7>
- Kerry, H., Jayant, B., Michael, F., Robert, A., & Rodney S., T. (2011). Power consumption and energy efficiency in the internet. In *IEEE Network* (Vol. 25, Issue 2, pp. 6–12).
- Krzysztof, G., & Tomasz, Z. (2015). Data Mining Techniques for Detecting Household Characteristics Based on Smart Meter Data. In *Energies* (Vol. 8, Issue 7, pp. 7407–7427).
- Laicane, I., Blumberga, A., Roša, M., & Blumberga, D. (2014). Determinants of household electricity consumption savings: A Latvian case study. *Agronomy Research*, 12(2), 527–542.
- Li, Y., Yingjun, R., Guang, Y., Fan, F., & Zhengwei, L. (2016). Analysis of Factors Influencing the Energy Consumption of Government Office Buildings in Qingdao. *Energy Procedia*, 104, 263–268.
- M. Reyasudin, B. K., Razali, J., & Jagadeesh, P. (2016). Multi-agent based distributed control architecture for microgrid energy management and optimization. *Energy Conversion and Management*, 112, 288–307.

- Marnay, C., Asano, H., Papathanassiou, S., & Strbac, G. (2008). Policymaking for microgrids. *IEEE Power and Energy Magazine*, 6(3), 66-77.
- Michael Angelo A., P., Ted D., S., & Iain F., M. (2010). Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services. In *IEEE Transactions on Smart Grid* (Vol. 1, Issue 2, pp. 134-143).
- Narseo, V.-R., & Jon, C. (2013). Energy Management Techniques in Modern Mobile Handsets. In *IEEE Communications Surveys & Tutorials* (Vol. 15, Issue 1, pp. 179-198).
- Philip H., S., & Hans, H. (1977). The decision tree classifier: Design and potential. In *IEEE Transactions on Geoscience Electronics* (Vol. 15, Issue 3, pp. 142-147).
- Qin, H., Cao, Y., Markovic, D., Vladimirescu, A., & Rabaey, J. (2004). SRAM leakage suppression by minimizing standby supply voltage. *Proceedings - 5th International Symposium on Quality Electronic Design, ISQED 2004*, 55-60. <https://doi.org/10.1109/isqed.2004.1283650>
- Raymond H., B., Tu A., N., David A., C., Babu R., C., & Imre, G. (2018). Energy Management and Optimization Methods for Grid Energy Storage Systems. *IEEE Access*, 6, 13231-13260.
- Resat, S., Arzu, S., & Ecir, U. (2011). *Data Mining Method For Energy System Applications*. InTech.
- Sahu, S. K. (2009). Trends and Patterns of Energy Consumption in India. *Munich Personal RePEc Archive Trends*, 16774, 32. https://mpra.ub.uni-muenchen.de/16774/1/MPRA_paper_16774.pdf <http://mpra.ub.uni-muenchen.de/16774/>
- Salam, A., & Hibaoui, A. E. (2018). Comparison of Machine Learning Algorithms for the Power Consumption Prediction : - Case Study of Tetouan city -. *2018 6th International Renewable and Sustainable Energy Conference (IRSEC)*, 1-5. <https://doi.org/10.1109/IRSEC.2018.8703007>
- Shaheen, A. T., & Taha, S. M. . (2017). Standby power analysis and minimization in dual size sub-threshold circuits". *Published in Conference Paper*, 1-7.
- Stankoski, S., Kiprijanovska, I., Ilievski, I., Slobodan, J., & Gjoreski, H. (2019). Electrical Energy Consumption Prediction Using Machine Learning. In S. Gievska & G. Madjarov (Eds.), *ICT Innovations 2019. Big Data Processing and Mining* (pp. 72-82). Springer International Publishing.

- Stetco, A., Dinmohammadi, F., Zhao, X., Robu, V., Flynn, D., Barnes, M., Keane, J., & Nenadic, G. (2019). Machine learning methods for wind turbine condition monitoring: A review. *Renewable Energy*, 133, 620–635. <https://doi.org/https://doi.org/10.1016/j.renene.2018.10.047>
- Susanne, A., & Hiroshi, F. (2007). Energy-efficient algorithms for flow time minimization. *ACM Transactions on Algorithms*, 3(4), 49-es.
- Tao, Y. (2016). Data-driven recommendation mechanism for flexible load management. *IEEE Power and Energy Society General Meeting, 2016-November*. <https://doi.org/10.1109/PESGM.2016.7741851>
- Tariq, W., Othmani, L., & Mustafa, A. (2017). Standby Mode Minimization and Periodic Controlling For Efficient Building Energy Management System Using Fuzzy Logic and Image". *Asian Journal Of Engineering, Sciences & Technology*, 2(ue 1), 1–9.
- Veleva, S., & Davcev, D. (2011). Multi-criterion mining algorithm for efficient home energy management system. In *12th IEEE International Symposium on Computational Intelligence and Informatics, CINTI 2011 - Proceedings* (pp. 481–486). IEEE. <https://doi.org/10.1109/CINTI.2011.6108554>
- Walker, S., Khan, W., Katic, K., Maassen, W., & Zeiler, W. (2020). Accuracy of different machine learning algorithms and added-value of predicting aggregated-level energy performance of commercial buildings. *Energy and Buildings*, 209, 109705. <https://doi.org/https://doi.org/10.1016/j.enbuild.2019.109705>
- Wang, J., & H., B. (2010). Standby Supply Voltage Minimization for Reliable Nanoscale SRAMs. In S. J. by (Ed.), *Solid State Circuits Technologies* (p. 462). <https://doi.org/10.5772/6876>
- Westskog, H., & Winther, T. (2014). Electricity Consumption: Should There Be a Limit? Implications of People's Attitudes for the Forming of Sustainable Energy Policies. *Consilience: The Journal of Sustainable Development*, 11(1), 39.
- Wright, R. E. (1995). Logistic regression. In *Reading and understanding multivariate statistics*. (pp. 217–244). American Psychological Association.
- Yanyu, Z., Peng, Z., & Chuanzhi, Z. (2015). *Optimization algorithm for home energy management system based on artificial bee colony in smart grid*.
- Yi-Tui, C. (2017). The Factors Affecting Electricity Consumption and the Consumption Characteristics in the Residential Sector—A Case Example of Taiwan. *Sustainability*, 9(8).

Yu, Z. J. (2012). Mining Hidden Knowledge from Measured Data for Improving Building Energy Performance. In *Thesis Paper on Building, Civil and environmental Engineering* (p. 1).

Zhao, L., Zhang, J., & Zhong, C. (2016). The Application of Data Mining Technology in Building Energy Consumption Data Analysis. *International Journal of Computer and Information Engineering*, 10(1), 81–85. <https://waset.org/publications/10003363/the-application-of-data-mining-technology-in-building-energy-consumption-data-analysis>

