An Intelligent Forecasting Method for Hierarchical Load Structure in a Residential Market

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I dedicate this thesis to my loving parents, who instilled in me the confidence to pursue my academic goals from the very beginning. I also dedicate it to my husband, whose unwavering support and encouragement made this journey possible. Finally, I give all my love to my newborn daughter, who gave me the final push to complete this work.

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Attestation of Authorship

I hereby declare that except where specific reference is made to the work of others, the contents of this thesis are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgments.

Barkha Parkash
May 2026

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Abstract

Electricity is an essential resource in the modern world, underpinning nearly all aspects of daily life. In recent years, the residential electricity consumption profile has evolved significantly due to the increasing penetration of non-linear loads such as electric vehicles (EVs) and localised generation from rooftop photovoltaic (PV) systems. These changes pose new challenges for utility operators, who must manage infrastructure while ensuring a stable balance between electricity demand and supply. Accurate load forecasting is, therefore, critical to avoid mismatches that may compromise grid reliability and efficiency.

In the residential sector, electricity consumption patterns vary widely between households, influenced by socio-demographic factors such as income, household size, and occupancy patterns. These contribute to diverse load profiles, necessitating a deeper understanding of their relationship with electricity usage to develop more accurate and responsive forecasting models.

This research advances residential load forecasting by developing a novel top-down (TD) hierarchical forecasting framework. Traditional TD methods typically use fixed historical ratios for disaggregation, which can fail to adapt to dynamic consumption patterns. In contrast, the proposed framework leverages input features from both the aggregated level and the target sub-level, along with cross learning features, to forecast loads across multiple layers of hierarchy. Two model variations are proposed: a two-stage model, where separate neural models are trained for aggregated and sub-level forecasts with the second model utilising output of first model, and an end-to-end model that integrates all inputs into a single learning structure. These approaches enable accurate forecasting across different levels of hierarchy without relying on static assumptions, improving both scalability and performance.

A second key contribution is the integration of socio-demographic features and EV charging data into the forecasting models. By incorporating variables such as household characteristics and EV charging behaviours, the study evaluates the impact that these have on the forecasting accuracy.

The third major contribution is the investigation of EV charging prices and their interaction with charging time and load forecasting accuracy. As market liberalisation has introduced time varying and dynamic pricing structures, consumers are increasingly responsive to price

signals. The thesis analyses how these pricing models affect EV charging patterns and, subsequently, the performance of the proposed forecasting models. It highlights that price driven charging behaviours introduce additional uncertainty and volatility into load profiles, which must be accounted for in effective forecasting strategies.

Together, these contributions offer a robust and adaptable framework for residential load forecasting that accommodates evolving consumption patterns. The proposed methodology is not only scalable and data efficient but also tailored for practical deployment in modern power systems, offering utility providers and stakeholders a valuable tool for planning and operational decision making.

Publications

Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. "Hierarchical structure based energy consumption forecasting in top-down approach." In 2022 7th Asia Conference on Power and Electrical Engineering (ACPEE), pp. 1732-1737. IEEE, 2022.

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Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. "AI-Based Electrical Load Forecasting for Residential Sector Using Smart Meter Data." In Engineering Applications of AI for Demand Forecasting (pp. 230-254). CRC Press

Table of contents

Copyright iii

Attestation of Authorship iv

Acknowledgements v

Publications viii

List of figures **xiii**

List of tables **xv**

Nomenclature **xvii**

1 Introduction **1**

1.1 Research Background 1
1.2 Scope and Significance 4
1.3 Research Aim and Objectives 5
1.4 Contributions 7
1.5 Organisation of the Thesis 9

2 Literature Review **11**

2.1 Introduction 11
2.2 Load Forecasting 11
2.3 Load Forecasting Techniques 14
2.3.1 Statistical Techniques 14
2.3.2 Machine Learning for Load Forecasting 17
2.3.3 Soft Computing Techniques 19
2.4 Existing Forecasting Models in Literature 21
2.5 Hierarchical Forecast Models 22

2.6 Building Hierarchical Structure 24
2.6.1 Clustering 25
2.6.2 Input Features for Clustering Algorithm 28
2.6.3 Cluster Evaluation 30
2.6.4 Load Forecasting Factors 31
2.7 Research Gap Analysis 33
2.7.1 Identified Research Gaps and Research Questions 34
2.8 Evaluation and Approval 35

3 A Top-down-based Hierarchical Forecast Model for the Residential Sector 36
3.1 Abstract 36
3.2 Methodology for Building Forecast Model 37
3.3 Procuring Data 39
3.4 Hierarchical Structure 41
3.5 Top-down based Load Forecasting 42
3.5.1 Two-Stage Approach 43
3.6 Case Study 1: Experiments and Results 44
3.6.1 Representative Load Profiles 44
3.6.2 Comparison and Analysis of Clustering Algorithms 45
3.6.3 Forecasting Model for Aggregated Level 48
3.6.4 Forecasting Model for Lower Hierarchical Levels 51
3.6.5 Evaluation of the Proposed Methodology Against the Bottom-Up Approach 53
3.6.6 Discussion 55
3.7 End-to-End (E2E) Learning Model 55
3.8 Case Study 2: Experiments and Results 58
3.8.1 Dataset Description 58
3.8.2 Hierarchical Structure 59
3.8.3 Performance Assessment of Forecast Models Using MAPE 61
3.8.4 Comparative Analysis of Two-Stage and End-to-End Learning Approaches via MASE 65
3.8.5 Performance Comparison of E2E Model and Bottom-Up Model . . 67
3.9 Discussion 68
3.10 Relation between socio-demographical features and residential consumption 70
3.10.1 Impact of socio-demographical features on the forecasting accuraccy 76
3.11 Feature Importance 78

4 Analysis and Modelling of Residential Load Profiles with Electric Vehicle Integration 80

4.1 Abstract . . . 80
4.2 Evaluation of Residential Load Profiles without Electric Vehicles . . . 80
4.2.1 Cluster 1 . . . 82
4.2.2 Cluster 3 . . . 83
4.2.3 Cluster 4 . . . 85
4.2.4 Cluster 5 . . . 86
4.2.5 Cluster 7 . . . 88
4.2.6 Cluster 8 . . . 90
4.2.7 Cluster 9 . . . 92
4.3 Impact of EVs on daily load profile . . . 94
4.3.1 Cluster 1 . . . 96
4.3.2 Cluster 3 . . . 97
4.3.3 Cluster 4 . . . 98
4.3.4 Cluster 5 . . . 100
4.3.5 Cluster 7 . . . 101
4.3.6 Cluster 8 . . . 106
4.3.7 Cluster 9 . . . 108
4.4 Methodology to incorporate EV charging profile in Forecast Model . . . 110
4.4.1 Monte Carlo Simulation Use Cases . . . 111
4.4.2 Importance of Monte Carlo Approach . . . 113
4.5 Monte Carlo Approach for Generating EV load Profile . . . 114
4.5.1 Methodology used for Monte Carlo Simulation . . . 114
4.6 Electric Vehicle Load Profiles Generated via Monte Carlo Simulation . . . 119
4.6.1 Simulated EV Charging Profile of an EV with 18 kWh Battery . . . 120
4.6.2 Simulated EV Charging Profile of an EV with 75 kWh Battery . . . 122
4.7 Assessment of forecast model with EV load profiles . . . 122
4.7.1 Different EV charging scenarios . . . 123
4.7.2 Discussion . . . 126

5 Impact of EV Charging Price Variations on Forecasting Models 129

5.1 Abstract . . . 129
5.2 Static Charging Price . . . 129
5.3 Smart Charging Strategies . . . 130
5.3.1 Stochastic Pricing . . . 130
5.3.2 Dynamic Pricing . . . 132

5.3.3 Menu Based Pricing 133
5.4 EV Charging Mechanism in the Residential Sector 134
5.5 Impact of Electric Vehicle Charging Price on Load Forecast Model 135
5.5.1 Methodology 137
5.5.2 Results 137
5.6 Discussion 140

6 Conclusion and Future Work **145**
6.1 Synopsis and Conclusion 145
6.1.1 Novel Hierarchical Forecast Model 145
6.1.2 Exploring Impact of Socio-demographics and Electric Vehicle Charging onto the Forecast Model 146
6.1.3 Correlation between Electric Charging Price and Charging Time with Impact Analysis onto the Forecast Model 147
6.2 Practical Implications 148
6.3 Limitations 148
6.4 Recommendations for Future Work 149

References **151**

List of figures

1.1 Global electricity consumption by sector [1] 2
1.2 Significance of top-down load forecast approach 6

2.1 Forecasting time horizons 12

3.1 Methodology for designing a forecast model 37
3.2 Cluster-based hierarchical structure 38
3.3 Two-stage Top-down forecasting approach for hierarchical structure 43
3.4 K-means algorithm results: Cluster 0 and Cluster 1 46
3.5 K-means algorithm results: Cluster 2 and Cluster 3 47
3.6 Hierarchy structure for considered houses of REFIT dataset 48
3.7 Auto correlation and partial autocorrelation plots of the training dataset . . 49
3.8 Heatmap illustrating the correlation between load consumption and features 50
3.9 Comparison of forecasting performance across clusters 52
3.10 Load Profiles Under Different Forecasting Scenarios for Cluster 0 54
3.11 End-to-End learning model 56
3.12 Seasonal representative load profile of a single household in 2013 59
3.13 Seasonal representative load profile of a single household in 2021 60
3.14 Load profiles of clusters (average) 61
3.15 Heatmap of MAPE for each hour of the day for all clusters 66
3.16 Comparison between actual and forecast values from both approaches . . . 68

4.1 Comparison of weekday and weekend profiles for Cluster 1 83
4.2 Comparison of weekday and weekend profiles for Cluster 3 84
4.3 Comparison of weekday and weekend profiles for Cluster 4 86
4.4 Comparison of weekday and weekend profiles for Cluster 5 87
4.5 Comparison of weekday and weekend profiles for Cluster 7 89
4.6 Comparison of weekday and weekend profiles for Cluster 8 91
4.7 Comparison of weekday and weekend profiles for Cluster 9 93

4.8 No. of charging sessions per type for House 6990 96
4.9 No. of charging sessions per type for House 1169 98
4.10 No. of charging sessions per type for House 3482 99
4.11 No. of charging sessions per type for House 2470 100
4.12 No. of charging sessions per type for House 4373 101
4.13 No. of charging sessions per type for House 1642 102
4.14 No. of charging sessions per type for House 2814 103
4.15 No. of charging sessions per type for House 5403 104
4.16 No. of charging sessions per type for House 8236 105
4.17 No. of charging sessions per type for House 9729 106
4.18 No. of charging sessions per type for House 7989 107
4.19 No. of charging sessions per type for House 9609 108
4.20 Monte Carlo Methodology for Creating EV Charging Profiles 115
4.21 PDF and CDF of rated average charging power of an EV with battery size of 18 kWh 120
4.22 PDF and CDF of start of charging hour of an EV with a battery size of 18kWh 121
4.23 Simulated daily charging profile of EV with a battery size of 18 kWh 121
4.24 PDF and CDF of rated average charging power of an EV with battery size of 75 kWh 122
4.25 Simulated daily charging profile of EV with a battery size of 75 kWh 123
4.26 Comparison between random and overnight charging under low EV penetration 125
4.27 Comparison between random and overnight charging under medium EV penetration 126
4.28 Comparison between random and overnight charging under high EV penetration 127

5.1 Load profile of Cluster 1 under peak and off-peak EV charging scenarios . . 140
5.2 Load profile of Cluster 3 under peak and off-peak EV charging scenarios . . 141
5.3 Load profile of Cluster 4 under peak and off-peak EV charging scenarios . . 142
5.4 Load profile of Cluster 8 under peak and off-peak EV charging scenarios . . 143
5.5 Load profile of Cluster 5 under peak and off-peak EV charging scenarios . . 143
5.6 Load profile of Cluster 7 under peak and off-peak EV charging scenarios . . 144
5.7 Load profile of Cluster 9 under peak and off-peak EV charging scenarios . . 144

List of tables

1.1 Comparison of hierarchical forecasting approaches 4

3.1 Public datasets with residential consumption data 39
3.2 Index of agreement for the RLPs 45
3.3 Performance comparison of various clustering algorithms 46
3.4 SARIMA model coefficients and AIC 49
3.5 Comparison of forecast models for the aggregated level using MAPE 51
3.6 Comparison between BU and Proposed Approach using MAPE 53
3.7 Statistical parameters of clusters 62
3.8 Input features utilised by the forecast model 63
3.9 Forecast model performance comparison using MAPE 64
3.10 Comparative evaluation of E2E learning and the two-stage model based on MASE 65
3.11 Comparison between E2E learning and BU approach using MAPE 67
3.12 Socio-demographical Features 72
3.13 Categorical input features of demographics 73
3.14 Impact of socio-demographic features on forecasting accuracy measured by MAPE 77

4.1 No. of EVs in each cluster 81
4.2 Monte Carlo assumptions and their expected influence on EV load profiles . 118
4.3 EV Models and battery capacity 120
4.4 EV Penetration in Each Cluster 123
4.5 Forecasting Accuracy for Different Penetration Levels Using MAPE 125

5.1 Electricity Rates 136
5.2 Forecasting Accuracy (MAPE) During Peak and Off-Peak EV Charging Periods 138

6.1 Potential Application for Stakeholders 148

Nomenclature

Abbreviation	Description
C_i	Battery capacity of EV i
L_t	Load at time t
P_{avg}	Average charging power
t_{start}	Charging start time
ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
ARIMA	Auto Regressive Integrated Moving Average
AUT	Auckland University of Technology
BU	Bottom Up
CDFs	Cumulative Distribution Functions
CNNs	Convolution Neural Networks
DERs	Distributed Energy Resources
DL	Deep Learning
DT	Decision Trees
E2E	End-to-End
ES	Exponential Smoothing
EVs	Electric Vehicles
FL	Fuzzy Logic

GAs	Genetic Algorithms
GRU	Gated Recurrent Units
IA	Index of Agreement
IRLS	Iterative Reweighted Least-Squares Technique
LSTM	Long Short Term Memory
LTFs	Load Tracking Features
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MCS	Monte Carlo Simulation
MO	Middle Out
NNs	Neural Networks
PACF	Partial Autocorrelation Function
PDFs	Probability Distribution Functions
RES	Renewable Energy Sources
RF	Random Forest
RLPs	Representative Load Profiles
RNNs	Recurrent Neural Networks
SOC	State of Charge
STLF	Short Term Load Forecast
SVM	Support Vector Machine
SVR	Support Vector Regression
TD	Top Down
TOU	Time of Use
WCSS	Within-Cluster Sum of Squares

Chapter 1

Introduction

1.1 Research Background

Electricity consumption spans all sectors including commercial, industrial, and residential. Out of these, the industrial sector has been the largest consumer of electricity, followed by the residential sector, as reported by the U.S. Energy Information Administration [1]. However, recent technological advancements such as the development of the Internet of Things (IoT), the deployment of artificial intelligence, smart automation and control systems, and the growing adoption of electric vehicles (EVs) have significantly increased electricity consumption within the residential sector. This upward trend in residential electricity demand is projected to continue, with forecasts suggesting that by 2050, residential electricity consumption will match that of the industrial sector [1], as illustrated in Fig. 1.1.

A key driver of these shifts is the urgent need to reduce greenhouse gas (GHG) emissions, given that electricity generation from fossil fuels remains one of the major contributors to global emissions. The most effective strategy to mitigate these emissions is to transition to cleaner renewable energy sources (RES). Consequently, there has been an increasing adoption of RES within power systems, particularly among residential consumers who frequently install rooftop photovoltaic panels [2]. Moreover, there is a growing trend in EV adoption within the residential sector. The integration of RES and other distributed energy resources (DERs), alongside the introduction of EV charging, has substantially transformed the characteristics of power systems. The presence of non-dispatchable generation from RES and the additional flexible yet uncertain load from EVs is now significantly impacting daily residential load profiles.

This shifting paradigm highlights the crucial need to focus on the residential sector, not only because of its increasing share of overall electricity consumption, but also due to the operational challenges it poses. The increased electricity demand in the residential sector

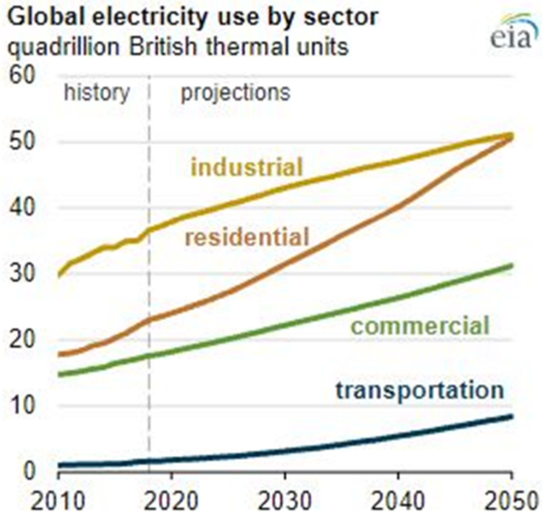


Fig. 1.1 Global electricity consumption by sector [1]

leads to greater variability in load profiles, driven by factors such as EV charging patterns, the adoption of DERs, and households' time-of-use behaviour. Renewable energy sources are inherently volatile, making it challenging to predict the extent to which consumers will rely on their self-generated energy versus the grid supply [3]. Additionally, EV charging patterns are highly unpredictable, as users choose charging times based on individual schedules and convenience. This variability complicates grid operators' ability to plan routine operations and maintenance effectively. Furthermore, for efficient power system planning and maintenance, it is imperative to have accurate forecasts of the load that the grid needs to supply. Reliable forecasts not only indicate the magnitude of demand but also provide insights into when this demand is expected to occur. Such information is crucial for the effective operation of the power system and supports the development and implementation of strategies, such as demand-side management to optimise grid performance and stability.

The three primary sectors of electricity consumption exhibit distinct patterns. While it is relatively straightforward to forecast load for industrial and commercial sectors due to their consistent daily routines, the same does not hold for the residential sector [4]. Residential electricity consumption varies significantly across households and is heavily influenced by weather conditions as well as socio-demographic factors such as income, family size, residents' age, and location [5],[6],[7]. These factors shape individual household consumption behaviour, posing challenges to accurately forecast residential load. Whereas, accurate load forecasting is essential for power system operators as it enables efficient system operations, including unit commitment, economic dispatch, scheduled maintenance, and security assessments [8]. To improve the forecasting accuracy of residential load, it is essential not only to understand the relationship between the various factors contributing to its volatility but also to incorporate these factors into the forecasting model itself. This approach supports the effective, reliable, and sustainable operation of the power system, particularly as it adapts to the growing integration of RES and the increasing adoption of EVs within the residential sector.

In light of these challenges, both academics and industry stakeholders have increasingly focused on developing accurate forecasting models for the residential loads. However, most existing models concentrate on forecasting the load consumption of either individual households or specific groups of households with similar consumption behaviours. While accurate forecasts at the individual household level are valuable, particularly for enabling consumers to adjust and optimise their usage, such models remain limited in scope as they address only one aspect of the broader power system. Within the residential sector, it is beneficial not only to forecast at the individual household level but also to have aggregated forecasts at the sector level, along with a clear understanding of the different consumer groups and their corresponding consumption patterns. Consequently, developing forecasts at multiple levels is essential to address the modern challenges faced by power systems. Aggregated forecasts are particularly critical for power system operators, as they provide insight into the total demand that must be met to ensure reliable system operation. Moreover, having forecasts for different consumer groups within the residential sector can inform targeted strategies to improve consumption behaviours and implement effective demand-side management interventions. These requirements can be addressed through hierarchical forecasting approaches, which provide forecasts at various levels within the sector, from individual households to aggregated community or sector-wide levels.

Hierarchical forecasting can be implemented using one of three approaches: top-down (TD), bottom-up (BU), or middle-out. The TD approach involves building a forecasting model at the highest level of the hierarchy, and forecasts for the lower levels are then derived by distributing the top-level forecast according to historical distribution ratios [9]. In contrast, the BU approach develops individual forecasting models for each lower-level series, and the forecasts for higher levels are obtained by aggregating these lower-level forecasts [9]. The middle out approach builds forecasting models at an intermediate level, with forecasts then being aggregated upwards or disaggregated downwards as required [9].

While BU and middle-out approaches can provide highly granular forecasts, they are computationally intensive as they require the development of multiple models, extensive data at the lower levels, and significant computational resources for implementation [9]. Additionally, the BU approach may suffer from data quality issues at the disaggregated level, where individual household data might be sparse, noisy, or unavailable, leading to inaccurate aggregated forecasts [9]. Similarly, the middle-out approach inherits the complexity of both BU and TD approaches, making it less practical for large scale residential sector forecasts. On the other hand, the TD approach offers a more computationally efficient solution as it requires building only a single model at the aggregate level. However, it requires the use of additional methodologies to improve the accuracy of forecasts at the disaggregated lower levels.

Table 1.1 Comparison of hierarchical forecasting approaches

Criterion	Top-Down	Bottom-Up	Middle-Out
Data Requirements	Low	Very high	High
Computational Cost	Low	Very high	Medium–High
Scalability	High	Poor	Medium

The key differences between these approaches are summarised in Table 1.1, where the TD approach clearly offers advantages in terms of data requirements, computational efficiency, and scalability; three aspects that are critical when working with large-scale smart-meter datasets. Consequently, the TD approach offered a more realistic, operationally feasible, and empirically effective solution for modelling residential demand with EV integration. Given these considerations, this study adopts the TD approach due to its practicality, reduced computational complexity, lower data requirements at disaggregated levels, and suitability for providing reliable aggregated forecasts needed by power system operators. Thus, this thesis focuses on developing hierarchical forecasting models for the residential sector using the TD approach to address these complex needs and support the effective planning and operation of modern power systems.

1.2 Scope and Significance

Based on the research background, this research aims to develop a robust short-term load forecasting (STLF) model specialized to the hierarchical load structure within the residential market. Load forecasting is a decisive component in power market design, underpinning optimisation, distribution, and planning processes [10]. Accurate and reliable forecasting techniques enhance power system reliability, operational efficiency, and grid resilience. Furthermore, they facilitate the practical functionality of load management systems, ultimately benefiting both consumers and energy utilities by ensuring a stable supply and effective demand-side management [11].

STLF plays a crucial role in providing grid operators with valuable insights not only to bridge the gap between electricity demand and supply but also to ensure system stability and market operation [4]. In particular, hierarchical forecasting for the residential sector holds significant importance, as it enables a comprehensive understanding of the sector's overall contribution while identifying common consumption patterns across residential households. This understanding is vital for developing targeted demand response strategies and supporting policy interventions that promote a sustainable energy future.

In hierarchical load forecasting, the selection of the appropriate approach is crucial. As discussed above, the BU and middle-out approaches are computationally extensive and requires extensive data and multiple forecast models. This research focuses on developing a forecast model for the residential sector using the TD approach. Unlike other methods, the TD approach directly generates forecasts at the aggregated level, offering significant advantages for utility operators, illustrated in Fig. 1.2. Additionally, this methodology facilitates the identification of distinct customer groups within the residential sector and their corresponding demand, enabling retailers to determine tariff rates for these groups. Moreover, this approach requires less data and fewer forecast models, making it well-suited for practical implementation.

With the increasing adoption of EVs among residential consumers, residential load forecast models are incomplete without incorporating EV integration. Moreover, EV uptake is strongly influenced by charging price structures, as consumers tend to favor cost-effective charging options. Consequently, understanding residential load profiles alongside EV adoption patterns and charging price models is crucial for producing accurate forecasts. For this reason, these factors have been incorporated into this thesis for evaluation.

1.3 Research Aim and Objectives

Given the importance of accurate load forecasting for the residential sector, it is essential to develop a precise model that provides deeper insights into the sector while assisting grid operators in managing operations effectively. Therefore, the focus of this thesis is to develop a hierarchical load forecasting model for the residential sector, while also examining the influence of key input features such as socio-demographic factors, EV charging profiles, and charging price on forecasting accuracy.

To achieve this aim, the following objectives were set:

1. Organise all selected households in a hierarchical structure using a suitable clustering algorithm, then apply a forecasting model for this hierarchical structure using the TD approach. In order to achieve this, the steps are set to:

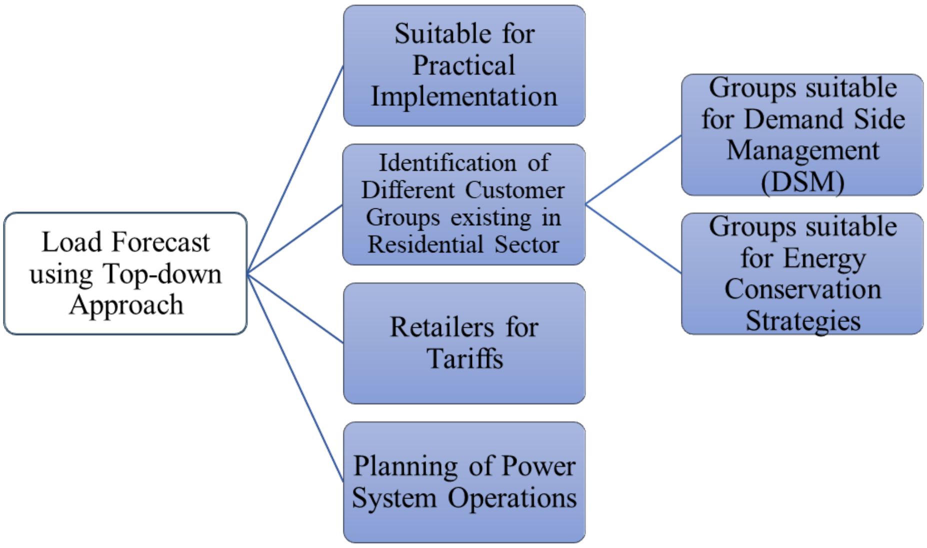


Fig. 1.2 Significance of top-down load forecast approach

- analyse the daily load profiles of selected houses.
- analyse various clustering algorithms and the input features utilised for clustering to construct the hierarchical structure.
- develop a forecast model for the entire hierarchy using TD approach.
- evaluate forecasting accuracy using mean absolute percentage error (MAPE) and mean absolute scaled error (MASE).
- compare the proposed forecast model with the commonly used models ARIMA, SVR and hierarchical BU approach.

2. Analyse the impact of socio-demographics and EV charging on daily residential consumption and incorporate it as an input to the forecasting model to evaluate its performance. This is achieved by:

   - assessing the impact of socio-demographic factors on the performance of the forecasting model.
   - examining daily load profiles of clusters, both with and without the integration of EV charging profiles.
   - employing the Monte Carlo method to generate supplementary EV load profiles.
   - evaluating the effect of integrating EV load profiles on the accuracy of the forecast model.

3. Investigate and establish the correlation between EV charging prices and the forecasting model.

    - examine various EV charging strategies in relation to electricity pricing.
    - formulate an approach to evaluate how electricity pricing influences forecasting accuracy in the absence of direct tariff information.
    - evaluate the effect of pricing on the accuracy of the forecast model.

1.4 Contributions

Through achieving the objectives set out for this work and fulfilling the overall goal of the thesis, this PhD research has made several significant contributions to the field of residential load forecasting, which can be categorised as major reflecting its originality and supporting the use for enhancing and complementing the original contributions.

- Major Contributions

    1. Development of a hierarchical load forecasting model: This research presents a novel TD-based hierarchical forecasting framework for the residential sector, enabling forecasts at multiple aggregation levels, from household groups to the sector-wide level, thus addressing operational needs across stakeholders. Two variations of the TD-based forecast model are introduced:

        – The first variation employs two separate forecast models, named the two-stage approach in this thesis.
        – The second variation, an End-to-End (E2E) learning model, is a refinement of the first, utilising a single model to achieve higher accuracy. Both variations are original contributions of this thesis.

    2. Impact of socio-demographic and EV charging data on the forecasting accuracy: The thesis incorporates socio-demographic features and EV charging profiles into the built load forecasting model, demonstrating their significant influence on forecast accuracy and providing deeper insights into consumption behaviours. This has been evaluated for the following reasons:

        – While existing literature has explored various socio-demographic factors that influence household electricity consumption, these features have not been systematically integrated to assess their impact on forecasting model performance. Given the established significance of socio-demographic factors in shaping residential consumption patterns, this research conducts a comparative analysis of forecasting accuracy with and without these features. Furthermore, a comprehensive guide is provided, outlining scenarios where incorporating socio-demographic data can enhance forecasting accuracy.

   – With the increasing penetration of EVs, which represent highly non-linear loads, this thesis also examines the differences in cluster load profiles with and without the inclusion of EV charging loads. To address data scarcity, a Monte Carlo simulation approach is developed to generate additional EV load profiles. These profiles are integrated into the forecast model, allowing for an evaluation of its accuracy under various scenarios.

3. Investigating the relationship between charging price, charging time, and forecast model performance: Given that charging times are strongly influenced by pricing, this thesis examines the various pricing models used in the residential sector and their effects on EV charging behaviour. Subsequently, it analyses the impact of these charging patterns on the performance of the developed forecasting model to understand how price-driven charging behaviours affect forecast accuracy and reliability.

- Supporting Contributions

   1. Hierarchical structure formation: The entire research is conducted using a real-world electricity dataset. Residential consumption data from U.S. households with complete records is analysed, ensuring practical applicability and relevance. The selected households are organised into a hierarchical structure by identifying common load consumption patterns. Clusters are created for each pattern, grouping households with similar consumption behaviours while separating those with distinct patterns. The quality of these clusters is validated using accuracy metrics.

   2. Assessment of forecast model performance: The thesis presents an evaluation of different hierarchical forecasting approaches, offering insights into their relative performance and computational efficiency within the residential sector context. That is, the developed forecast model is tested across different scenarios and demonstrates its potential to deliver high-accuracy results.

Further, different research articles have been published, accepted, or submitted as part of this PhD research work. The details of the said articles are as follows.

- Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. "Hierarchical structure based energy consumption forecasting in top-down approach." In 2022 7th Asia Conference on Power and Electrical Engineering (ACPEE), pp. 1732-1737. IEEE, 2022 [12].
- Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. "End-to-End Top-Down Load Forecasting Model for Residential Consumers." Energies 17, no. 11 (2024): 2550 [13].
- *Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. "AI-Based Electrical Load Forecasting for Residential Sector Using Smart Meter Data." In Engineering Applications of AI for Demand Forecasting (pp. 230-254). CRC Press* [14]

1.5 Organisation of the Thesis

The remainder of this thesis provides a detailed explanation of how the objectives were achieved, leading to the development of the major contributions outlined in this chapter. Chapter 2 presents a comprehensive literature review covering various load forecasting techniques and existing forecast models, with a particular focus on hierarchical forecasting models. The chapter also identifies research gaps based on the literature review.

Chapter 3 presents the novel methodology proposed for the forecasting model, addressing the first objective of the thesis which involves analysing and understanding the daily load profiles of residential consumers and to apply clustering algorithms for the development of a hierarchical structure. This chapter provides an in-depth discussion of the proposed forecasting methodology, which is evaluated using real-world datasets. The forecasting accuracy is evaluated under various scenarios, including a comparison with the commonly used statistical ARIMA forecast model and hierarchical BU approach. Additionally, the chapter explores the inclusion of socio-demographic features and their impact on forecasting accuracy.

In Chapter 4, the impact of EV charging profiles on the proposed forecasting model is evaluated. It examines various charging scenarios and analyses the forecasting accuracy for each case. Whereas, Chapter 5 examines the role of electricity pricing in shaping EV charging behaviour and its subsequent impact on residential load forecasting. It investigates different charging strategies in the context of tariff structures, establishes the correlation between EV charging prices and model performance.

Chapter 6 summarizes the major findings of the thesis and the outcomes of the research conducted. It also provides recommendations for future research directions.

Chapter 2

Literature Review

2.1 Introduction

The previous chapter established that the core aim of this thesis is to develop a hierarchical load forecasting model for the residential sector using the TD approach, and to evaluate how key factors influencing residential load, such as socio-demographics and EV penetration, impact forecast model performance. This chapter presents an in-depth literature review, which forms the foundation of this research by clearly identifying existing research gaps. It provides a detailed overview of load forecasting and the commonly used forecasting techniques, along with an in-depth discussion of the various models available in the literature. Given that the focus of this thesis is on hierarchical forecasting models, it also reviews hierarchical forecasting approaches. Furthermore, as any forecasting model is incomplete without consideration of its influencing factors, a comprehensive review of input factors is conducted.

2.2 Load Forecasting

Electrical load forecasting poses a significant challenge for power system operators, as it plays a crucial role in scheduling generation, transmission, distribution, and integrated resource planning [8]. This indicates that load forecasting is essentially important for the efficient and economic operation of a power system. Various computational techniques and methodologies have been implemented in the electricity market to forecast load accurately.

Development of an accurate forecast model presents significant challenges due to the inherent complexity of real-world systems. These systems consist of numerous interdependent variables, many of which are difficult to quantify or fully capture, making realistic simulation a challenging task. Furthermore, most forecasting models rely heavily on data quality, and any inconsistencies, such as missing values, errors, or biases, can significantly impact their performance and accuracy [15]. Even minor discrepancies in input data can lead to substantial deviations in predictions, underscoring the importance of robust data preprocessing techniques and model validation methods to ensure reliability. This has further complicated the situation due to the presence of different energy storage systems such as EVs, batteries, and customer-owned generation, making it extremely difficult to come up with models that lead to accurate forecasting of electrical demand [16], [17]. Moreover, there is no single standard approach to load forecasting, as it is categorized based on factors such as forecasting time horizon, methodologies employed, and the specific focus area, as discussed below.

1. Time horizon-based forecasting: This category includes very short-term, short-term, medium-term, and long-term forecasting as shown in Fig. 2.1.

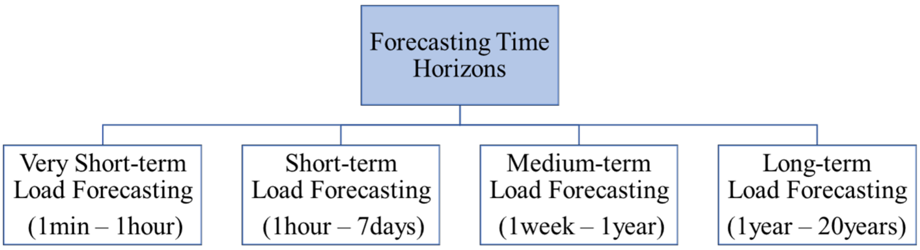


Fig. 2.1 Forecasting time horizons

  - Very short-term forecasting (VSTF) targets forecasting from minutes to 1 hour ahead.
  - Short-term forecasting (STF) focuses on the predictions ranging from few minutes to 24 hours ahead, typically used for real-time grid operations and scheduling.
  - Medium-term forecasting (MTF) projects electricity demand for about a few months ahead, aiding in maintenance planning and mid-term operations.
  - Long-term forecasting (LTF) looks decades ahead, supporting infrastructure development and long-term policy planning.

2. Granularity-based forecasting: This category pertains to the level of detail in the forecasts.

  - Individual level forecasting targets specific households, accounting for individual consumption patterns. This may be useful for energy management of that particular household [18].

- Aggregate level forecasting focuses on forecasting for groups of houses, such as neighborhoods, cities, or regions [19]. This may be used for long-term planning.
- Hierarchical forecasting integrates both granular levels, offering insights into individual and aggregate consumption. This approach is particularly useful for power system operators, as it provides a comprehensive understanding of electricity demand patterns [19].

3. Forecasting technique: Each category may employ various forecasting techniques. Classical methods, such as ARIMA and SARIMA, are commonly used for simpler forecasting problems. Meanwhile, advanced machine learning techniques and artificial intelligence (AI) based models are increasingly adopted for handling complex and dynamic forecasting challenges due to their ability to process large datasets and capture intricate patterns [20], [21].

The first step in building a forecast model is to determine the forecasting time horizon. This is the period for which the model is designed and implemented to predict. Very short-term load forecasting (VSTLF) focuses on predictions ranging from a few minutes to one hour ahead, while STLF covers a broader range, extending from one hour up to seven days or even a month. On the other hand, MTLF predicts load trends between one week and one year, whereas LTLF extends beyond a year, often projecting up to 20 years into the future [22]. The selection of the forecasting time horizon depends on its intended application. For instance, STLF is crucial for the day-to-day operations of the utility industry, including electricity generation, transmission management, real-time dispatch and cost efficient grid reliability [4], [23]. In contrast, LTLF is primarily used for strategic planning, such as infrastructure expansion, new power generation projects, and modifications to energy supply systems [22]. This research focuses on STLF.

Extensive research has been conducted to determine the most effective forecasting techniques for different lead times. For VSTLF, models such as numerical weather prediction models [24], time series models [25], machine learning models [26], probabilistic models [27], and hybrid approaches [28] have been widely explored. Similarly, STLF frequently relies on numerical prediction models [29], time series analysis [23], machine learning techniques [23], and hybrid methods [30] to enhance accuracy [23]. Given the variety of forecasting approaches available, it is essential to examine and evaluate these techniques to identify the most appropriate methodology for this thesis.

2.3 Load Forecasting Techniques

Numerous studies have emphasized various methods for load forecasting. These methods are classified based on the degree of mathematical involvement in the forecasting models. Based on the existing research and conducted studies, the load forecasting techniques could be grouped into the following major groups as described in [31], [32], [33], [34], [35].

2.3.1 Statistical Techniques

The methods in this group are commonly used and are based on mathematical principles. Some of the techniques include regression, multiple regression, exponential smoothing, and the iterative reweighted least-squares technique (IRLS) [31]. These methods include linear models based on classical statistical methods, providing output based on a function characterized by the combination of other dependent variables [36]. Some of the techniques are described below.

Linear Regression

Regression method is a widely used technique for forecasting a continuous variable. It models the relationship between the output, i.e. the variable to be forecasted and one dependent variable. It is based on the mathematical equation given by Equation 2.1,

$$L(t) = L_n(t) + ax(t) + e(t) \tag{2.1}$$

where L is the variable to be forecasted, $L_n(t)$ is the normal or standard load at time t, a is the estimated slowly varying coefficient, $x(t)$ is the influencing factors such as weather, $e(t)$ is the white noise, and n indicates the number of observations. It is relatively simple as it deals with only one variable.

Multiple Regression

Multiple regression is another commonly used method, which is employed when the forecasted variable is influenced by a range of factors, such as weather conditions, economic variables, and price. It is based on Equation 2.2

$$L(t) = V_t a_t + e(t) \tag{2.2}$$

where t is sampling time, L is the variable to be forecasted, V_t is a vector of adopted variables such as time, temperature, light intensity, and a_t is a transposed vector of regression coefficients, and $e(t)$ is the model error at time t. This is computationally complex than linear regression due to the mapping of multiple relationships.

Iterative Reweighted Least-Squares Method

It is a statistical technique commonly used in forecasting, where the goal is to identify the best-fitting model for a given dataset by minimizing the sum of squared differences between the observed and predicted values. This involves solving a linear estimation equation, as shown in Equation 2.3, where Y is a vector of observations, X is a matrix of known coefficients derived from previous load data, β is a vector of unknown parameters, and e represents a vector of random error. The objective is to determine the optimal value of β.

$$Y = X\beta + e \tag{2.3}$$

Moving Average (MA)

It is another statistical technique used mainly for forecasting time series data [31]. In MA, the value is forecasted by calculating the average of a fixed number of recent data points [34]. It is given by Equation 2.4.

$$MA(t) = \frac{X(t) + X(t-1) + \ldots + X(t-n+1)}{n} \tag{2.4}$$

where $X(t)$ represents the value of the time series at time instant t, n is the number of past data points in the moving average window, and $MA(t)$ is the moving average value at time t which is the forecasted output.

Exponential moving average (EMA) is a variation of MA where greater weight is given to recent observations. This allows the model to converge faster [31]. The benefit of using this technique is that it eliminates the effect of noise from the data. Hence, it is most suitable for time series forecasting or data smoothing [31].

Exponential Smoothing (ES)

Exponential smoothing is a time series forecasting technique used for univariate data, where the forecasted value is a weighted linear sum of past observations [37]. The weights assigned to these observations decrease exponentially as they move further back in time [37]. An extension of this method is holt-winters exponential smoothing, which incorporates both trend and seasonality in the data. This extended method allows for more accurate predictions by considering three smoothing parameters: level, trend, and seasonality [31]. As a result, holt-winters smoothing is particularly effective for forecasting data that exhibit both trends and seasonal patterns, such as monthly load forecasts, sales projections, and weather predictions, etc [34].

Auto-Regressive Integrated Moving Average (ARIMA)

One of the most widely used approaches for STLF is based on time series methods. These methods leverage the internal structure of the data, such as autocorrelation, trend, and seasonality, to make accurate predictions [32]. Time series models can be formulated in various ways, such as using autoregressive (AR) models, or by combining the autoregressive approach with moving averages to form AIRMA models. The choice of model depends on the specific characteristics of the data [38], and through analysis, the most suitable forecasting model can be identified for a given use case.

For instance, when working with non-stationary time series data, it is essential to transform the data into a stationary form before applying these methods [38]. Stationarity refers to the statistical properties of the data, such as the mean and variance, that remain constant over time [38]. To achieve stationarity, the process of differencing is often used, which involves subtracting the previous observation from the current observation. This transformation helps to remove trends or seasonality, making the data more suitable for ARMA models. The ARIMA model is well-suited for time series data that exhibits a trend but not necessarily seasonality. It consists of three primary components: auto-regressive, integrated, and moving average.

The AR component models the relationship between an observation and its previous values, suggesting that the current value depends linearly on its past observations. The order of the AR model determines how many past lags are used to predict the current value [32]. The I component addresses non-stationary data by applying differencing to make it stationary. The order of differencing specifies how many times the data needs to be differenced to achieve stationarity, ensuring that the statistical properties remain constant over time [32]. The MA component models the relationship between an observation and the residual errors from previous forecasts [32]. It helps account for random noise or shocks in the data by smoothing out past errors [38]. The order of the MA model indicates the number of past forecast errors used to predict the current value. In summary, ARIMA combines these three components to model and forecast time series data with a trend, adjusting for non-stationarity and random errors.

Seasonal Auto-Regressive Integrated Moving Average (SARIMA)

Time series data that exhibits seasonality requires an extension of the ARIMA model, known as SARIMA (Seasonal ARIMA) [32]. While the SARIMA model is built upon the ARIMA framework, it introduces additional parameters to account for the seasonal patterns present in the data. In essence, SARIMA combines the ARIMA components, i.e., auto-regressive, integrated, and moving average with seasonal components that capture the repetitive and periodic fluctuations that occur over specific intervals, such as daily, monthly, or yearly cycles.

ARIMA is effective for time series data with trends but without seasonality [38]. It models the data by incorporating lagged observations and random errors. SARIMA, on the other hand, is designed to handle both trend and seasonality. It includes seasonal versions of the AR, I, and MA components, which are specifically designed to model the seasonal effects. These seasonal components work in conjunction with the non-seasonal parameters, allowing the model to capture periodic cycles more accurately. Many time series datasets are strongly influenced by seasonal patterns, making SARIMA the preferred model in situations where seasonality plays a significant role. This includes applications like weather forecasting and load forecasting, where variables exhibit regular seasonal fluctuations, such as changes in energy consumption due to seasonal weather variations. In these cases, SARIMA's ability to model and predict seasonal trends makes it a suitable choice.

2.3.2 Machine Learning for Load Forecasting

Classical forecasting methods do not account for changes in pattern; therefore, those methods are modified to include changes in conditions. The modified methods update model parameters itself according to changes in conditions [24]. The techniques that fall in this category include decision trees, random forests, and support vector machines (SVM).

Decision Trees (DT)

A DT is a rule-based machine learning approach used for forecasting, where explanatory variables, known as features, are utilised to predict the dependent variable [39]. The prediction process follows a series of decision rules that systematically classify or estimate values based on the input data provided. In a DT, the dataset is recursively split into smaller subsets based on feature values, forming a tree-like structure [39]. Each branch represents a decision rule, while each leaf node provides a predicted value [40]. Decision trees are applicable for both classification and regression-based forecasting, making them a versatile choice for various predictive tasks.

For time series forecasting, decision trees use historical observations as input features to predict future values. Unlike traditional statistical models such as ARIMA, which assume a linear relationship between variables, decision trees are capable of capturing complex, non-linear dependencies, making them particularly useful for datasets with intricate patterns and interactions [34].

Several studies have demonstrated the effectiveness of DT-based models for load forecasting. For example, Tso and Yau in [41] compared multiple forecasting approaches, including regression, neural networks, and decision trees, showing that DTs can achieve competitive accuracy with the added benefit of interpretability. Similarly, Abdulsalam et al. in [42] employed decision tree algorithms such as CART and REPTree for short-term load forecasting, highlighting their ability to identify key explanatory variables influencing demand. However, DTs also have limitations. A single decision tree is prone to overfitting, particularly when demand data is noisy or highly variable, as is often the case for individual households [43]. Overall, while decision trees are not the most dominant approach in electricity load forecasting compared to statistical or deep learning methods, they remain an important methodology in the literature due to their interpretability, flexibility, and ability to incorporate a wide range of explanatory variables.

Random Forest (RF)

Random Forests are an extension of DTs used for forecasting, but instead of relying on a single tree, they utilise an ensemble of multiple decision trees, enhancing robustness and accuracy [44]. By aggregating the predictions from multiple DTs, RFs produce a more stable and reliable output, reducing the risk of overfitting and improving generalization [34], [35].

In the context of load forecasting, RFs have shown strong performance due to their ability to handle non-linear relationships and high-dimensional feature spaces, such as weather variables, socio-demographics, and appliance-level data. For example, Lahouar and Slama in [45] applied RFs for short-term electrical load forecasting and demonstrated improved accuracy compared to conventional regression and single-tree approaches, particularly when handling complex and noisy residential datasets. However, the use of RFs can be computationally demanding, particularly with large datasets or many trees, and their improved predictive performance often compromises model interpretability [46].

Support Vector Machines (SVM)

This is a robust forecasting method based on statistical principles, designed to analyse and recognize patterns that facilitate classification or regression-based forecasting [47]. They are particularly effective for time series forecasting in cases involving high-dimensional data [32]. The methodology operates by identifying an optimal hyperplane that separates data points within the feature space, enabling precise predictions [34]. This approach is well-suited for non-linear large datasets, as it incorporates advanced techniques to model complex relationships. However, the process of tuning hyperparameters in SVMs is computationally intensive and complex, often presenting practical challenges that may lead to model instability if not properly optimized [35].

2.3.3 Soft Computing Techniques

Soft computing is an emerging approach, designed to mimic the human mind's ability to reason and continuously learn from its environment [31]. This method requires training a computer-based intelligent system to learn from the environment in which it is placed and respond accordingly. In these techniques, the employment of reasoning modes is approximate rather than exact, as is the case in traditional statistical techniques. This method constitutes a collection of disciplines that are discussed below.

Fuzzy Logic (FL)

It is a computational method that allows truth values to range between completely true and completely false, unlike binary systems where outcomes are strictly true or false [31]. This approach is particularly effective in real-world scenarios where variables are non-linear and information is uncertain. In a fuzzy forecasting system, inputs are transformed into degrees of truth through a process called fuzzification. These fuzzified inputs are then evaluated using a set of IF-THEN rules to determine the output [48], [49], [50].

Fuzzy logic has been widely applied in electrical load forecasting across various contexts. For instance, it has been employed for short-term load prediction by incorporating weather and consumption data, demonstrating its ability to model complex time series relationships [51]. It has also been used in interconnected power systems to forecast demand based on factors such as temperature, humidity, and seasonal variations, improving operational efficiency [52]. Additionally, fuzzy logic has been applied in long-term load forecasting, where it successfully captures the influence of weather parameters over extended periods [53]. These studies highlight the strengths of fuzzy logic in handling uncertainty and non-linearity, although the design of membership functions and rules can be subjective and computationally demanding.

Genetic Algorithms (GAs)

Genetic algorithms are powerful optimization techniques designed to improve the accuracy of predictive models [31]. They work by iteratively searching for optimal forecasting parameters through the simulation of biological processes such as selection, crossover, and mutation. This evolutionary strategy is highly effective in complex forecasting scenarios where traditional deterministic models struggle to capture non-linear relationships and high-dimensional data patterns [31]. The process begins with the generation of a population of potential forecasting parameter sets. Each set is evaluated using a fitness function, typically based on accuracy metrics like mean absolute error (MAE) or root mean square error (RMSE). Models with higher fitness scores are selected to form the next generation through reproduction, ensuring that the most effective forecasting traits are retained. This cycle of selection, reproduction, and variation continues iteratively until a stopping criterion is met, such as reaching a predefined number of generations or achieving the desired level of forecasting accuracy [32], [54].

Neural Networks (NNs)

Neural networks are inspired by the functionality of the human brain, consisting of interconnected neurons that process and transmit information [55]. This interconnection enables them to effectively learn and extract valuable insights from input data [32]. The classical algorithms often struggle with complex patterns in raw data, whereas neural networks offer flexible architectures that make them suitable for a wide range of applications. Additionally, NNs possess an inherent ability to generalize, which is crucial for forecasting. Instead of merely memorizing the characteristics of the training data, they identify underlying patterns, allowing them to perform well on unseen data. This generalization capability is particularly important for STLF [32], [35]. Neural networks are broadly classified into artificial neural networks (ANNs) and deep learning (DL) models. Each of these categories include various types of networks, distinguished by their architectural and functional differences.

1. Artificial Neural Networks (ANNs): These use data analysis algorithms to establish mathematical relationships between input features and the desired output. This is achieved through a training process designed to identify patterns that link the inputs to the outputs. The predicted output is then compared with the actual output, and the model parameters are adjusted to enhance forecasting accuracy. The number of hidden layers in a neural network depends on the complexity of the problem, with the multi-layer perceptron (MLP) being the most commonly used architecture [56].

2. Deep Learning (DLs): Deep learning encompasses various deep neural networks (DNNs), an advanced type of ANNs distinguished by their increased number of hidden layers [55]. This enables DNNs to handle larger datasets effectively and enhances their generalization capability [34]. Additionally, their architectural design makes them well-suited for applications that involve modeling temporal dependencies in sequential data [35]. These include models like long short term memory (LSTM), recurrent neural networks (RNNs), gated recurrent unit (GRUs) and convolution neural networks (CNNs).

   RNNs are specifically designed to capture temporal dependencies between data points [57]. They achieve this by repeatedly using the same network structure to predict the desired output. This architecture relies on a mathematical framework that preserves information from previous stages during the optimization process. In contrast, LSTM networks, a specialized type of RNN, incorporate memory units that can store and retrieve information over long sequences, allowing them to handle long-term dependencies more effectively [34], [35].

Thus, a variety of techniques are available for forecasting, and the choice of forecasting technique depends on the intended use. The following section examines application of various forecasting methods in the literature, with a specific focus on approaches used for time series load estimation.

2.4 Existing Forecasting Models in Literature

Load forecasting is an emerging field, and several forecasting models have been developed for various applications in power systems. Some of the existing forecasting models in the literature are discussed in this section. In [58], the authors employed statistical techniques, including SARIMA and Holt-Winters models, to forecast the total load demand of Korea, utilising historical data to design the models. There are some pre-requisites for designing an accurate forecast model; out of which, analysis and pre-treatment of data are the most important ones. Analysis of data revealed that the load profile was the same for all weekdays, whereas it was different for a Sunday. Since Sunday is a non-working day, it leads to more people at home, causing consumption to be significantly different. Therefore, the energy consumption profiles were classified into weekday, weekend, and other public holidays using a k-nearest neighbour (kNN) algorithm. The classified data was used for training and testing the forecasting model, and both models were evaluated for weekends and weekdays. The accuracy of both models differs by a small margin. However, winters' model was found to be a better choice for short-term load forecasting. However, the model presented is based solely on historical load data and does not consider other dependencies, such as weather conditions and day events, which may have the potential to further improve forecasting results.

Another model presented in [59] aims to provide accurate short-term forecasts at the distribution level using support vector regression (SVR). Here, the historical data was normalised first, and optimal parameters of the model were found using an optimization method based on a grid traverse algorithm (GTA) and particle swarm optimization. The proposed method was compared against ARIMA and conventional SVM. It was found that the proposed method led to the least forecasting error and had faster computation time. However, in real-time, the load profiles are highly dependent on other factors, such as temperature and work time, which have not been considered in this literature. Various algorithms have been explored in past research, including regression, fuzzy logic, statistical learning, and neural networks [8], [60]. For instance, [22] conducted extensive research categorizing load forecasting models based on input features, scale, and time horizon. They concluded that while regression models, due to their simplicity, are more suitable for LTLF, artificial intelligence-based models such as ANN, fuzzy logic, and SVM are better suited for STLF.

Most forecasting models in existing literature primarily target system-level predictions, such as at the distribution or substation levels, while overlooking consumption profiles at lower levels, which tend to exhibit greater variability than system-level demand [61]. With the widespread deployment of smart meters, electricity usage at lower levels can now be measured directly, enabling the estimation of demand at higher aggregation levels. Accurate forecasts across different levels are essential for effective load management. Reliable regional-level predictions can assist system operators in determining the required grid supply, while insights into the consumption patterns of various customer groups can support the design of tailored demand-side management programs.

Many researchers have focused on developing load forecasting models designed for individual customer needs. This research study, in contrast, aims to design a hierarchical load forecasting model. This approach is preferred for its ability to provide a comprehensive view of the entire sector, rather than concentrating on individual consumers. The following section offers an overview of hierarchical forecasting models and reviews the existing literature in this area.

2.5 Hierarchical Forecast Models

A hierarchical forecast model is a family-based forecast approach that satisfies a variety of forecast information requirements. It helps in decision-making for many users by providing information at different levels of hierarchy [19]. Designing a forecast model for a hierarchical load structure is possible by following either of the three approaches: TD, BU, and middle out [19]. While each of these approaches has been extensively studied across various applications, hierarchical load forecasting predominantly relies on BU or middle-out models [11], [62]. These approaches lead to accurate results but require extensive investigation into the houses' consumption behaviour and are also computationally intensive [11]. These methods work well for non-frequent testing scenarios. However, they might not be suitable for practical implementation of regular strategic operation due to the extent of information required. Designing a forecasting model for the aggregated level using the BU approach requires the collection of data for individual customers, which is a very tedious task and would cause additional burden on the utility operators. Wherein, the middle-out approach requires the creation of several forecasting models for every customer class, which is computationally extensive [63]. Thus, these models are limited in terms of their practical application in the power sector.

Bottom-up Approach

Many ongoing studies have focused on developing accurate forecasting models for hierarchical load structures within the residential sector, with the majority relying heavily on the BU approach. In the BU approach, forecasting is performed for each series at the lowest level of the hierarchy, and these forecasts are then aggregated to obtain higher-level forecasts. A major advantage of this method is its ability to preserve detailed information by forecasting at the most granular level, thus avoiding any data loss due to aggregation. However, data at the bottom level can be quite noisy, making it challenging to model and forecast accurately [9], [19]. Additionally, obtaining detailed data for each series at the lower level is often laborious and time-consuming.

While this method provides detailed forecasts, it is highly dependent on extensive data collection from individual households, increasing both the complexity and resource requirements of model development and maintenance [9]. Furthermore, it necessitates continuous cooperation from household owners to share detailed and often sensitive consumption data, which raises concerns about privacy and data security. In [64], the authors proposed a method to improve forecasting accuracy by grouping customers based on their consumption pattern using the K-means algorithm, and then designing an individual forecast model for each cluster. The forecast results of all the clusters were summed up to estimate the load consumption at the aggregated level. This methodology was tested on residential datasets of the United States of America and Ireland. Although this method leads to high accuracy, the determination of aggregated level forecast requires multiple forecast models, turning out to be computationally extensive for practical implementation. In addition to historical load consumption data, the designed model used calendar variables such as day of the week, holidays, and temperature. Some models focus on forecasting load consumption for hierarchical loads, but they rely on the BU approach. As mentioned earlier, the BU approach requires detailed data at the individual house level, which can be challenging to obtain in practical scenarios.

Top-down Approach

TD approach generates forecasts at the highest level of the hierarchy and then distributes them to lower levels using distribution ratios derived from historical load consumption and related factors [19]. A key advantage of this method is its simplicity, as it requires modeling only the aggregated top-level series, making it computationally efficient and well-suited for situations involving low-count data. However, a limitation of the TD approach is the potential loss of information due to aggregation, which can reduce accuracy at lower hierarchical levels, especially when distribution factors change over time [9], [63].

Despite this, the TD approach offers several practical benefits. It demands less granular data, reduces computational complexity, and minimizes dependency on individual household data, aligning well with the operational needs of modern power systems [65]. Grid operators increasingly require reliable aggregated load forecasts for effective planning, resource allocation, and maintaining grid stability, particularly in the context of growing renewable energy integration and the implementation of demand-side management strategies [65].

Middle-Out Approach

The middle-out approach is a midway option between TD and BU in which the lowest levels are grouped based on certain similarities such as geographical region, functionality, etc., and then an individual forecast model is created for every sub-group which is summed up to get a reasonable estimate at the aggregated level [9]. First, a middle level is selected, and forecasts are generated for all the series at this level. For series above the middle level, coherent forecasts are produced using the BU approach by aggregating the middle level forecasts upwards. For series below the middle level, coherent forecasts are generated using a TD approach by disaggregating the middle level forecasts downwards [9], [19].

2.6 Building Hierarchical Structure

Designing a hierarchical forecasting model begins with constructing an appropriate hierarchy. For residential consumers, this involves identifying groups of households with similar characteristics and organising them into a hierarchical load structure. At the top level, the hierarchy represents the aggregated consumption of all consumers, followed by intermediate levels comprising different consumer clusters, and finally the lowest level, which includes individual households within each cluster. Clustering algorithms are employed to establish this hierarchy.

2.6.1 Clustering

Clustering is an unsupervised technique used to group data points in such a way that points within the same group are more similar to each other than to those in other groups [66]. It plays a crucial role in data analysis and machine learning applications, such as regression and prediction. The primary goal of clustering is to organise data patterns into subsets where similar patterns are grouped together [67]. A variety of clustering algorithms exist, some grounded in statistical theories and others based on principles of artificial intelligence [68]. The most commonly used clustering techniques are discussed below.

Partition-based Clustering

These techniques rely on dividing the dataset into overlapping subsets, where each data point belongs to exactly one cluster [67]. This technique includes algorithms like K-means and K-medoids. This technique is especially efficient for large datasets, however, it requires identification of the optimal number of clusters prior to clustering and is quite sensitive to initialization and outliers [67].

In the context of load forecasting, partition-based clustering has been extensively used to identify patterns in electrical consumption data. For instance, K-Means clustering has been applied to segment residential and industrial load profiles, allowing tailored short-term and medium-term forecasting models for each cluster [69]. In another paper, [70], ultra short-term power load forecasting method has been proposed based on similar day clustering. The K-Means clustering algorithm is utilised to divide historical data into different clusters, enhancing the forecasting accuracy by identifying patterns in similar days. These approaches help reduce the complexity of forecasting by grouping similar consumption patterns, enabling more accurate load predictions and supporting demand-side management strategies.

The most commonly used clustering algorithms [71] are described below.

- The K-means algorithm is a widely utilised unsupervised learning technique designed to partition a dataset containing n observations into K clusters. Each data point is assigned to the cluster with the nearest mean, known as the centroid [72]. In this approach, the number of clusters K is always less than the total number of observations n. Data points are grouped based on their proximity to the nearest cluster centroid [72].

The algorithm begins by selecting the desired number of clusters and randomly initializing the centroids from the data points [66]. The Euclidean distance between each data point and the centroids is then computed, with points assigned to the cluster corresponding to the closest centroid. Subsequently, the centroids are recalculated as the mean of all data points within each cluster. This process of assignment and centroid recalculation is repeated iteratively until the centroids stabilize and no longer change [72], [73]. Determining the optimal number of clusters is a key requirement of the K-means algorithm. Several methods are available in the literature to address this, including:

1. Elbow Method: This involves calculating the within-cluster sum of squares (WCSS) for different values of K. A plot of WCSS against various K values is generated, and the value of K above which the rate of decrease in WCSS significantly slows down resembling an 'elbow' indicates the optimal number of clusters [73], [74].
2. Silhouette Method: This method assesses how similar a data point is to its cluster compared to other clusters, producing a silhouette score ranging from -1 to 1. Higher scores reflect better-defined clusters [73], [74].
3. Dunn Index: This metric evaluates the ratio between the minimum inter-cluster distance and the maximum intra-cluster distance. A higher Dunn index suggests that clusters are both well-separated and compact [73], [74].

Among these techniques, the elbow method is the most commonly used [75]. Therefore, this thesis relies on the elbow method to determine the optimal number of clusters.

- Follow the Leader: It is also possible to cluster data points using another technique known as follow the leader, which does not require the number of clusters to be specified in advance [71], [76]. Instead, clustering is based on a distance threshold, where the distance between each observation and the centroid of an existing cluster is calculated [71], [76]. If the distance falls below the defined threshold, the data point is assigned to that cluster. Conversely, if the distance exceeds the threshold, the data point forms a new cluster and becomes its leader. This process is repeated iteratively until all data points have been assigned to clusters.

Hierarchical Clustering

This technique constructs a tree-like structure known as a dendrogram, which visually represents the clustering process [77]. Clustering can be performed using either an agglomerative or a divisive approach. In the agglomerative approach, individual data points are iteratively merged until all points are grouped into clusters. Conversely, the divisive approach begins with all data points in a single large cluster, which is then recursively split into smaller clusters [73], [78]. One key advantage of this method is that it does not require specifying the number of clusters beforehand. However, it is computationally intensive for large datasets and highly sensitive to noise [78].

The application of this technique involves creating an MxM similarity matrix using the normalized Euclidean distance, where M represents the number of data points. Based on this similarity matrix, data points are grouped into clusters using a linkage criterion, which determines the similarity between clusters at each level. Common linkage criteria include minimum, maximum, ward's method, and average distance [77]. This process continues iteratively until all clusters are merged into a single cluster at the highest hierarchical level [77]. For example, Agglomerative Hierarchical Clustering (AHC) combined with Dynamic Time Warping (DTW) has been used to classify residential daily load curves based on their consumption patterns [79].

Density-based Clustering

This technique forms clusters based on regions of high data density while distinguishing outliers as noise, making it particularly robust to outliers. Additionally, it does not require any predefined number of clusters. The following algorithms are commonly used within this approach [67]:

- Density-based spatial clustering of applications with noise (DBSCAN) identifies clusters of arbitrary shapes and effectively detects noise [67].
- Ordering points to identify clustering structure (OPTICS) is an extension of DBSCAN that accommodates clusters with varying densities.
- Hierarchical DBSCAN (HDBSCAN) integrates hierarchical clustering with DBSCAN for improved cluster identification.

For instance, DBSCAN has been applied to detect abnormal consumption behaviours and cluster similar usage patterns for short-term forecasting, particularly in heterogeneous datasets with outliers [80]. Density-based methods have also been integrated with machine learning models to improve forecasting performance by preprocessing load data into meaningful clusters, thereby reducing variability and enhancing prediction accuracy [81].

Among the clustering algorithms discussed, K-means is the most widely used due to its simplicity. In the residential sector, K-means and hierarchical clustering are the most commonly applied techniques [73]. To identify the most suitable algorithm for this thesis, a comparative analysis of various clustering methods was carried out, the details of which are presented in later sections.

2.6.2 Input Features for Clustering Algorithm

The selection of a clustering algorithm is primarily driven by the specific application; however, its effectiveness is largely dependent on how well the data is utilised to extract meaningful input features. These features play a crucial role in enhancing the performance and accuracy of the clustering process. With the widespread deployment of smart meters, it has become feasible not only to analyse household electricity consumption patterns but also to leverage time-series consumption data for feature extraction. These extracted features serve as essential inputs in clustering algorithms, enabling the identification of distinct consumption patterns. To ensure the successful application of any clustering technique, it is imperative to determine appropriate input features that accurately represent the load consumption characteristics of each household.

Researchers in this field have analysed data using various approaches based on their specific objectives. For instance, the authors in [73] examined consumption data obtained from smart meters to identify patterns on annual, daily, and seasonal scales. These identified patterns, along with the processed data, were subsequently used as input features for clustering algorithms. To construct annual profiles, they computed the monthly mean of daily electricity consumption. Given that the meters recorded data at a 15-minute resolution, the readings were resampled to generate hourly daily load profiles. Additionally, seasonal variations were incorporated by identifying and analysing the hottest and coldest months of the year. Their approach primarily relied on time-based features, which are particularly useful for segmenting customers based on their energy usage behaviour.

In contrast, the method presented in [82] focuses on reducing raw time-series data through a technique known as stratification. This approach calculates the mean load level based on selected time intervals and outdoor temperature ranges. While the time of day captures behavioural attributes of end-users, temperature variations highlight changes in load demand due to increased heating or cooling usage. After the data reduction step, the dataset undergoes normalization using a min-max method, ensuring that the clustering process is influenced by the shape of the load profile rather than absolute load levels [82].

Another study that employs the K-means algorithm for clustering incorporates dimensionality reduction through the use of autoencoders [83]. In this approach, daily residential consumption data is first subjected to a normalization process. The normalized data is then fed into an autoencoder, which reduces its dimensionality. The compressed representations generated by the autoencoder serve as input features for the clustering process [83].

In summary, clustering algorithms rely on input features that effectively represent the underlying data points. When clustering residential consumers, it is essential to capture a meaningful representation of their consumption behaviour. The key objective is to identify representative load profiles (RLPs) of consumers and use them as input features for clustering algorithms. This characterization of customers can be achieved through direct or indirect shape features extracted from both the time and frequency domains [68], which are designed to represent consumer load curves.

The simplest approach for feature extraction involves normalizing load measurements in the time domain and utilising either all or a subset of the normalized power measurements. This method requires no additional post-processing, allowing the extracted features to be directly used for clustering. The mathematical representation of these load pattern features is provided in Equation 2.5 [75].

$$C = (C^{(m)}, m = 1, ..., M) \tag{2.5}$$

$$c^m = [c_1^{(m)}, ..., c_1^{(H)}]^T$$

Here, M represents the number of customers, while H is a selectable parameter that should not exceed the resolution of the smart meter. When using direct time-domain features, the goal is to determine each customer's RLP, which serves as a basis for further analysis. RLPs can be obtained through two distinct methods. The method, as described in [75], employs a two-stage clustering approach. In this technique, each customer is clustered individually based on their daily load profiles from the entire dataset. The cluster containing the highest number of load profiles is identified as the representative cluster for that customer. The RLP is then derived by averaging all load profiles within this representative cluster. The method, proposed in [84], involves computing the average of a customer's daily load profiles and subsequently normalizing it with respect to its maximum power value. The mathematical representation of this approach is provided in Equation 2.7.

$$Average = \frac{\sum dailyloadprofile}{d} \tag{2.6}$$

Where, d is given as number of days that belong to the representative cluster.

$$RLP = \frac{Average}{P_{max}} \tag{2.7}$$

Another way of characterising customer for clustering is to use the indirect shape features which are determined by dividing the 24 hours hourly consumption into various periods such as consumption during daylight (8:00 to 18:00), during lunchtime (12:00 to 14:00), and night (22:00 to 6:00). The shape features is then calculated by using Equation 2.8 to Equation 2.13, and they are in the range of 0,1. These are calculated for each customer [68].

$$S_{d1} = \frac{p^{AV,day}}{p^{max,day}} \tag{2.8}$$

$$S_{d2} = \frac{p^{AV,daylight}}{p^{max,daylight}} \tag{2.9}$$

$$S_{d3} = \frac{p^{min,day}}{p^{AV,day}} \tag{2.10}$$

$$S_{d4} = \frac{1}{3}(\frac{p^{AV,night}}{p^{AV,day}}) \tag{2.11}$$

$$S_{d5} = \frac{1}{5}(\frac{p^{AV,lunchtime}}{p^{AV,daylight}}) \tag{2.12}$$

$$S_{d6} = \frac{p^{min,daylight}}{p^{AV,daylight}} \tag{2.13}$$

The alternate method represents load curves of customers by transforming them into frequency domain where magnitude and phase related information is extracted for each customer which is used for clustering [68].

In summary, the hierarchy creation process begins with data pre-processing, followed by clustering to structure households into a hierarchical framework. The clustering input features are extracted from consumption data, with each household represented by an RLP generated using hourly consumption data. Given the seasonal variations in consumption patterns, an RLP is created for each household across different seasons. These seasonal RLPs serve as the input features for the clustering process in this thesis.

2.6.3 Cluster Evaluation

It is essential to assess the quality of clusters, which can be achieved by utilising certain accuracy metrics. One of the metrics, the index of agreement (IA), identifies the goodness of created clusters [85]. IA is a dimensionless quantity which is expressed in Equation 2.14 as follows:

$$IA = 1 - \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} (|\bar{P}_i| - |\bar{O}_i|)^2} \tag{2.14}$$

$$\bar{P}_i = P_i - \bar{O}$$

$$\bar{O}_i = O_i - O$$

where P_i is the predicted variable at time i, O_i is the observed variable, n is equivalent to the number of observations, and $\bar{O}$ is the mean value of the observed variables over n observations.

Another accuracy indicator commonly used, the Davies-Bouldin index (DBI), evaluates overlapping of clusters, shown in Equation 2.15 [71]. It is determined by calculating the average intra-cluster distance, represented by $diam(C_i)$, and comparing it for all pairs of clusters. Smaller values of DBI indicate that the clustering algorithm has separated the data well [71].

$$DBI = \frac{1}{K} \sum_{i=1}^{K} \max_{j \neq i} \left(\frac{\mathrm{diam}(C_i) + \mathrm{diam}(C_j)}{d(C_i, C_j)} \right) \tag{2.15}$$

In this thesis, cluster quality is assessed using IA, as it has been proven effective in a comparable scenario discussed in [85]. As a result of the clustering process, a hierarchical structure of the residential sector is established.

2.6.4 Load Forecasting Factors

The efficiency and accuracy of any forecasting model are highly dependent on its input features, making feature selection a crucial step in model development. For instance, [86] highlights that input feature selection can be effectively achieved through detailed dataset analysis. Their study found that energy consumption exhibits a cyclic nature, repeating daily, but with notable differences between weekdays and weekends, which are significantly influenced by temperature variations [86]. Based on this analysis, the authors selected features such as the hour of the day, day of the week, previous day's average load, and temperature for their forecasting model. In another study, [87] aimed to improve forecasting accuracy by modifying traditional Bayesian neural networks. They conducted a comprehensive correlation analysis to identify suitable input features from augmented historical load data, focusing on load consumption at different time lags to enhance model performance.

Moreover, [22] presents an extensive review, emphasizing that although existing residential sector forecasting models often utilise historical data and weather conditions as input features, they tend to overlook household lifestyle factors. In the residential context, energy consumption is significantly influenced by residents' behavioural habits, which are closely linked to their socio-demographic characteristics. These include occupant-related features such as the number of residents, presence of children, annual household income, dwelling characteristics including dwelling type, number of bedrooms, heating systems, and appliance-related factors such as appliance ownership levels, power demand, and usage patterns [5]. Additionally, [61] identifies three major groups for characterizing household electricity consumption: physical dwelling characteristics, HVAC equipment and fireplaces, and occupant profiles. Their study concludes that combining daily load consumption data with household and resident information is a powerful tool for distinguishing customer groups, which can inform targeted energy conservation and efficiency strategies.

Designing an accurate load forecasting model, therefore, requires comprehensive consideration of all factors influencing electricity consumption. Incorporating such factors helps generate scenarios that closely mirror real-world conditions, leading to more reliable and robust forecast outcomes. A review of the literature reveals that most forecasting models predominantly rely on historical load consumption data and weather-related variables [22]. While these are undoubtedly important, socio-demographic characteristics such as household size, income levels, occupancy patterns, and lifestyle behaviours have largely been overlooked. Therefore, this thesis addresses this gap by integrating socio-demographic features into the forecasting model and evaluating their impact on forecast accuracy. By doing so, it aims to capture the behavioural dimensions of energy consumption, providing a more comprehensive understanding of residential load patterns.

Furthermore, the accuracy of load forecasting models is highly sensitive to the inclusion of emerging load components, such as EV charging. Currently, the rapid EV adoption has introduced significant shifts in residential load consumption. EV charging behaviour, as highlighted in [88], tends to create concentrated power demands at specific times, resulting in pronounced peaks in load curves. Additionally, EV charging is often uncoordinated and highly variable in terms of frequency, duration, and intensity, as discussed in [89], which further complicates the challenges faced by grid operators in maintaining system stability.

Various strategies have been proposed to mitigate these challenges. For example, [90] presents models to forecast both photovoltaic (PV) generation and the load demand of a commercial building, combining these outputs to predict the residual load, which was then used to schedule EV charging and optimise PV power utilisation. Inspired by such integrated strategies, this thesis incorporates EV penetration as a key input variable in its forecasting model. By including EV-related load profiles, the research aims to assess their impact on forecast performance and explore potential strategies for effectively integrating EV charging behaviour into residential load forecasting.

In conclusion, this thesis proposes incorporating both socio-demographic factors and EV charging profiles to evaluate whether these features enhance the robustness and accuracy of the proposed forecasting model. By emphasizing the inclusion of these critical input features, it aims to contribute to developing effective solutions that address emerging challenges in modern power systems.

2.7 Research Gap Analysis

Accurate load forecasting has become essential for effective strategic planning and operation, particularly with the shift of power systems from regulated to deregulated structures and the increasing integration of renewable energy sources in the residential sector. This growing necessity has attracted considerable attention from researchers and key stake holders in the power sector, including grid operators, market operators, planners, and retailers, resulting in extensive efforts to develop improved forecasting models. Nonetheless, despite these advancements, load forecasting remains a dynamic area of research with several unresolved challenges requiring further exploration.

To contribute towards addressing these challenges, this research conducts a comprehensive critical analysis of existing literature. The objective of this gap analysis is to identify the limitations of current models and to formulate relevant and feasible research objectives for this study. It is important to note that this analysis builds upon and acknowledges the contributions of prior research, serving as a foundation for further development rather than undermining existing work.

The literature review reveals that most existing approaches primarily focus either on individual households or on aggregated consumer groups, leading to several limitations, including:

- High variability in residential consumption: Models trained on data from a single household often fail to generalise effectively to others due to significant consumption volatility.

- Data intensity requirements: Many current models require substantial amounts of household-specific data to achieve accurate forecasts, posing challenges for their practical application.

In response to these limitations, this thesis proposes a novel hierarchical forecasting model based on the TD approach, which effectively utilises smart meter data while incorporating demographic-driven variations. The specific research gaps addressed in this study are outlined below.

2.7.1 Identified Research Gaps and Research Questions

Research Gap 1

Most existing forecasting models for the residential sector focus either on individual households or on groups of households with similar consumption patterns. However, there is a lack of models targeting forecasts at different levels within the residential load hierarchy. Furthermore, the few studies that do consider hierarchical forecasting predominantly employ the BU approach. Although the BU approach can provide detailed forecasts, it is computationally intensive, requiring multiple forecasting models and large amounts of granular data such as household usage behaviour and physical characteristics, making practical implementation challenging. Conversely, the TD approach has not been widely evaluated in this context, primarily due to concerns regarding its accuracy at lower hierarchical levels. Nevertheless, if implemented effectively, the TD approach holds practical potential, as a single model can provide forecasts across multiple levels. In light of this identified research gap, the first question addressed in this thesis is:

- How can a hierarchical load forecasting model for the residential sector be developed using the TD approach while ensuring that forecast accuracy is maintained across all levels of the hierarchy?

Research Gap 2

The majority of forecasting models in the literature utilise historical consumption data, calendar variables, and weather conditions as input features. However, other significant non-linear factors that influence residential consumption, such as socio-demographic characteristics and EV charging behaviour, have not been comprehensively integrated into forecasting models. Therefore, the second objective studied in this thesis is

- What is the impact of incorporating socio-demographic factors and EV charging profiles as input features on the performance and accuracy of residential load forecasting models?

Research Gap 3

Although charging prices are known to influence EV charging times, the literature does not evaluate whether incorporating them as input features improves forecasting models. Consequently, their impact on forecast performance has not been systematically examined. Therefore, the final research question addressed in this study is

- How does charging price correlate with EV charging time, and what is its impact on the performance of residential load forecasting models? Can the inclusion of charging prices improve model accuracy, and how can this relationship be effectively integrated within forecasting frameworks?

2.8 Evaluation and Approval

Evaluation is a crucial preliminary step before embarking on the design and simulation phases. At this stage, the identified research gaps and the corresponding objectives of this study are rigorously assessed to determine their relevance, feasibility, and reliability within the wider context of energy efficiency and conservation. This assessment ensures that the gaps identified are pertinent and that addressing them will contribute meaningfully to current or emerging challenges. Furthermore, the practicality of the proposed methodology to effectively resolve these gaps within existing systems is thoroughly evaluated.

This process forms the foundation for selecting an appropriate design approach and provides a comprehensive justification for the research undertaken. The evaluation for this study has been conducted by the academic supervisory team at Auckland University of Technology (AUT), alongside the PhD thesis proposal defense (AUT-PGR9) and its examination panel.

Chapter 3

A Top-down-based Hierarchical Forecast Model for the Residential Sector

3.1 Abstract

This chapter presents the methodology developed to construct the proposed hierarchical residential load forecasting framework. It introduces the forecasting model designed in this research, describing its hierarchical structure, implementation using the selected dataset, and the preprocessing procedures applied prior to model development. In addition, the chapter examines the influence of socio-demographic characteristics on residential electricity consumption and evaluates how their inclusion can impact forecasting performance. The two-stage forecasting framework and the end-to-end modelling approach are both presented, followed by a comparative assessment of their performance across different forecasting scenarios to identify the most suitable approach for residential demand prediction. In this Chapter, the presented details in terms of methodology and corresponding results and analysis regarding the proposed forecast model have been published in [12], [13]. The said manuscripts are as follows:

1. Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. "Hierarchical structure based energy consumption forecasting in top-down approach." In 2022 7th Asia Conference on Power and Electrical Engineering (ACPEE), pp. 1732-1737. IEEE, 2022.

2. Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. "End-to-End Top-Down Load Forecasting Model for Residential Consumers." Energies 17, no. 11 (2024): 2550

3.2 Methodology for Building Forecast Model

Fig. 3.1 illustrates the core framework adopted in this study for developing the forecasting model, along with the specific techniques applied at each stage. The process begins with the acquisition of relevant data, which is then used by clustering algorithms to construct the hierarchical structure.

A critical requirement for any forecasting model is access to a dataset that accurately reflects real-world conditions to ensure robust training. For STLF in the residential sector, the most effective approach involves leveraging smart meter consumption data, as it offers granular insights into household usage patterns. This data is not only essential for model training but also plays a pivotal role in establishing the hierarchical structure of residential loads.

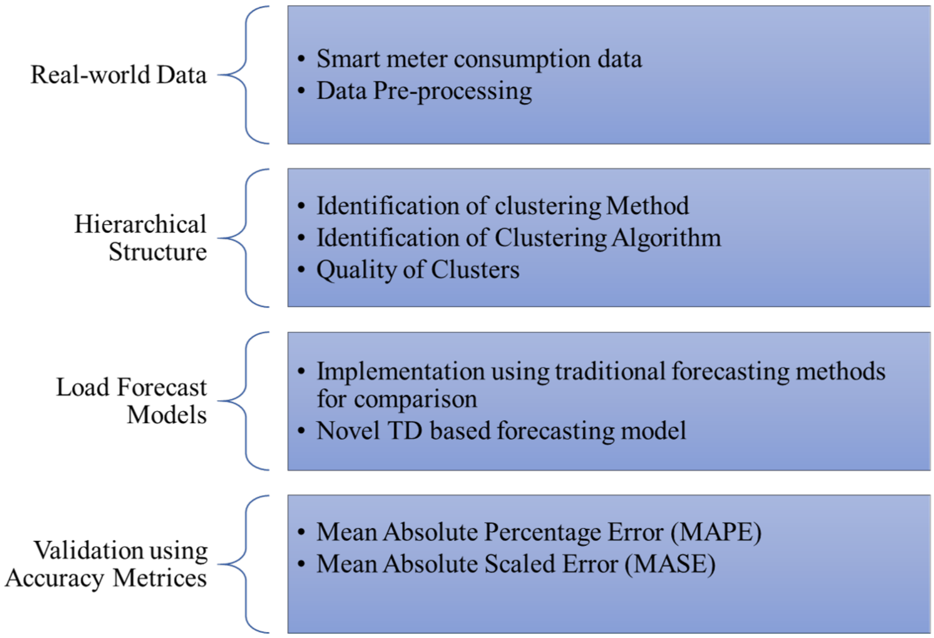


Fig. 3.1 Methodology for designing a forecast model

Before developing the forecasting model, it is necessary to construct an appropriate hierarchy, which can be achieved by implementing clustering algorithms using input features derived from historical consumption data. Fig. 3.2 presents a basic hierarchical structure for the residential sector, with the top level representing the aggregate load of all households, and subsequent levels comprising distinct groups, each containing a varying number of houses based on the chosen clustering criterion.

Following the creation of this hierarchy, the forecasting model is developed. The primary focus is to design an innovative forecasting model for the residential sector based on the

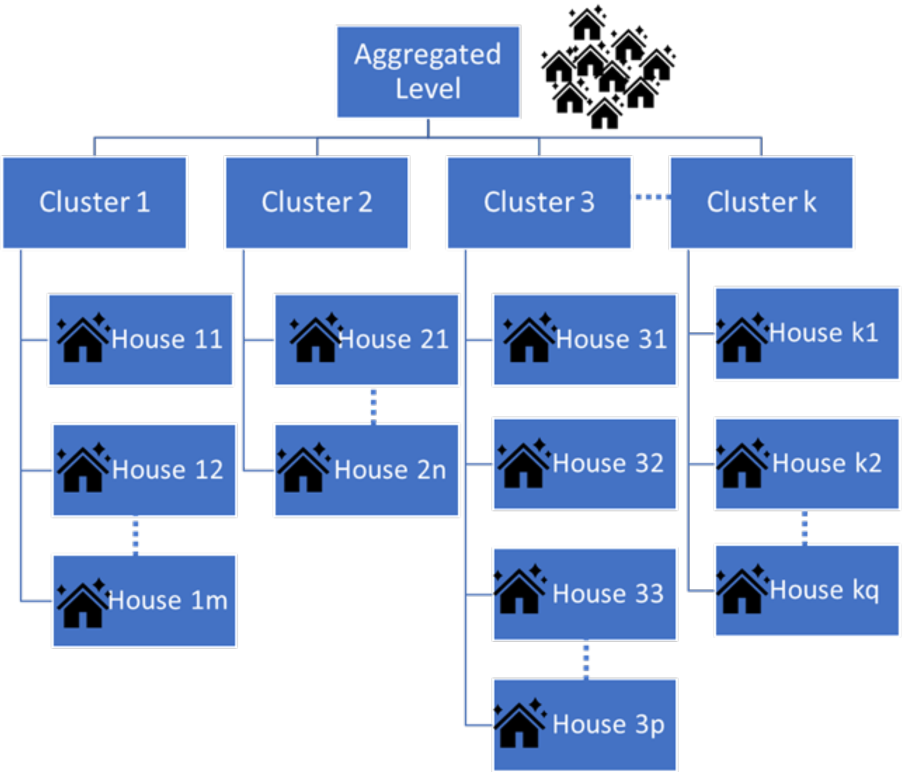


Fig. 3.2 Cluster-based hierarchical structure

principles of the TD approach. However, to evaluate its effectiveness, it is essential to establish baseline models for comparison. In this study, two types of baselines are considered:

- Classical forecasting models: These include well-established techniques such as ARIMA and SVR.
- Bottom-Up approach: This conventional method for hierarchical load forecasting serves as a benchmark to assess the performance of the TD-based model.

Finally, the proposed model is evaluated using two key accuracy metrics: mean absolute percentage error (MAPE) and mean absolute scaled error (MASE), as defined in Equations. 3.1 and 3.2, respectively [91], [92]. MAPE quantifies forecasting accuracy by measuring the percentage error between predicted and actual values, where A_i denotes the actual value, F_i the forecast value at time instant i, and n the total number of observations.

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} abs \frac{(A_i - F_i)}{A_i} \tag{3.1}$$

$$MASE = \frac{MAE}{Naive} \tag{3.2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} abs(A_i - F_i) \tag{3.3}$$

$$Naive = \frac{1}{n-1}\sum_{i=2}^{n} abs(A_i - A_{i-1}) \tag{3.4}$$

MASE assesses model performance relative to a naive forecasting approach, which predicts the current value to be equal to the previous observed value, as shown in Equation 3.4. It is calculated as the ratio of the mean absolute error (MAE), defined in Equation 3.3, to the error of the naive forecast, as expressed in Equation 3.2. A MASE value of 1 indicates parity with the naive forecast, while values lower than 1 suggest superior forecasting accuracy, highlighting the model's effectiveness in capturing load dynamics beyond simple historical repetition.

3.3 Procuring Data

To develop and evaluate the proposed forecasting model, access to high-quality residential electricity consumption data is essential. Smart meter datasets are particularly valuable for this purpose due to their granular recording of household usage patterns. Although numerous public databases provide such data, not all are suitable for the specific objectives of this research. A thorough review of the literature identified several datasets that align well with the requirements of this study. Table 3.1 presents a summary of the most relevant publicly available datasets, highlighting their key characteristics and limitations.

Table 3.1 Public datasets with residential consumption data

Dataset	No. of Households	Access Rights
Low Carbon UK data [93]	5	Free
REFIT [94]	20	Free
NZ Green Grid [95]	25	Free
Pecan Street Inc. Dataport [96]	722	Paid

Among the datasets reviewed, three were freely available. However, the Carbon UK [93] and NZ Green Grid [95] datasets contained only a few days of consumption data, which was insufficient for robust model training and validation. Such short data spans limit the model's ability to capture long-term consumption patterns and seasonal variations, both of which are essential for accurate forecasting. In contrast, the REFIT dataset [94] provided detailed household energy consumption data spanning six-month period. Its extended duration and free availability made it an ideal choice for the initial evaluation of the forecasting model, enabling preliminary testing and model refinement.

The REFIT dataset [94] served as a valuable starting point for testing the concept of the TD hierarchical forecasting approach. It also facilitated the identification of suitable clustering algorithms and methods for generating RLPs to be used as input for clustering. The initial evaluations using the REFIT dataset [94] indicated the potential of the proposed methodology, highlighting the importance of further assessing its scalability and performance on a larger dataset with extensive historical coverage.

Therefore, after careful evaluation, the Dataport dataset from the Pecan Street Inc. (PECAN) project [96] was selected as an additional dataset for in-depth analysis, offering extensive historical coverage to complement the initial evaluations conducted using the REFIT dataset [94]. This dataset offers 15-minute interval consumption data from approximately 700 households in the United States, covering multiple years. Extensive historical load data is essential for effectively training the forecasting model. Its large sample size, high temporal resolution, and comprehensive historical coverage make it well-suited for capturing diverse consumption behaviours and evaluating model performance across a range of scenarios.

Following data acquisition, several preprocessing steps are undertaken to prepare the dataset for analysis. The raw data is first resampled to match the desired temporal resolution, ensuring consistency across all data points. The dataset is then thoroughly examined for anomalies, such as outliers, erroneous readings, and missing values, which could adversely affect the accuracy of the forecasting model. Erroneous samples are identified and removed using statistical thresholds and data validation techniques.

To address missing data, various imputation methods can be employed depending on the nature and extent of the gaps. In this study, missing values were filled using a historical averaging approach, where the gaps were replaced with the average consumption from the same time and day of the week in previous weeks. This method helps preserve the temporal patterns inherent in residential load profiles while minimizing the introduction of bias. The completion of these preprocessing steps ensures that the data is clean, consistent, and suitable for the development, training, and evaluation of the proposed forecasting model. After preprocessing the data, the subsequent steps focus on optimally utilizing it to develop the residential hierarchical structure of the considered households, followed by the design and development of a load forecasting model for this hierarchy.

3.4 Hierarchical Structure

To establish the hierarchical structure of residential households, it is essential to identify common characteristics shared among the households and categorize them based on these similarities. Grouping households based on shared attributes enables a structured approach to load forecasting and analysis. Various methods can be employed to achieve this grouping, as outlined below:

- Based on geographical location: In this approach, households located within the same geographical area, such as those sharing the same postal code or neighborhood, are grouped together. This method helps capture regional consumption trends influenced by factors like climate, infrastructure, and local energy policies.
- Based on socio-demographics: This method involves grouping households with similar socio-demographic features, such as income levels, household sizes, age distribution, or employment status. These factors significantly influence energy consumption behaviours, making this grouping method valuable for understanding demand patterns across different social segments.
- Based on consumption patterns: This technique focuses on analysing load profiles to identify households with similar energy usage patterns. By clustering households with comparable daily, weekly, or seasonal consumption trends, this method enables a more dynamic and behaviour-driven classification, which can enhance the accuracy of load forecasting models.

Each of these grouping methods provides distinct insights and can be utilised individually or in combination, depending on the analysis objectives and data availability. The selection of a grouping approach significantly influences the structure of the residential hierarchy and, consequently, the performance of load forecasting models.

This research work focuses on the optimal utilisation of smart meter consumption data, minimizing reliance on additional intrinsic data that are often difficult to obtain in real-world scenarios. Therefore, the hierarchical structure is developed by focusing on identifying common consumption patterns among households. This is achieved through the application of clustering algorithms, which enable the effective grouping of households based on their load profiles.

Although socio-demographic attributes are considered in this research, they are used solely for evaluating the performance of the forecasting model rather than for clustering. In this study, clustering is performed exclusively based on consumption data. Subsequently, each cluster is analysed to identify the demographic characteristics associated with it. To enhance understanding of the formed clusters, various socio-demographic features of households are assessed, such as the number of occupants and their age distribution. Clusters are further characterised by the percentage of occupants in different age groups, the proportion of appliance ownership, and the insulation thickness of the buildings. This analysis provides valuable insights into how demographic and structural factors influence energy consumption patterns, thereby supporting more accurate demand forecasting and effective energy management strategies.

Following the establishment of the hierarchical structure, the next step involves developing the load forecasting model, as discussed in the subsequent section.

3.5 Top-down based Load Forecasting

This thesis examines the construction of a hierarchical load forecasting model using TD approach. Traditionally, a TD approach involves developing a forecast at the highest hierarchical level, which is then disaggregated into lower levels using mathematical distribution ratios [63]. The forecasting model itself can be based on various methodologies, ranging from statistical models to advanced machine learning techniques, depending on the requirements. In a TD framework, distribution ratios are typically derived from historical data, often calculated as either the average of historical proportions or the proportion of historical averages [63]. While this method is effective for forecasting at higher aggregation levels such as monthly peak demand, total daily consumption, or weekly sales, it is less suitable for predicting hourly load consumption. This limitation arises because historical proportions used for disaggregation fail to account for temporal variations, leading to less accurate forecasts at lower hierarchical levels [63].

This research work proposes an enhanced hierarchical load forecasting model that extends traditional TD principles beyond the reliance on fixed mathematical ratios. The proposed approach aims to improve forecast accuracy across all hierarchical levels by leveraging smart meter consumption data and incorporating cross-learning mechanisms between different levels of the hierarchy. This research presents two variations of the proposed TD hierarchical forecasting model: the two-stage approach and the End-to-End (E2E) approach, with the E2E approach developed as an enhancement of the two-stage model. Both approaches, along with their respective results and analyses, are discussed in detail in the following sections.

3.5.1 Two-Stage Approach

This section introduces the two-stage approach, which develops a forecasting model capable of predicting energy consumption across different levels of a hierarchy by employing two distinct forecasting models operating sequentially.

The first model, model A, is a neural forecasting model designed to predict load consumption at the aggregated level. Its input features are derived from historical smart meter data, with the most relevant features selected based on their spearman correlation coefficients [6], [97], [98]. The key features include previous hour consumption, averages of the past three and six hours, and consumption at the same time on the previous day.

Traditionally, TD hierarchical load forecasting generates forecasts at the highest level and distributes them to lower levels using static mathematical distribution ratios calculated from historical data. While straightforward, this method often lacks accuracy as it fails to capture dynamic changes in consumption patterns at lower levels [63]. To address this limitation, the approach proposed in this study integrates a second model, model B, which refines the forecasts at the cluster level. Instead of solely relying on static ratios, model B uses the aggregated forecast from model A as an input, alongside additional cluster-level features, to produce more accurate forecasts for each cluster. Both neural network models are trained independently: model A is optimised for aggregated load prediction, while model B focuses on cluster-level forecasting by leveraging cluster-specific characteristics in combination with model A's outputs.

This two-stage neural forecasting framework ensures consistency across hierarchical levels while improving accuracy through a structured, data-driven methodology. The conceptual design of this approach is illustrated in Fig.3.3.

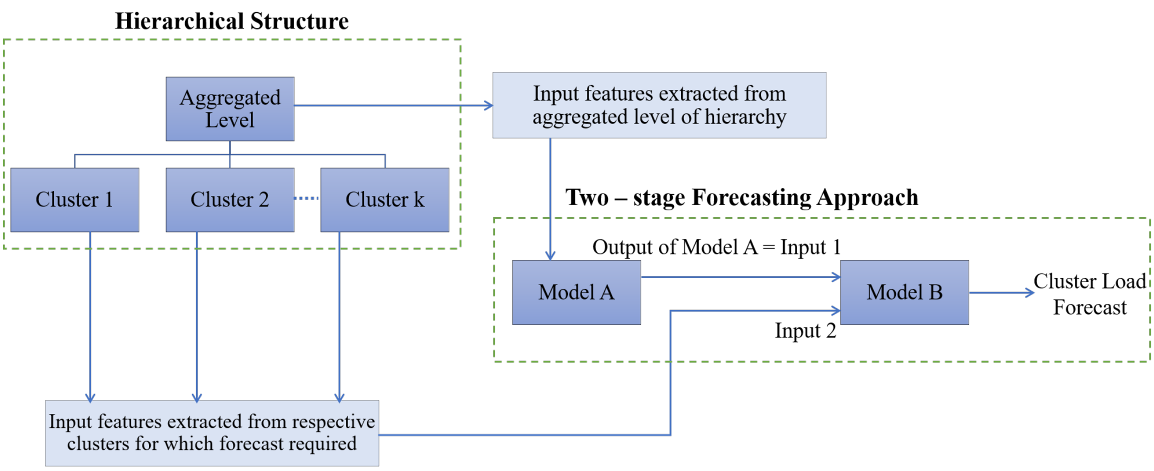


Fig. 3.3 Two-stage Top-down forecasting approach for hierarchical structure

The first step involves extracting input features from the hierarchical structure, where each level represents time-series consumption data corresponding to that level. The two distinct types of input features are derived: one set from the aggregated level and another from the cluster-level consumption time-series.

Overall, this methodology aligns with hierarchical forecasting principles by preserving structural dependencies between levels while addressing the limitations of conventional approaches. By dynamically linking forecasts across levels and leveraging neural networks, the proposed approach enhances accuracy through data-driven learning at each stage of the hierarchy.

3.6 Case Study 1: Experiments and Results

For evaluating the proposed methodology, the REFIT electrical load measurement dataset [94] was utilised. This dataset contains aggregated household electricity consumption data, measured in Watts, for 20 residences at 8-second intervals. The data were down-sampled to obtain hourly consumption values. During the preprocessing stage, it was identified that four of the households contained missing records. As a result, 16 households were selected for preliminary testing of the methodology, using historical consumption data from May and June 2014. The initial step of the proposed methodology involves determining which of the two methods outlined in Section 2.6.2 for creating RLPs is most suitable for the given scenario. This is followed by the development of a forecasting model based on the hierarchical structure that has been constructed.

3.6.1 Representative Load Profiles

The two methods discussed in Section 2.6.2 are implemented to generate the RLPs of customers, which are then used as input for the K-means clustering algorithm. The results are summarized in Table 3.2. The analysis considers 16 households, grouped into four clusters using the K-means algorithm, and the index of agreement (IA) is calculated for both methods used to create RLPs.

The results show that while the highest IA value (0.81) is achieved for Cluster 0 using the two-stage clustering method, the average RLP method consistently outperforms the two-stage method across all four clusters. Specifically, the average RLP method produces higher IA values in Clusters 1, 2, and 3. This consistency across multiple clusters highlights the robustness of the average RLP approach.

Table 3.2 Index of agreement for the RLPs

Cluster No.	No. of houses per cluster		Index of Agreement (IA)	
	Two-stage Clustering RLPs	Average RLPs	Two-stage Clustering RLPs	Average RLPs
C0	4	6	0.81	0.77
C1	7	1	0.61	1.00
C2	1	5	1	0.73
C3	4	4	0.71	0.75

Additionally, the results suggest that the two-stage clustering method, although capable of providing high IA for certain clusters, may be more sensitive to variations in customer load patterns. In contrast, the average RLP method, which aggregates load profiles more uniformly, captures overall consumption trends more effectively.

Therefore, based on the overall performance across all clusters, it is concluded that the average RLP method is more suitable for creating representative load profiles for the considered dataset. This finding supports the selection of the average method for further forecasting and analysis.

3.6.2 Comparison and Analysis of Clustering Algorithms

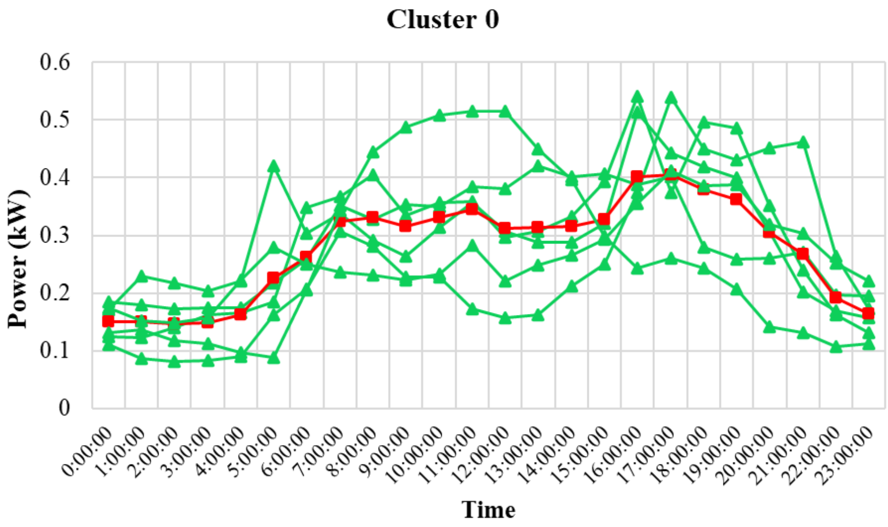
The clustering algorithms discussed were implemented using average RLPs as input, and the resulting clusters, along with their respective IA values, are presented in Table 3.3. Among the three algorithms, the follow-the-leader algorithm achieves the highest IA. However, it results in five clusters, three of which consist of only a single household, indicating poor cluster compactness and reduced generalizability.

In contrast, the results obtained from K-means and hierarchical clustering are more consistent and closely aligned. Nevertheless, hierarchical clustering shows degraded performance as the number of households increases, making it less suitable for larger datasets. Therefore, K-means clustering was selected for further analysis due to its better scalability and balanced clustering performance.

The clustering results from the K-means algorithm are illustrated in Fig. 3.4 and 3.5, where all customers are grouped into distinct clusters without overlap. In the figure, the green lines represent the RLPs of individual households within each cluster, while the red line denotes the cluster centroid, providing a clear representation of average consumption patterns within the group.

Table 3.3 Performance comparison of various clustering algorithms

Cluster No.	No. of Houses per Cluster			Mean IA		
	K-means	Hierarchical Clustering	Follow the Leader	K-means	Hierarchical Clustering	Follow the Leader
0	6	11	10	0.77	0.77	0.79
1	1	2	3	1.00	0.73	0.92
2	5	2	1	0.73	0.91	1
3	4	1	1	0.75	1	1
4	N/A	N/A	1	N/A	N/A	1



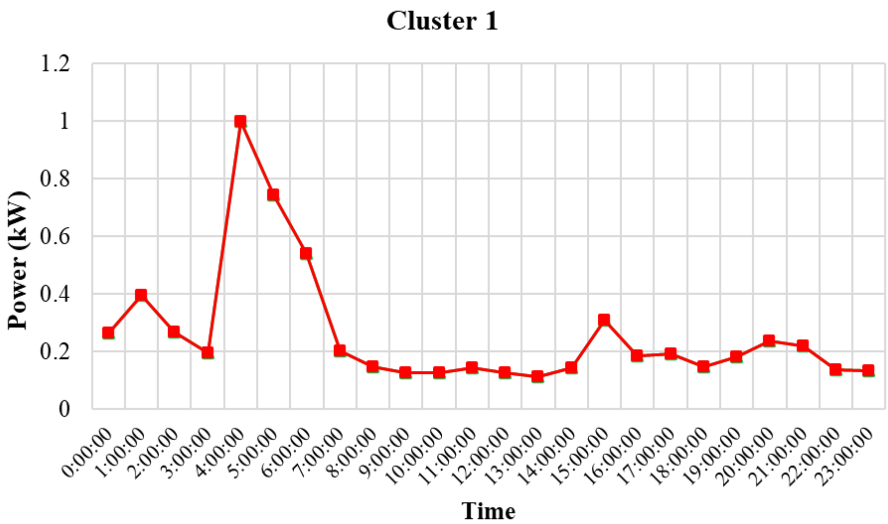


Fig. 3.4 *K*-means algorithm results: Cluster 0 and Cluster 1

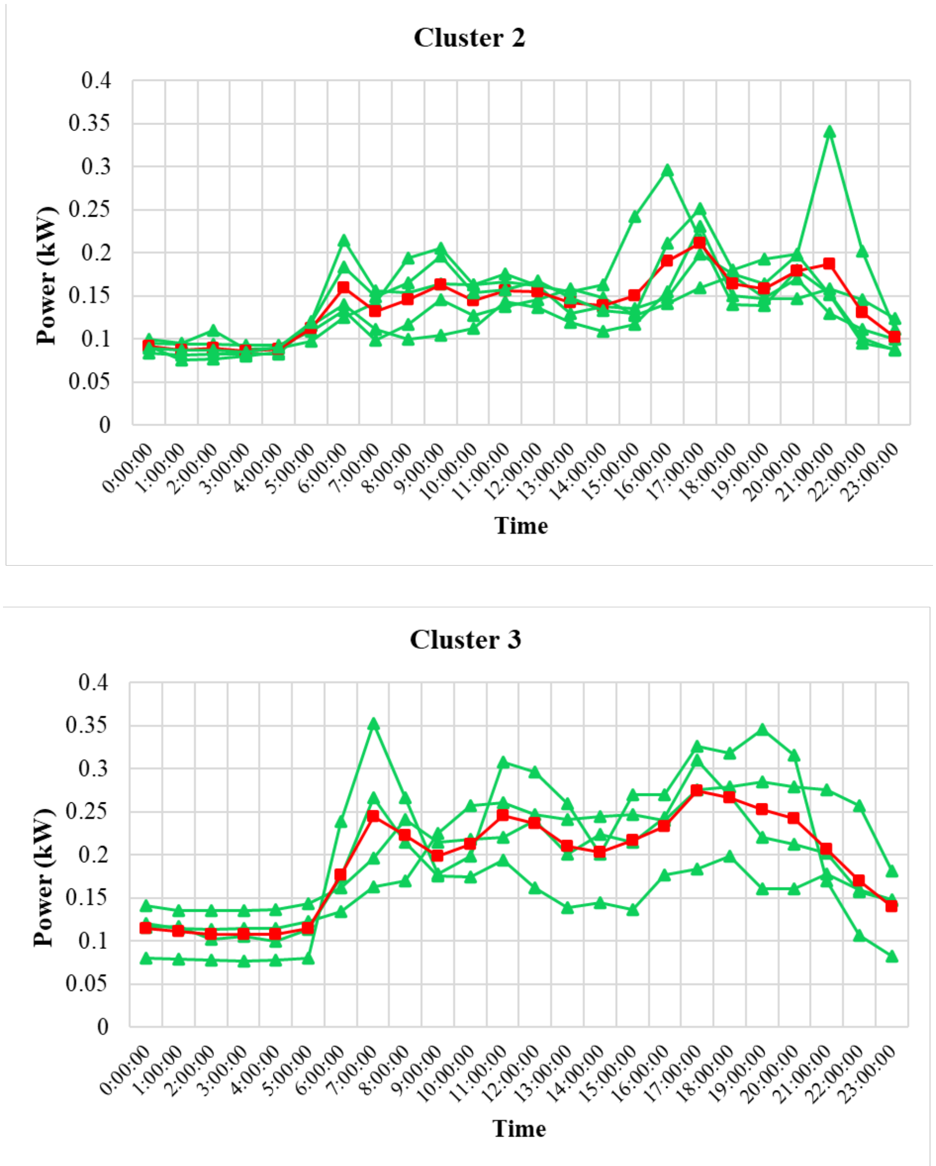


Fig. 3.5 K-means algorithm results: Cluster 2 and Cluster 3

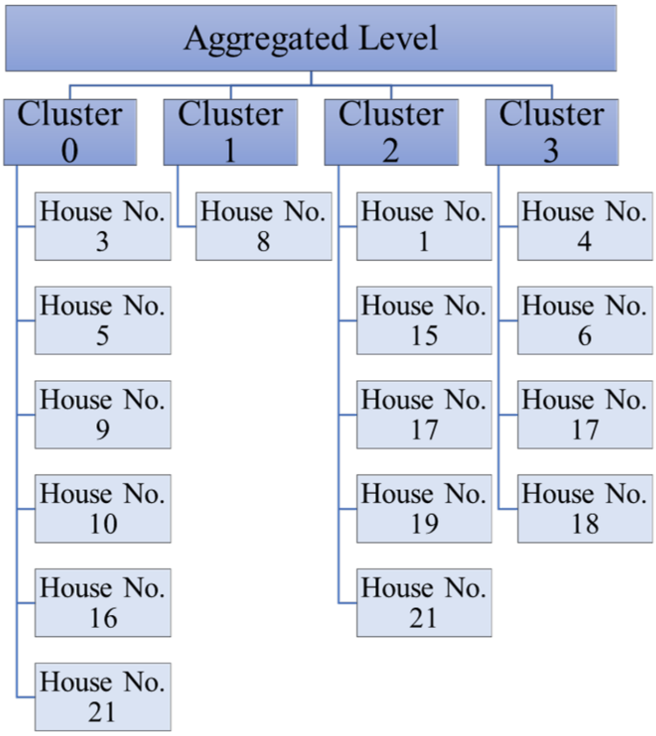


Fig. 3.6 Hierarchy structure for considered houses of REFIT dataset

Following the clustering phase, a hierarchical structure of the households was constructed using the K-means results. The hierarchical arrangement, shown in Fig. 3.6, forms the basis for the subsequent forecasting model by organising the households into a tree-like structure based on their load profile similarities. The number specified in the figure corresponds to the respective ID of the house.

As depicted in Fig. 3.6, this hierarchical structure is integral to testing the proposed forecasting methodology. To evaluate model performance, the complete dataset was divided into training and testing sets, with 80% allocated for training and the remaining 20% for testing. This split ensures that the model is trained on a substantial portion of the data while retaining enough unseen data to assess generalization capabilities.

3.6.3 Forecasting Model for Aggregated Level

The aggregated level forecasting was performed using two models: a SARIMA model and an LSTM-based neural network model. The model parameters of the SARIMA model (p, d, q) (P, D, Q, m) were determined through an analysis of autocorrelation (ACF) and partial autocorrelation (PACF) plots, as shown in Fig. 3.7. The time-series data were tested for stationarity using the augmented Dickey-Fuller (ADF) test [99], [100]. In the ACF and PACF

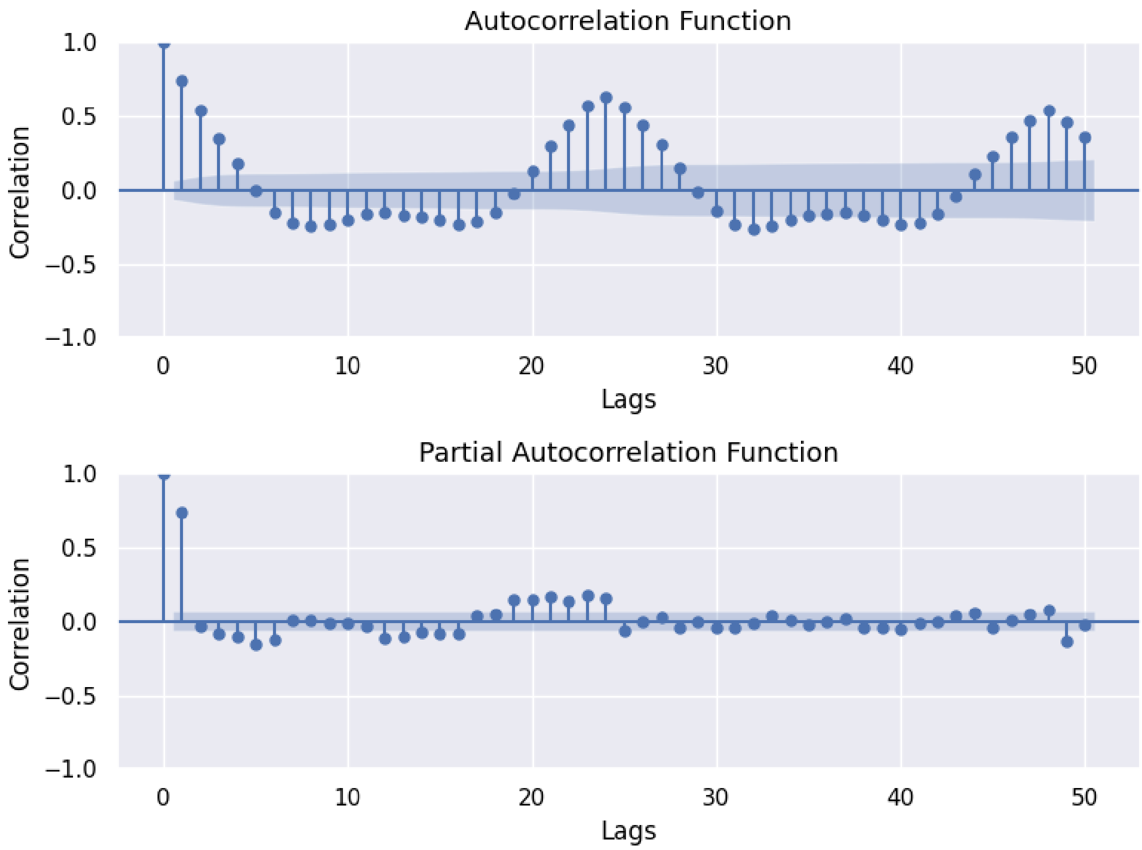


Fig. 3.7 Auto correlation and partial autocorrelation plots of the training dataset

plots in Fig. 3.7, a significant spike at lag 1 in the PACF indicated an autoregressive term p of 1. In contrast, a repetitive spike at lag 24 highlighted the presence of daily seasonality, suggesting a seasonal autoregressive term P of 1 with a seasonal period m of 24 hours.

To identify the optimal SARIMA model, various combinations of (p, d, q) (P, D, Q, m) parameters were evaluated based on the Akaike Information Criterion (AIC) [101], as presented in Table 3.4. After comparing multiple configurations, the model with parameters (1,0,2)(1,0,3,24) was found to have the lowest AIC value, indicating the best fit for the time series data.

Table 3.4 SARIMA model coefficients and AIC

p	d	q	P	D	Q	m	AIC
1	0	3	1	0	3	12	4541.65
1	0	2	1	0	3	12	4540.70
1	0	2	1	0	3	24	4428.27

For comparison, an LSTM neural network model was developed for load forecasting. LSTM models are effective for capturing long-term dependencies in time series data, making them suitable for load forecasting [102]. To select input features for the LSTM model, relevant features were extracted from historical load consumption data, including lagged data, windowed averages, and calendar-based variables. The Spearman correlation coefficient was used to identify features with the highest correlation to aggregated load consumption.

Fig. 3.8 shows the heatmap of the Spearman correlation coefficients between load consumption and candidate features (e.g., previous hour consumption, average consumption of past three hours, and same time on the previous day). Based on the heatmap, five features were selected due to their strong correlation with aggregated level load consumption:

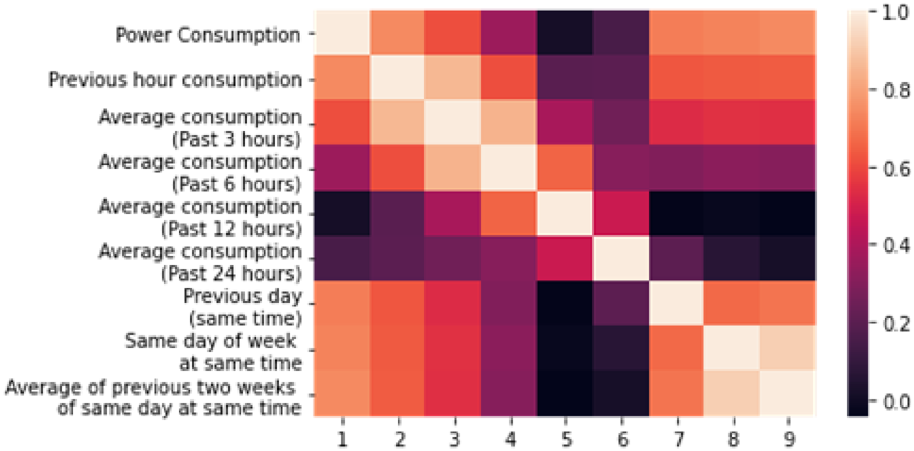


Fig. 3.8 Heatmap illustrating the correlation between load consumption and features

1. Previous hour consumption L_{t-1}
2. Average consumption of the past three hours $L_{avg-t-3}$
3. Consumption at the same hour on the previous day L_{t-24}
4. Consumption at the same hour on the same weekday in the previous week L_{t-168}
5. Average consumption on the same weekday over the past two weeks L_{avg}

The LSTM-based forecasting model (model A) was designed with a sequential architecture. It begins with an input layer that receives the selected time series features. This is followed by two LSTM layers, the first with 64 hidden units and the second with 32 hidden units, allowing the model to capture temporal dependencies in the data. To prevent overfitting, a dropout layer is included after the LSTM layers. The model employs the rectified linear unit

(ReLU) activation function to introduce non-linearity, enabling it to learn complex patterns. The Adam optimizer is used for model training due to its efficiency and adaptability in adjusting learning rates. The MSE is selected as the loss function to measure the prediction error during training. Overall, this architecture is designed to effectively capture long-term dependencies in the time series and produce accurate load forecasts.

The forecasting performance of the SARIMA and LSTM models was compared using the MAPE, with results presented in Table 3.5. The SARIMA model achieved a MAPE of 12.47%, while the LSTM model produced a lower MAPE of 11.98%. Although both models provided accurate forecasts, the LSTM-based model demonstrated superior performance due to its lower error rate. Additionally, the LSTM model showed greater adaptability to non-linear patterns and variations in load consumption compared to the linear SARIMA model, making it more suitable for capturing complex temporal dependencies.

Table 3.5 Comparison of forecast models for the aggregated level using MAPE

Level	MAPE (%)	
	SARIMA	Neural Network
Aggregated	12.47	11.98

Given its higher forecasting accuracy, the LSTM-based model was selected for implementing the proposed methodology. Its ability to leverage historical consumption patterns and temporal dependencies makes it more suitable for forecasting residential load profiles with embedded EV integration effects. In subsequent sections, the results from the LSTM model will be integrated into the proposed hierarchical forecasting framework to evaluate its effectiveness in forecasting load at both cluster and aggregate levels.

3.6.4 Forecasting Model for Lower Hierarchical Levels

To forecast load consumption for the created clusters, model B was developed, incorporating both historical load features and socio-demographic attributes as input. The cluster-level features were extracted using the same methodology as for model A, with additional demographic-based input features. Specifically, the study considered features such as the occupants' age groups and the number of appliances owned by each household. The occupants' ages were categorized into three ranges: below 15 years, between 15 and 44 years, and above 45 years. The analysis revealed that the load consumption patterns for Cluster 0 were highly influenced by previous hour consumption, consumption at the same time on the previous day, and the difference between the current consumption and that of the same hour on the

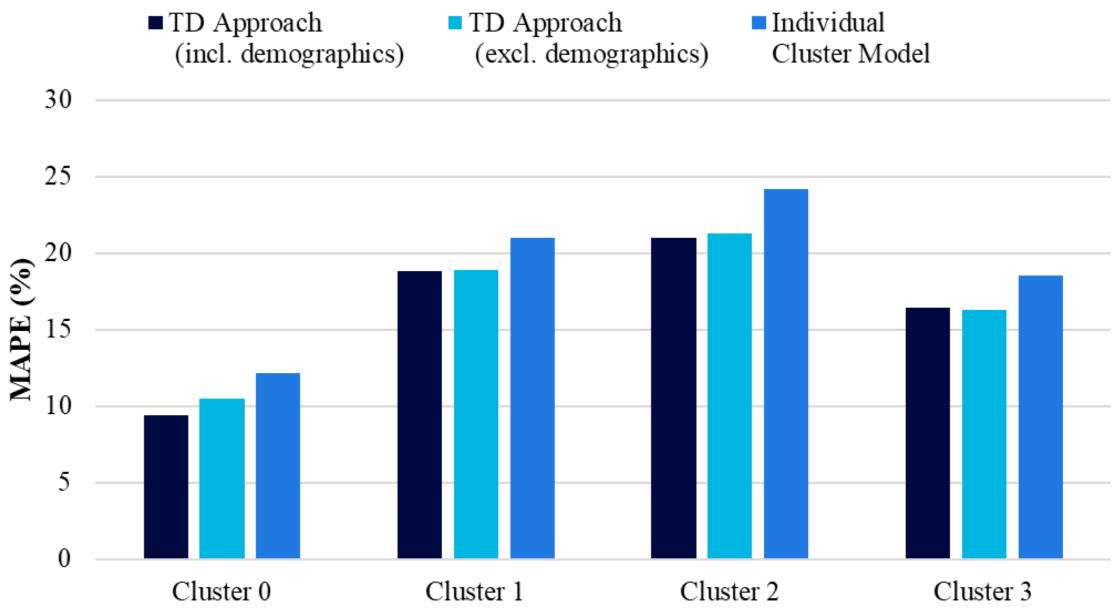


Fig. 3.9 Comparison of forecasting performance across clusters

previous day. A demographic analysis of Cluster 0 showed an almost equal distribution of occupants across the three age ranges, with 31.8%, 31.8%, and 33.6%, respectively. In contrast, Cluster 2 exhibited a distinct demographic pattern, with 53.8% of its residents aged above 45 years. The percentage distribution of occupants' ages within each cluster was one of the demographic inputs encoded and provided to model B.

To evaluate the proposed forecasting methodology, three simulation scenarios were tested. In the first scenario, the proposed two-stage TD forecasting approach was employed, incorporating socio-demographic features alongside the aggregated level forecast. The second scenario applied the same TD approach but excluded socio-demographic features. The third scenario involved forecasting each cluster's consumption separately without leveraging aggregated-level predictions. The results of these simulations are illustrated in Fig. 3.9.

The comparison of results indicates that the third scenario, which forecasts each cluster independently, yielded the lowest performance for Clusters 0, 2, and 3. This demonstrates the limitations of using individual cluster forecasts without leveraging aggregated level information. The only exception was Cluster 1, which consists of a single household. The consumption pattern for Cluster 1 was highly volatile and noisy, making it difficult for the TD approach to produce accurate forecasts without additional features. This indicates that the performance discrepancy for Cluster 1 is due to its unique, highly individualized consumption behaviour rather than the methodology itself.

The impact of including demographic features was particularly notable in Clusters 0, 1 and 2. For these clusters, incorporating demographic attributes led to a reduction in MAPE of 1.09%, 0.05%, and 0.3%, respectively. However, the improvement for Cluster 1 was minimal, as the cluster's single house composition and high volatility limited the gains from demographic inputs. This finding suggests that Cluster 1 would require additional, more granular features for a significant reduction in forecasting error.

The results presented in Fig. 3.9 also demonstrate that using demographic features consistently improved forecasting accuracy across multiple clusters, reinforcing the value of incorporating socio-demographic attributes into load forecasting models. Although the study included only a limited set of demographic features, it is evident that adding more distinct socio-demographic attributes, such as household income levels or working hours, could lead to further improvements in forecasting performance.

Overall, the proposed TD forecasting approach combined with socio-demographic features outperformed both the baseline TD approach without demographics and the individual cluster forecasts. This outcome clearly highlights the effectiveness of integrating aggregated level forecasts with demographic information. Moreover, it underscores the advantages of the hierarchical TD approach over standalone cluster based forecasts, particularly in residential load forecasting scenarios where demographic patterns significantly influence consumption behaviour.

3.6.5 Evaluation of the Proposed Methodology Against the Bottom-Up Approach

The proposed two-stage methodology was evaluated against the BU approach, specifically for Cluster 0, to assess its potential. In the BU approach, distinct forecasting models were created for each of the six houses within Cluster 0, and their individual forecasts were aggregated to estimate the cluster's total load consumption. The results demonstrated that the BU approach produced a MAPE of 18.41%, while the proposed TD methodology achieved a notably lower MAPE of 9.37%, as shown in Table 3.6. Fig. 3.10 presents the comparison between actual and forecasted load consumption for the testing dataset.

Table 3.6 Comparison between BU and Proposed Approach using MAPE

Cluster	MAPE (%)	
	BU Approach	Proposed Approach
C0	18.41	9.37

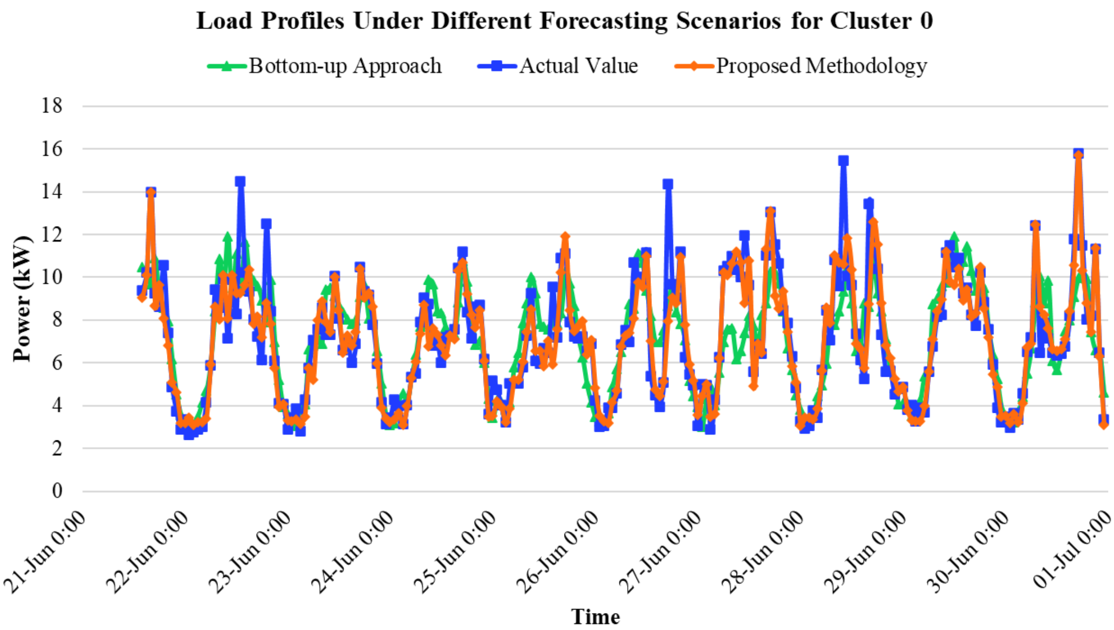


Fig. 3.10 Load Profiles Under Different Forecasting Scenarios for Cluster 0

The high error rate in the BU approach can be attributed to the increased variability and noise at the individual household level. Unlike aggregated load profiles, which smooth out random fluctuations, individual household consumption patterns are highly unpredictable and often influenced by occupant behaviour, lifestyle, and appliance usage patterns. As a result, building accurate forecasting models for individual households becomes more challenging due to the inherent volatility in their load profiles.

The BU approach is also highly dependent on the quality of the data. The missing values, outliers, or anomalies in the consumption data of even a single household can propagate through the model, leading to significant deviations in the aggregated forecast. Additionally, the approach struggles with scalability since modeling each household separately becomes computationally expensive and impractical as the number of households increases.

In contrast, the proposed methodology leverages aggregated-level data to capture broader consumption patterns while integrating cluster-level features, such as socio-demographics and historical consumption trends, to refine forecasts. This integration results in more stable and reliable predictions compared to summing individual household forecasts. The reduced MAPE of the proposed methodology demonstrates its superiority in handling the variability of residential load profiles, particularly within clusters where occupant behaviour significantly impacts consumption patterns.

Moreover, the results underscore the limitations of the BU approach in residential forecasting scenarios where data from smart meters can be noisy and incomplete. The proposed methodology, by focusing on aggregated patterns with meaningful cluster-level features, not only improves forecasting accuracy but also offers a more scalable and robust solution for load forecasting in residential energy management systems.

3.6.6 Discussion

The two-stage approach requires training two separate models to achieve cluster-level forecasting, with each model necessitating its own optimization and fine-tuning. While this methodology demonstrates the potential of applying TD hierarchical forecasting principles, it also reveals opportunities for further improvement. Specifically, although effective, relying on two independent models can increase implementation complexity and computational requirements.

Moreover, while the two-stage is motivated by traditional TD principles, it does not explicitly capture the inter-dependencies between aggregated and lower levels within the hierarchy. This limitation suggests that forecasting accuracy could be enhanced by adopting an approach that simultaneously learns these hierarchical relationships.

To address this, the methodology was refined to incorporate both TD forecasting principles and a cross-learning mechanism within a single model framework. This led to the development of an E2E learning model, which offers the advantage of producing forecasts for both aggregated and cluster-levels within the hierarchy using one integrated model. Such an approach simplifies implementation, reduces computational overhead, and better captures dynamic relationships across hierarchical levels, ultimately enhancing forecast performance.

3.7 End-to-End (E2E) Learning Model

An E2E learning model consists of a single model that takes all relevant inputs and directly outputs the forecast. Unlike the two-stage approach, which involves training two separate models to achieve forecasts at the cluster level, the E2E model produces these forecasts in a single step. Although it also builds upon the principles of the TD approach, the E2E model offers greater implementation efficiency and simplicity by removing the need for multiple models. Additionally, it effectively integrates TD forecasting concepts with cross-learning capabilities, enhancing forecast accuracy while maintaining hierarchical consistency. The architecture of the proposed methodology, including the E2E learning model, is illustrated in Fig. 3.11.

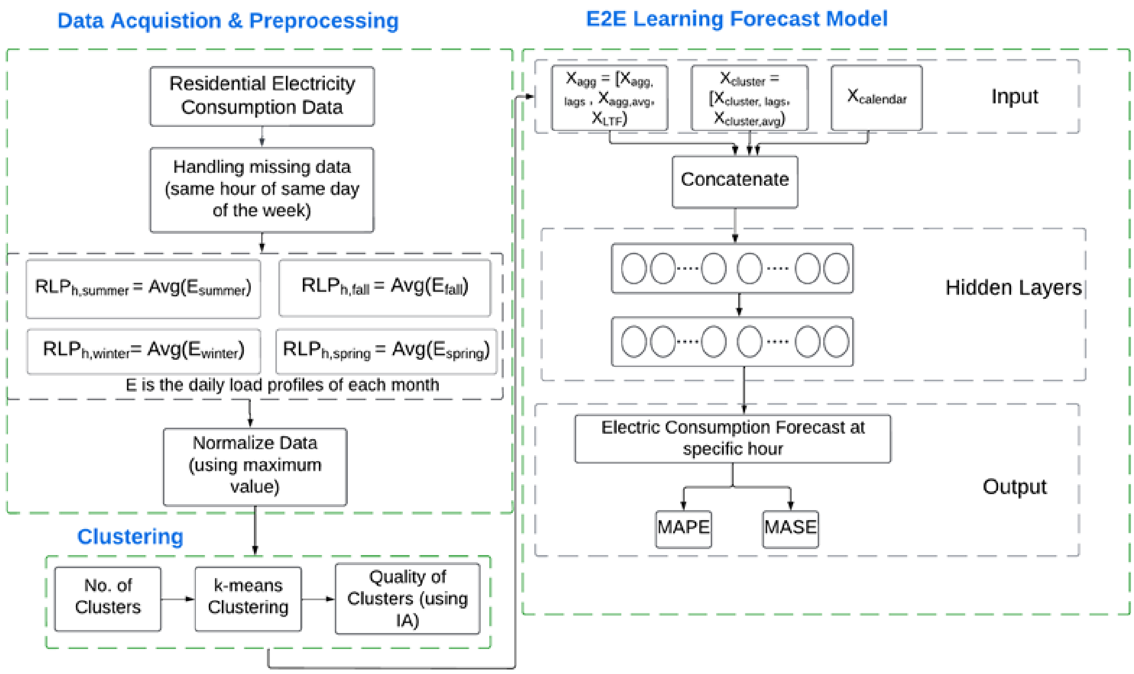


Fig. 3.11 End-to-End learning model

The E2E model estimates load at any point in the hierarchy by leveraging inputs from the aggregated dataset as well as from the node of interest. Unlike the two-stage approach, which relies on separate models to forecast cluster consumption, the E2E approach employs a single neural network model that directly predicts load at any level. This unified model integrates input features derived from both aggregated and cluster levels, along with an additional key feature that explicitly captures the relationship between different hierarchical levels.

The model is built upon a single feed-forward neural network and is enhanced with dropout regularization to prevent overfitting. It is designed to accommodate both aggregated level and cluster level forecasting, depending on the forecasting requirements of the application. The model utilises three categories of input features, briefly outlined below, and will be elaborated in later sections.

1. Aggregated level features to capture the overall consumption trends.

2. Cluster level features for representing localized consumption patterns.

3. Calendar variables accounting for temporal variations such as day of the week and seasonality.

An essential aspect of the proposed approaches is that all input features for forecasting are derived from historical consumption data, ensuring the full utilisation of smart meter data. The aggregated level input features include lag variables, the mean consumption of the preceding hour, and load tracking features (LTFs). In time-series data, hourly load consumption is influenced not only by the absolute values of past consumption but also by the temporal patterns of change. Accordingly, LTFs are incorporated into the model, as detailed in [103]. These features assist the model in capturing the rate of change in load. The LTFs are derived from variations in hourly and daily consumption, as presented in Equation 3.5 to Equation 3.9, where DLC and HLC represent the daily load change and hourly load change, respectively, with subscript D and H representing the forecasting day and forecasting hour. For example, $L_{D,H}$ denotes the load during the current hour of the forecasted day.

$$LTF_1 = L_{D,H-1} + DLC_{D-1,H} \tag{3.5}$$

$$LTF_2 = L_{D-1,H} + HLC_{D-1,H} \tag{3.6}$$

$$LTF_3 = L_{D,H-1} + mean(HLC_{D-1,H} + HLC_{D-2,H}) \tag{3.7}$$

$$LTF_4 = L_{D,H-1} + HLC_{D-7,H} \tag{3.8}$$

$$LTF_5 = L_{D,H-1} + mean(HLC_{D-1,H} + HLC_{D-7,H}) \tag{3.9}$$

The cluster-level features comprise the mean consumption of preceding hours, lag variables, and a ratio quantifying the relationship between aggregated and cluster level demand. Additionally, calendar-related variables such as hour of the day, day of the month, and month are incorporated as cyclic features. All features are derived exclusively from historical consumption data, with no inclusion of exogenous variables. Although numerous features can be extracted from historical load profiles, the optimal subset is identified using the spearman correlation coefficient to reduce dimensionality [97], [104].

These input features are concatenated and fed into the model's hidden layers. The first hidden layer consists of 100 neurons, followed by a dropout layer, which enhances generalization by reducing overfitting. The activation function used is the ReLU, ensuring efficient gradient propagation and faster convergence. To optimize performance, hyperparameters are fine-tuned for maximum forecasting accuracy. The model is compiled using the Adam optimizer, which adapts learning rates dynamically for faster convergence, and the MSE is employed as the loss function to minimize forecasting errors. Overall, the E2E learning model provides a more streamlined and robust forecasting solution, effectively balancing hierarchical structure preservation with the advantages of data-driven learning.

The following section presents the results of applying the methodology to an additional dataset, evaluating the two proposed variations of the TD hierarchical forecasting approach to identify the optimal scenario.

3.8 Case Study 2: Experiments and Results

The REFIT data [94] were mainly used to test the potential of the proposed hierarchical forecast methodology based on TD principles. The testing of the proposed methodology on the smaller REFIT dataset demonstrated its potential, indicating that a forecasting model based on the TD hierarchical principle holds significant promise for load forecasting applications. This initial evaluation motivated further testing on a larger dataset to assess its scalability and effectiveness. Moreover, the application of the two-stage approach to the REFIT data provided valuable insights into the practicality of TD based forecasting while also revealing opportunities to simplify the framework. This led to the development and implementation of an alternative variation, the E2E learning methodology.

The following section presents the results of implementing the methodology on a different dataset. It compares the performance of both variations of the proposed TD forecasting model with other commonly used models. The comparison demonstrates the superior performance of the E2E model relative to existing approaches reported in the literature.

3.8.1 Dataset Description

The PECAN Street dataset's dataport [96] contains half-hourly electricity consumption time-series data recorded by smart meters installed in residential properties across the United States of America (USA) over a span exceeding nine years. For this study, the data were resampled to a daily resolution, producing 24-hour load profiles for each household. The analysis focuses on 50 selected households, with consumption records covering the period from 2013 to 2021. Preprocessing steps were applied to correct erroneous entries, and missing values were imputed by calculating the mean consumption for the same time on corresponding weekdays. STLF was performed to predict electricity usage for the subsequent hour. The dataset was split into 80% for training and 20% for testing, with 10% of the training set reserved for validation. To preserve temporal consistency, the partitioning was conducted in chronological order.

3.8.2 Hierarchical Structure

Representative seasonal load profiles are generated for each year, with winter defined as December to February, spring as March to May, summer as June to August, and fall as September to November. Fig. 3.12 and 3.13 present seasonal RLPs for a single household in 2013 and 2021, respectively. Notably, seasonal differences are evident, with the highest consumption occurring in summer due to elevated temperatures. This aligns with the dataset's origin, a city in Texas, USA, where high summer demand is typically driven by cooling requirements. To account for year-to-year variability, these annual seasonal profiles are used as input to the K-means clustering algorithm. Prior to clustering, each profile is normalized by its maximum value. Seasonal RLPs are created for each of the 50 selected households, and K values from 4 to 15 are tested, with the WCSS used as the evaluation metric. A knee point is observed with the value of K as 10, leading to the formation of 10 clusters. The quality of clustering is validated using the Index of Agreement [85].

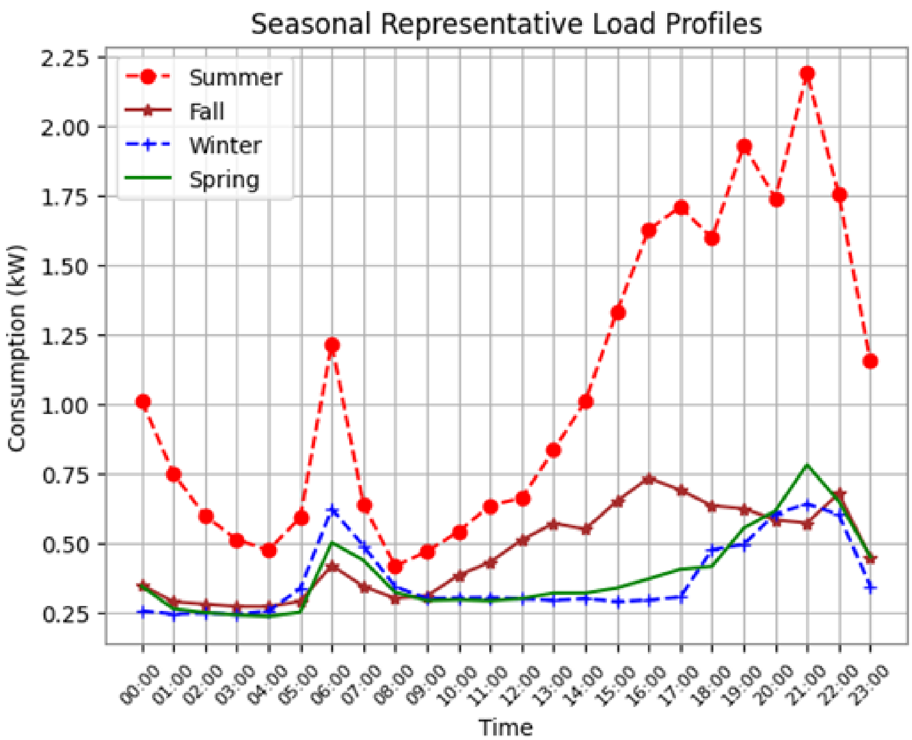


Fig. 3.12 Seasonal representative load profile of a single household in 2013

Fig. 3.14 illustrates the 24-hour average load profiles of these clusters, where each curve represents the mean profile of all houses within that cluster. Distinct temporal and magnitude patterns are observed across clusters. For example, Cluster 0 maintains relatively stable usage throughout the day, while Clusters 1, 3, and 8 display pronounced peaks at specific

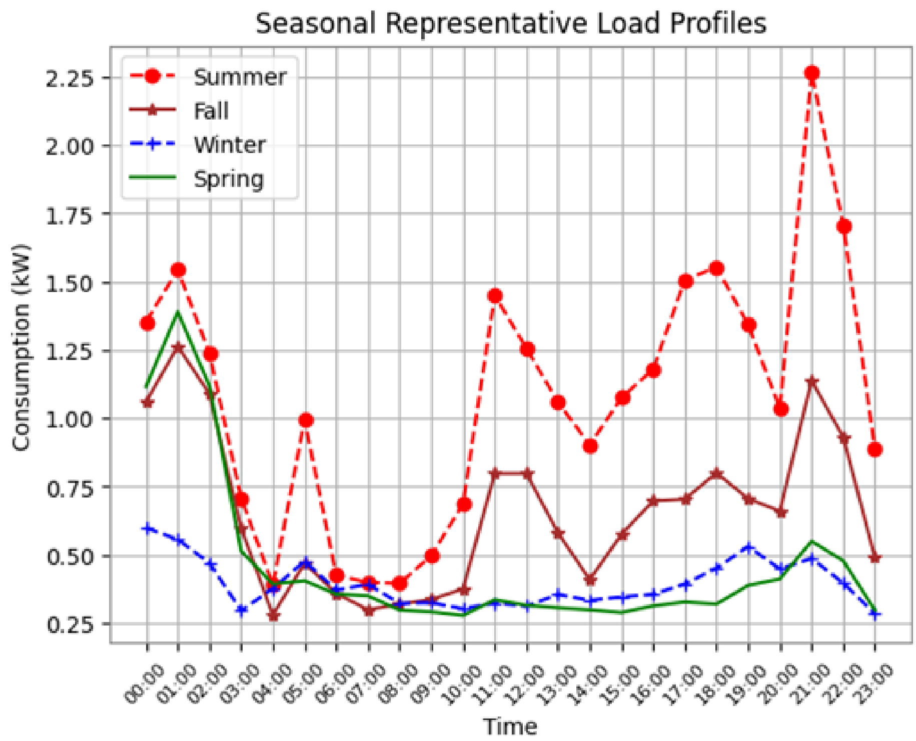


Fig. 3.13 Seasonal representative load profile of a single household in 2021

times. Cluster 1 peaks in the morning around 08:00 with a smaller evening peak close to 18:00, whereas Cluster 3 peaks early in the morning around 04:00 to 05:00 and again around 20:00. Cluster 8 maintains steady daytime usage before peaking at 20:00. Clusters 2, 4, and 6 show lower variability; Cluster 2 peaks late morning around 11:00 and 12:00 and Cluster 6 maintains low, steady usage overnight, rising slightly after 8:00. Clusters 7 and 9 have generally low daily consumption with minor fluctuations.

Table 3.7 reports statistical parameters for each cluster over the nine years from 2013 to 2021, including peak instance timings. These may differ from the average profiles shown in the figures, as they reflect actual yearly peak times rather than mean behaviour. For instance, Cluster 3's peak timings differ by three hours, while Clusters 1 and 8 peak at similar times but exhibit different mean magnitudes. These differences highlight the unique characteristics of each cluster and confirm the effectiveness of the clustering method.

Following the creation of the hierarchical structure, the forecasting model is applied to predict load consumption for each cluster. Household level forecasting is not prioritised due to the high volatility of individual residential demand and because stakeholders generally require insights at the aggregated group level. Forecasts for these consumer clusters provide more actionable information for decision-making in the power sector.

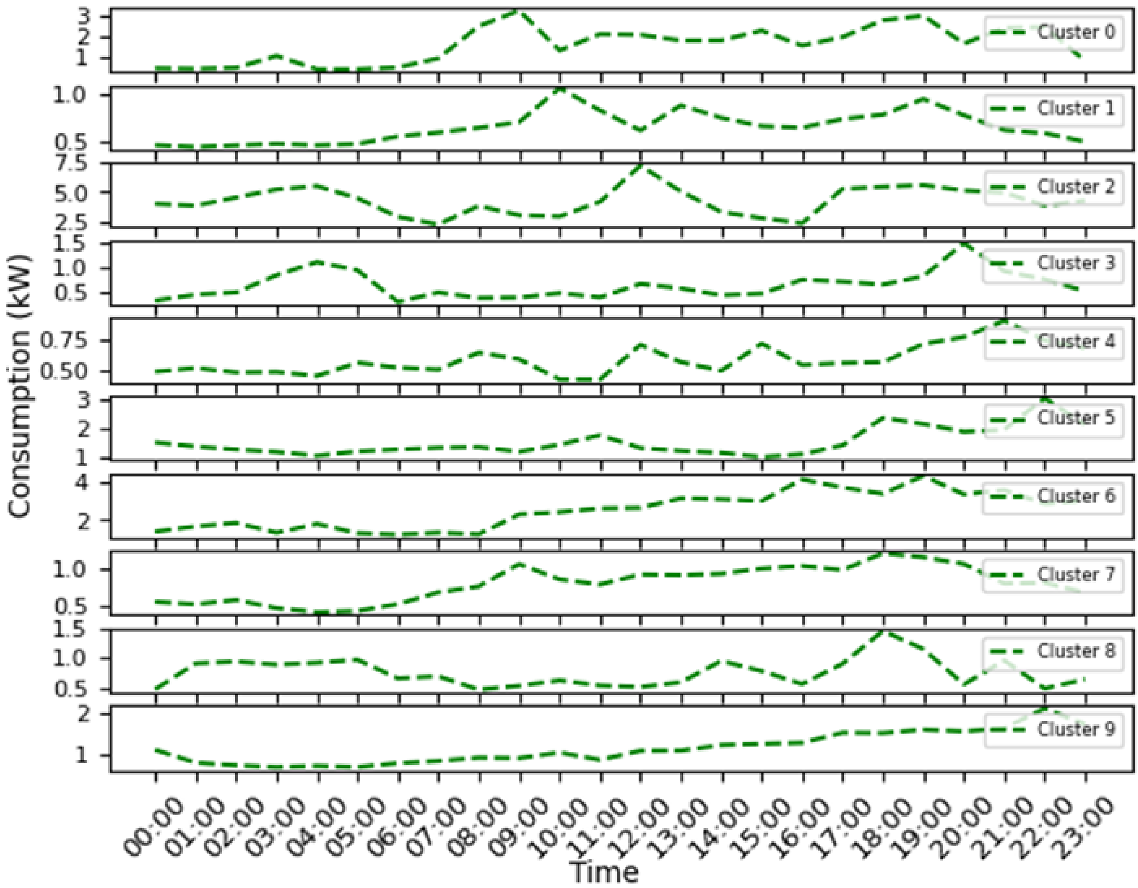


Fig. 3.14 Load profiles of clusters (average)

3.8.3 Performance Assessment of Forecast Models Using MAPE

To assess the effectiveness of the proposed E2E model with cross-learning features, it is compared against a two-stage methodology and two widely used forecasting models; SARIMA and SVR [105, 106]. The SARIMA models extend the ARIMA framework by incorporating seasonal components and are parameterized by (p,d,q) for the non-seasonal elements and (P,D,Q,m) for the seasonal component, where m represents seasonality. The parameter selection for SARIMA is performed through analysis of ACF and partial PACF plots [107]. The second benchmark, SVR, is a supervised regression-based approach that determines the optimal hyperplane for fitting the data [106]. It employs kernel functions such as linear, polynomial, or radial basis function (RBF) to map the data into higher-dimensional spaces. The regularization parameter C plays a critical role, controlling the trade-off between minimizing training error and limiting model complexity, thereby affecting generalization performance. Kernel choice and C values are hyper-tuned to achieve optimal results.

Table 3.7 Statistical parameters of clusters

Cluster	Mean	Peak Value	Standard Deviation	Peak Instant
C0	2.11	14.70	1.52	13:00
C1	5.12	25.41	3.80	17:00
C2	3.96	17.56	2.04	18:00
C3	2.46	12.52	1.46	21:00
C4	7.48	31.6	4.65	19:00
C5	3.88	17.230	2.60	18:00
C6	2.14	10.8	1.39	18:00
C7	15.08	58.56	9.61	17:00
C8	3.69	27.45	2.53	16:00
C9	19.07	63.67	11.11	18:00

Given the importance of input features for model accuracy, the data undergo preprocessing, and feature selection is performed as outlined in Table 3.8. All models are trained and tested on the same dataset, and accuracy is evaluated using Mean Absolute Percentage Error (MAPE). Table 3.9 reports MAPE values for all 10 clusters within the hierarchy across the four approaches. The results indicate that SARIMA yields the highest mean MAPE, followed by SVR, the two-stage method, and, with the lowest error, the proposed E2E model.

Table 3.8 Input features utilised by the forecast model

Level	Input Features	Description
Aggregated level	L_{avg_3h}, $L_{avg\_t\_d}$	Average load consumption over the previous 3 hours and average load consumption of the same days of the week at the same time
	L_{t-24}, L_{t-d}, L_{t-1}, L_{t-2}, L_{t-3}, L_{t-21}, L_{t-22}, L_{t-23}	Load consumption at the same time as the previous day and at the same time on previous days of the week
	LTF_1, LTF_2, LTF_3, LTF_4, LTF_5	Load tracking features [103]
Cluster level	L_{c,avg_t_d}	Average cluster-level daily load consumption
	$L_{c,t-24}$, $L_{c,t-1}$	Cluster-level load consumption at previous day and previous hour
	R_c	Ratio between aggregated and cluster-level consumption
Calendar features	h_{sine}, h_{cos}, d_{sine}, d_{cos}, m_{sine}, m_{cos}, H	Cyclic encoding of hour, day, and month of the year to capture periodic patterns

Table 3.9 Forecast model performance comparison using MAPE

Cluster	MAPE (%)			
	SARIMA	SVR	Two-stage	E2E
C0	19.41	23.7	6.19	3.4
C1	12.7	13.6	1.5	1.12
C2	16.22	16.7	6.35	5.4
C3	32.87	34.6	7.73	3.49
C4	14.41	13.8	5.02	2.6
C5	25.9	21.60	1.22	1.37
C6	34.7	26	3.1	2.07
C7	29.82	13.9	0.69	0.88
C8	34.9	28.5	3.32	1.71
C9	34.8	11.6	3.75	0.71

The SARIMA and SVR models show weaker performance, particularly because they are best suited for datasets with primarily linear structures [13]. In contrast, residential load consumption is inherently non-linear due to numerous influencing factors. SVR assumes a deterministic relationship between inputs and outputs, which does not hold true for residential load patterns. Furthermore, SVR's performance declines with larger datasets due to computational demands and the complexity of selecting an optimal kernel. Similarly, SARIMA struggles to capture non-linear input–output relationships. Enhancing these models would require substantial computational resources, larger memory allocation, and additional feature engineering steps, which present practical implementation challenges.

In contrast, both variations of the proposed methodology; the two-stage and E2E learning models achieve low MAPE values, supporting the suitability of the TD design approach. The chosen hyperparameters are optimized to perform well across the hierarchy while keeping MAPE within acceptable limits. Overall, the E2E model outperforms all other methods, maintaining a percentage error below 6% for all clusters. Although the two-stage method yields a lower MAPE for Cluster 5 and Cluster 7, both remain below 2% for these clusters. In all other clusters, the E2E approach delivers better accuracy. The two-stage model's highest MAPE is 7.73% that is observed for Cluster 3, whereas the E2E model's highest MAPE is observed for Cluster 2 that is 5.4%. Notably, for 9 out of 10 clusters, the E2E model achieves MAPE values below 5%, with the remaining cluster close to this threshold. These variations in accuracy are acceptable given the overall low forecasting errors across the hierarchy.

3.8.4 Comparative Analysis of Two-Stage and End-to-End Learning Approaches via MASE

Both the two-stage and E2E models, based on the TD hierarchical forecasting concept, demonstrate strong performance in terms of MAPE. To further validate this, their effectiveness is also evaluated using MASE, with results summarised in Table 3.10. Both models outperform the naive forecasting approach, which has a benchmark MASE of 1. Notably, the results indicate that the E2E model surpasses the two-stage model significantly in terms of MASE, consistently achieving lower values. This finding highlights the advantage of the E2E model in delivering more accurate forecasts across the entire hierarchical structure.

Table 3.10 Comparative evaluation of E2E learning and the two-stage model based on MASE

Cluster	MASE	
	Two-stage	E2E
C0	0.10	0.07
C1	0.11	0.07
C2	0.2	0.2
C3	0.25	0.09
C4	0.38	0.15
C5	0.05	0.05
C6	0.14	0.06
C7	0.04	0.05
C8	0.11	0.06
C9	0.33	0.06

A key advantage of the E2E model is its ability to forecast load consumption for all sub levels within the hierarchy using a single unified model. This approach not only simplifies the forecasting process but also reduces the computational workload by eliminating the need for multiple separate models for each sub level. Additionally, the model's design ensures better forecasting accuracy by simultaneously optimizing predictions across all hierarchical levels.

To further assess the model's performance, the E2E learning model computes the MAPE for every hour of the day across all clusters within the hierarchy. This hourly evaluation is crucial for understanding the model's effectiveness across different time periods, capturing variations in load patterns throughout the day. The results are visually represented in a heatmap, shown in Fig. 3.15, which displays the MAPE for all clusters over a 24-hour period. In the heatmap, the color gradient on the right indicates MAPE values, with lighter colors

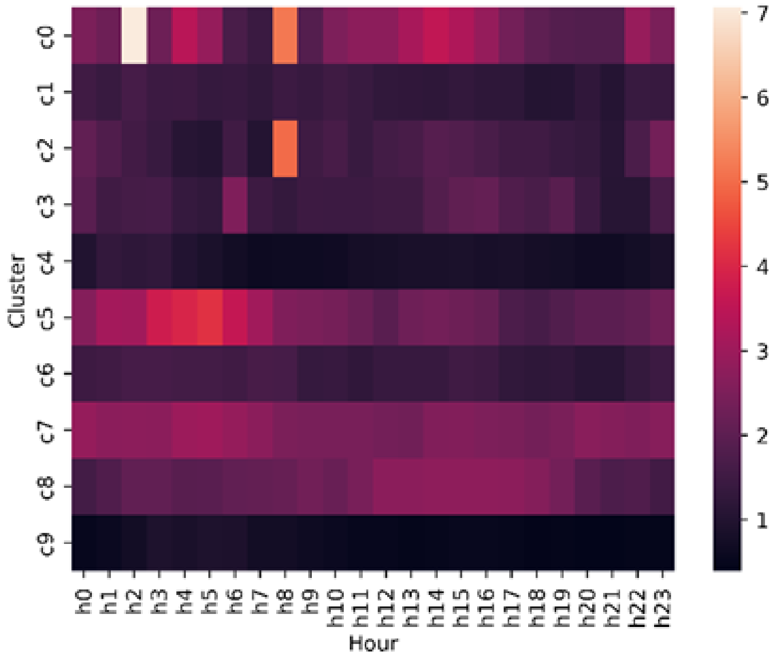


Fig. 3.15 Heatmap of MAPE for each hour of the day for all clusters

signifying higher MAPE, i.e., lower accuracy, and darker colors representing lower MAPE, i.e., higher accuracy.

The analysis reveals that, for each hour of the day, the MAPE for every cluster remains below 5%, except for three clusters. Specifically, Cluster 0 records a MAPE of 7.06% at 2:00., Cluster 2 exhibits a MAPE of 4.98% at 8:00., and Cluster 5 shows a MAPE of 4.19% at 5:00. These deviations highlight specific periods and clusters where load forecasting is more challenging, likely due to variations in consumption behaviour or outliers in the data. Despite these exceptions, the overall performance of the proposed E2E methodology remains strong.

The results demonstrate that the proposed E2E learning model achieves an overall MAPE of less than 10% across all clusters and periods throughout the 24-hour cycle. This performance not only surpasses that of the two-stage model but also outperforms other baseline models. The findings underscore the robustness and reliability of the E2E model, especially in its ability to handle complex load patterns while maintaining high forecasting accuracy. Overall, the proposed methodology offers a scalable and efficient solution for hierarchical load forecasting, making it a valuable approach for large scale energy management applications.

3.8.5 Performance Comparison of E2E Model and Bottom-Up Model

This E2E learning model builds on the principles of the TD approach. In contrast, the widely adopted BU approach requires developing separate local models for each group. In the BU framework, each cluster is modeled independently using only the features relevant to that specific cluster, along with calendar variables. Aggregated-level features are intentionally excluded, as their use would contradict the core premise of the BU method

Table 3.11 Comparison between E2E learning and BU approach using MAPE

Cluster	MAPE (%)	
	E2E	BU Approach
C0	3.4	15.22
C1	1.12	10.21
C2	5.4	14.7
C3	3.49	14.28
C4	2.6	11.19
C5	1.37	14.5
C6	2.07	13.97
C7	0.88	10.51
C8	1.71	14.78
C9	0.71	8.76

The local models for BU in this study are also neural network based, incorporating the same cluster features used in the E2E model, plus calendar variables. Forecasts from these individual models are summed to estimate the aggregated level demand. The comparative results are presented in Table 3.11, showing that the BU approach yields significantly higher MAPE values than the proposed cross-learning E2E model, for the reasons outlined below.

Existing literature indicates that BU generally outperforms TD when forecasting load at sub-hierarchy levels, but this advantage comes at the expense of requiring substantial additional data to maintain accuracy. In the residential domain, BU models often rely on physics based modeling and behavioural input features. These include appliance specifications, energy consumption rates, operating schedules, usage patterns, and residents' habits [108]. However, in practice, such detailed data are often unavailable. Conversely, smart meters provide rich, readily accessible consumption data, which can be leveraged to enhance forecast performance as demonstrated in the proposed E2E model. By drawing on historical consumption, the E2E model extracts relevant features and uses cross-learning across multiple hierarchy levels to improve accuracy.

Fig. 3.16 compares the aggregated level 24-hour MAPE between the two methods. The E2E model achieves an MAPE range of 0.08%–1.85%, whereas BU ranges from 0.04%–18.3%. The E2E predictions track actual values closely, while BU shows greater deviations. This superior aggregated level performance is consistent with the known strength of TD-based approaches at higher hierarchy levels.

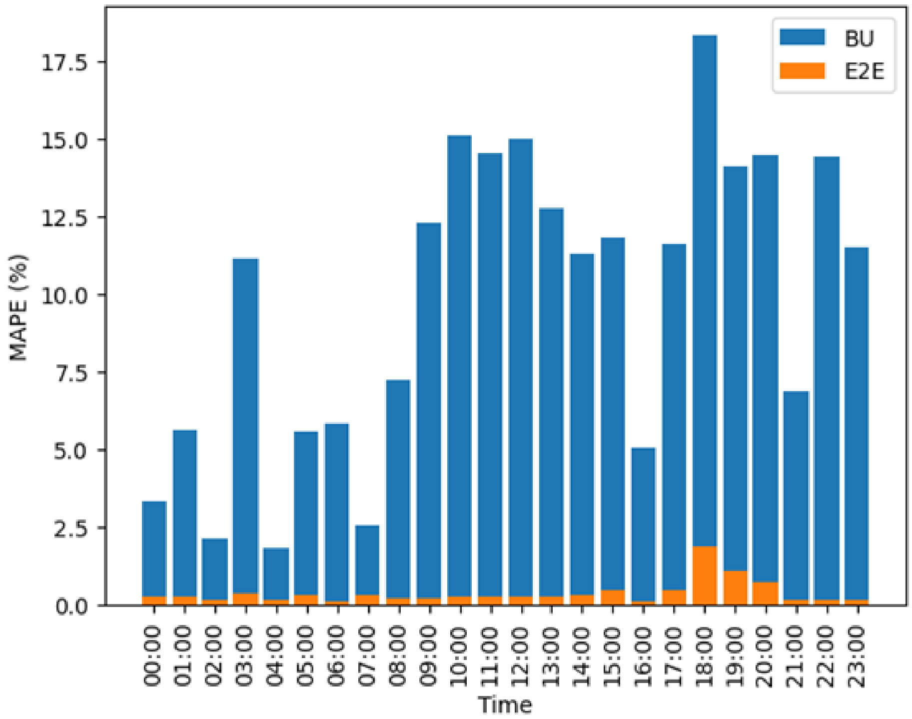


Fig. 3.16 Comparison between actual and forecast values from both approaches

Moreover, the proposed model demonstrates robustness across clusters, adapting effectively to varying consumption patterns. Nonetheless, retraining is still necessary to optimize performance within each cluster due to its distinct characteristics. Despite this, the E2E model consistently delivers high accuracy across diverse clusters, reinforcing its effectiveness and flexibility. This serves as proof of concept that the cross-learning E2E framework holds significant potential for residential forecasting applications across different geographic and demographic contexts.

3.9 Discussion

This study develops and evaluates an E2E learning model for forecasting residential electricity consumption within a hierarchical structure. The hierarchical load forecasting model employs the TD approach, which remains less common than the BU approach in hierarchical forecasting. Unlike BU models, which require detailed feature sets for each cluster, the TD approach offers a more practical alternative by using aggregated information. BU-based models, while effective, demand granular data for all clusters in the hierarchy, posing challenges for real-world implementation due to data volume and computational complexity. The proposed E2E model addresses these issues by leveraging features derived from historical load data, calendar variables, and other key predictors that establish the relationship between the aggregate level and the sub-level clusters requiring forecasts. This section evaluates the model's performance through comparative analysis with traditional models, discusses its strengths and limitations, and outlines opportunities for future research.

The E2E learning model achieved promising results, with a MAPE of less than 6% across all clusters in the hierarchy. This level of accuracy outperforms common statistical methods, such as SARIMA and SVR, which fail to achieve comparable accuracy across all clusters. A notable advantage of the proposed E2E model is its ability to deliver consistent performance without the need for cluster-specific hyperparameter tuning, which is typically required in SARIMA and SVR models. By integrating cross-learning features, the model effectively captures diverse consumption patterns across different clusters. This cross-learning capability enables a single model to adapt and forecast load consumption across all clusters simultaneously, thereby simplifying the modeling process and reducing computational overhead.

A significant drawback of most existing hierarchical load forecasting models is their reliance on the BU approach, where forecasts are generated at lower levels of the hierarchy and then aggregated upwards. While this approach may yield reasonable accuracy, it often presents practical challenges, such as the need for large-scale data processing and the risk of forecasting bias and incoherence across different levels. In contrast, the proposed E2E learning model offers a more efficient solution by eliminating the need for exogenous input features and relying solely on historical load data. Furthermore, the results demonstrate the superior performance of the proposed model, with improvements in mean MAPE of 91%, 85.8%, and 82.24% over SARIMA, SVR, and a conventional BU hierarchical model, respectively. These improvements highlight the effectiveness of the E2E approach in capturing load patterns while maintaining coherence across hierarchical levels.

Another key strength of the proposed E2E model is its adaptability across clusters with distinct load profiles. The model's unified architecture and consistent hyperparameters enable it to handle diverse patterns without modification. Despite these strengths, the model has certain limitations. First, its forecasting accuracy may degrade when sudden extreme changes or anomalies occur in the data, such as during power outages or unusual peak events.

Additionally, while the model performs well across clusters using the same architecture, separate model training is still required for each cluster, which may increase computational time. A further limitation is the model's reliance on a large volume of historical data for effective training. Smaller utilities or regions with limited historical data may struggle to implement this approach effectively.

Future research in hierarchical load forecasting could address these limitations through several avenues. First, incorporating deep neural network architectures, such as LSTM networks, could improve sequence modeling capabilities and enhance forecasting accuracy, especially for time-dependent patterns. Additionally, evaluating the model's performance on diverse datasets from different regions will help assess its generalization ability and robustness. Another promising direction is the exploration of transfer learning techniques, which could enable the model to perform well with limited data by transferring knowledge from similar datasets.

Despite these challenges, this study makes a significant contribution to hierarchical load forecasting by demonstrating how an E2E learning model with cross-learning features can improve forecasting accuracy while reducing computational complexity. By addressing issues associated with traditional BU approaches and outperforming conventional statistical models, the proposed E2E model offers a robust solution for large-scale energy management applications. In conclusion, this research highlights the potential of machine learning techniques, such as E2E models, in advancing load forecasting accuracy. The findings not only contribute to the academic field of energy forecasting but also offer practical implications for utilities and policymakers in optimizing energy distribution and promoting sustainable energy management practices.

3.10 Relation between socio-demographical features and residential consumption

In the residential sector, several consumer-specific factors influence electricity consumption, including the unique characteristics of the dwelling type and the behaviour and demographic traits of the residents. Residential energy consumption patterns result from a complex interaction of multiple factors, including household characteristics, occupant behaviour, and technological factors. Understanding these patterns is essential for developing accurate load forecasting models, implementing effective demand-side management strategies, and promoting energy efficiency initiatives. This section explores the key determinants that have the greatest impact on electricity usage among residential consumers and examines their role in shaping consumption behaviours.

Socio-demographics refer to the social and demographic characteristics of a population, categorized based on specific criteria such as age, family size, income, and other socio-economic factors. In the context of residential households, each household is classified by the demographics of its occupants, including age, gender, education level, and income, as well as by characteristics of the house itself, such as location, floor size, and the presence of energy efficient technologies. These factors are pivotal in the energy sector, as they significantly influence how and when electricity is consumed. For example, a household where all members are employed may exhibit lower electricity usage during the day, with consumption peaks occurring in the early morning and evening. In contrast, a household with children or adults at home throughout the day may have more consistent electricity consumption patterns. Similarly, households with higher incomes tend to own more appliances, increasing their base load, while larger households with more occupants often exhibit complex usage patterns with multiple consumption peaks.

Extensive research has been conducted to understand the various factors that impact electricity consumption. One study found that social and demographic characteristics, including personal attributes, socio-economic status, and socio-demographic factors, are directly related to electricity consumption [7], [71]. Table 3.12 represents the various socio-demographic features studied in the literature, highlighting those with significant impacts on consumption. Among the factors studied, income status proved to be the strongest indirect predictor of the number of electrical appliances owned, highlighting its strong link to increased electricity consumption. Other factors that showed positive and significant correlations include educational level, gender, and employment status [109]. For instance, households with higher educational backgrounds are more likely to adopt energy-efficient technologies, reducing their per capita consumption despite owning multiple appliances. Conversely, families with lower education levels may have less awareness of energy conservation practices, leading to higher consumption.

To assess the impact of socio-demographic characteristics on electricity consumption, the selected houses were evaluated based on their maximum consumption values and compared against their unique features to identify correlations. The socio-demographic factors considered in this study include income, family size, house floor area, and ownership of EVs or PV systems. For each house, the income range and floor area in square meters were provided. It is preferable to categorize income and floor area rather than use absolute values, as this approach allows for easier pattern identification and clustering within the data, as shown in

Table 3.12 Socio-demographical Features

Features	Description
Family size	Family size plays a significant role in influencing household energy consumption. Larger households typically consume more electricity due to increased usage of appliances and lighting.
Age of the occupants	Household electricity consumption is closely linked to the age of its occupants. Teenagers often contribute to higher energy use through modern electronic devices. Retirees, spending more time at home, also drive up daytime energy consumption.
Income	Higher-income families tend to own more modern appliances and larger homes equipped with advanced lighting and centralized temperature control, contributing to increased electricity usage.
Education background	Individuals with higher educational backgrounds often have higher incomes, leading to increased electricity consumption. However, those with strong educational backgrounds may also adopt energy-efficient technologies.
Dwelling type	Electricity consumption varies by dwelling type (e.g., detached, semi-detached, terraced houses, or apartments). Larger floor areas typically result in higher electricity usage.
Floor size of the house	Larger floor sizes generally increase electricity consumption due to higher lighting needs and the use of centralized heating and cooling systems.
No. of electrical appliances	A higher number of electrical appliances directly increases electricity consumption, as more devices contribute to the household's overall energy load.

Table 3.13. Categorization helps address the non-linear relationship between these features and electricity consumption, thereby reducing the impact of outliers.

To better understand maximum consumption patterns, the specific time at which it occurs is also considered. For most houses, peak consumption occurs during the daytime, which is why the period from 11:00 to 23:00 is divided into four quarters: 11:00 to 14:00, 14:00 to 17:00, 17:00 to 20:00, and 20:00 to 23:00. This segmentation allows for a detailed analysis of how different household characteristics influence consumption patterns throughout the day. For example, households with young children or retirees are more likely to experience peak consumption between 11:00 and 14:00, while dual-income households often experience peaks between 17:00 and 20:00 when occupants return home from work.

The relationship between socio-demographic attributes and electricity consumption patterns has been well documented in previous research. However, while significant work has been done to explore these relationships, there has been comparatively less focus on

Table 3.13 Categorical input features of demographics

Income ($)	Categories	Floor size (m^2)	Categories
< 50k 50k - 74.9k	Low income	< 900 900 - 1499	Small house
75k - 99k 100k - 149k	Medium income	1500 - 1999 2000 - 2499	Medium house
150k - 300k > 300k	High income	2500 - 2999 >3000	Big house

using these features to predict consumption patterns and improve load forecasting models. Socio-demographic attributes, if effectively integrated into forecasting models, can help improve prediction accuracy by providing insights into behavioural trends that influence consumption. For example, models that incorporate demographic features such as household income, family size, and employment status can better capture seasonal and daily load variations, especially during peak hours.

Additionally, socio-demographic attributes play a vital role in segmenting customers for demand response programs. Identifying patterns, such as increased daytime consumption in households with retirees or children, enables utilities to design more targeted demand-side management strategies. Furthermore, incorporating these attributes can enhance clustering techniques in machine learning models, leading to more homogeneous groups with similar consumption patterns and improving overall model performance. Consequently, the resulting clusters and their associated socio-demographic characteristics are analysed and correlated, with the key insights presented below.

- Cluster 0 comprises a single household, distinguished by its significantly higher maximum consumption compared to other houses. This elevated consumption level is primarily attributed to the house's larger size, which likely results in greater energy demands for heating, cooling, and appliances. Additionally, the household's higher income may contribute to increased usage of energy intensive devices and amenities, further driving up consumption levels.

- Cluster 1 comprises houses with similar maximum consumption values, all of which occur during the third quarter of the day, between 17:00 and 20:00. This peak period aligns with typical evening activities, such as cooking, lighting, and the use of household appliances, which collectively drive up energy demand. The consistent timing of peak consumption across these houses suggests a shared pattern of daily routines, likely influenced by standard working hours and evening home occupancy.

- Cluster 2 consists of smaller houses; however, the residents' higher income levels play a significant role in driving the maximum consumption value to 17 kW. Despite the limited physical size of these homes, increased disposable income often leads to the use of multiple energy-intensive appliances, such as electric heating systems, air conditioning units, and high-end entertainment devices.

- Cluster 3 comprises houses with varying sizes, demonstrating how demographic factors such as income, floor size, and occupancy influence energy consumption patterns. Among these houses, two have the same number of occupants and similar income levels; however, one exhibits a significantly higher maximum consumption due to its larger floor area, which likely results in greater energy demands for heating, cooling, and lighting. The third house presents a contrasting pattern: despite having only one occupant and a smaller floor size, it reaches a higher maximum consumption, primarily driven by the occupant's high income. This suggests the presence of energy intensive appliances, electric vehicles, or luxury amenities, which contribute to elevated consumption levels even in a smaller living space. Overall, the analysis of Cluster 3 highlights that income and floor size have a more substantial impact on consumption than the number of occupants. Notably, when one demographic factor; either income or floor size stands out significantly, it becomes the dominant driver of energy consumption. This finding underscores the importance of considering both socioeconomic and physical housing characteristics when analysing residential load profiles.

- Cluster 4 stands out due to its diverse demographic characteristics, yet the houses within the cluster exhibit similar maximum consumption levels. This indicates that despite differences in household profiles, their energy usage patterns converge. Among these homes, some have lower income and medium-sized floor areas, suggesting that their consumption is likely driven by essential energy needs such as heating, cooling, and appliances, rather than luxury items. In contrast, other houses in the cluster may have higher incomes or larger floor areas but demonstrate comparable peak consumption, possibly due to energy-efficient technologies or different lifestyle patterns.

- Cluster 5 comprises houses with identical demographic profiles, including the same family size, large homes, and high income levels, resulting in similar peak consumption values. The combination of large floor areas and affluent lifestyles likely drives energy-intensive usage patterns, such as central heating or cooling systems, multiple appliances, and home entertainment devices.

- Cluster 6 exhibits a maximum consumption value that falls between those of clusters 0 and 2. Although this cluster consists of only one house, its consumption pattern is distinct due to its moderate income level and floor size. This contrasts with cluster 0, where the larger floor area drives higher energy demand, and cluster 2, where elevated income leads to increased consumption through energy-intensive appliances and technologies. The house in cluster 6 reflects a balanced profile, where neither income nor floor size dominates consumption, resulting in an intermediate peak value. This highlights how a combination of demographic factors, rather than a single dominant attribute, can shape residential energy usage patterns.

- Cluster 7 primarily comprises households with EVs, which results in higher maximum consumption values due to increased charging demands. These homes are predominantly occupied by residents with medium to high incomes and typically feature medium-sized floor areas. The presence of EVs contributes significantly to peak load patterns, reflecting the additional energy consumption from vehicle charging. In contrast, households within the same cluster that do not own EVs exhibit lower maximum consumption levels, even if they fall into the medium to high-income categories or have medium to large floor sizes. This disparity underscores the substantial impact of EV ownership on electricity demand, highlighting the importance of accounting for EV charging behaviour when analysing load profiles

- Cluster 8 exhibits varying maximum consumption values, influenced by differences in household composition, income levels, and EV ownership. Notably, one household, consisting of a family of five, records the highest maximum consumption within the cluster. This elevated usage is attributed to a combination of factors, including high income, a large floor area, and EV ownership, which together contribute to greater overall energy demand, particularly during peak periods. In contrast, another household within the cluster, despite having the highest income and a similarly large floor area, demonstrates a comparatively lower maximum consumption. This discrepancy is primarily due to a smaller family size, which results in fewer energy intensive activities and reduced overall demand. The absence of additional consumption drivers, such as multiple occupants or EV charging, further limits peak usage. These contrasting consumption patterns within cluster 8 highlight the diverse nature of residential energy demand, emphasizing that while income and property size can influence consumption, household composition and EV ownership play critical roles in determining maximum load levels.

- Cluster 9 records the highest maximum consumption within this group, primarily driven by households with very high incomes, which often correlates with greater energy usage from multiple appliances, large living spaces, and luxury amenities. This cluster highlights a clear link between income level and peak demand, as higher-income households typically have more energy-intensive lifestyles.

However, integrating socio-demographic features into load forecasting models presents several challenges. First, obtaining accurate and current socio-demographic data can be challenging due to privacy concerns and limited data accessibility.

Second, the relationship between these attributes and consumption is often non-linear and may vary across regions, making it essential to use advanced modeling techniques such as neural networks or ensemble methods to capture these complexities. Third, socio-demographic attributes can become less predictive over time as household behaviour evolves due to factors such as remote work trends or increased adoption of energy-efficient technologies.

Therefore, the next section will delve deeper into the impact of demographics on electricity consumption and discuss how these factors influence the accuracy of load forecasting. By analysing these relationships and integrating them into forecasting models, this research aims to address existing gaps in the literature and contribute to developing more accurate and reliable residential load forecasting models. The results of this analysis will be used to enhance the feature selection process for the proposed forecasting models, ensuring that socio-demographic attributes are appropriately weighted and leveraged to improve model performance.

In conclusion, socio-demographic attributes are key determinants of residential electricity consumption, offering valuable insights for load forecasting models and demand-side management programs. While challenges exist in their integration, the potential benefits in improving forecasting accuracy and tailoring energy efficiency programs are significant. The findings from this section will contribute to the broader analysis in this thesis, helping to build more comprehensive forecasting models that capture both technical and behavioural drivers of electricity consumption.

3.10.1 Impact of socio-demographical features on the forecasting accuraccy

For the evaluation, the chosen dataset comprising 50 residential houses was selected, each with specific socio-demographic and energy consumption characteristics. The primary features identified as significant in influencing residential energy usage include family size, household income, and floor size. Additionally, differences in ethnicity among households were noted, making it essential to consider all four socio-demographic features when analysing energy consumption patterns. The dataset includes household-level information on both demographics and power consumption. The socio-demographic attributes were recorded for each house, encompassing family size (number of occupants), ethnicity (categorized groups), income levels (low, middle, high), and the total floor area (square meters or square feet). These features were further analysed to investigate their correlation with energy consumption patterns.

While demographic attributes were considered in the analysis, they were not used as criteria for clustering. Instead, clustering was based on consumption patterns, which resulted in groupings where socio-demographic characteristics varied within clusters. Each house was analysed individually, and then the aggregated socio-demographic features were computed at the cluster level, indicating the proportion of houses in each cluster exhibiting specific demographic characteristics. This method allowed for a broader understanding of how different demographic compositions influence energy consumption trends within clusters.

The proposed methodology, which employs an E2E learning model, has demonstrated superior performance compared to alternative forecasting approaches. Given that energy consumption in the residential sector is heavily influenced by socio-demographic factors, the impact of these features on forecasting accuracy was critically assessed and presented in Table 3.14.

Table 3.14 Impact of socio-demographic features on forecasting accuracy measured by MAPE

Cluster No.	Without socio-demographic features	With socio-demographic features
C0	3.4	2.67
C1	1.12	1.25
C2	5.4	2.26
C3	3.49	1.72
C4	2.6	0.96
C5	1.37	1.41
C6	2.07	1.72
C7	0.88	2.44
C8	1.71	1.99
C9	0.71	2.52

A key observation emerged when comparing forecasting accuracy with and without demographic data:

- Clusters with low demographic variability: When a cluster exhibits low variability in its demographic composition (i.e., most households within the cluster share similar income levels, family sizes, and home sizes), incorporating demographic data as input features significantly improves forecasting accuracy.
- Clusters with high demographic variability: Conversely, in clusters where demographic variability is high, such as clusters 7 and 9, including socio-demographic data in the forecasting model sometimes led to a decline in accuracy. This suggests that in highly diverse clusters, consumption patterns are less predictable using demographics alone, potentially requiring additional behavioural or appliance usage data to enhance forecasting reliability.

The findings underscore the strong influence of demographics on residential energy consumption while also highlighting the complex interplay between demographic diversity and forecasting performance. Although demographics contribute valuable context, their effectiveness as input features depends on the homogeneity or heterogeneity within the clusters. These insights emphasize the need for adaptive forecasting models that account for both individual household characteristics and broader consumption patterns.

3.11 Feature Importance

To further interpret the forecasting performance presented in the previous sections, an assessment of the relative importance of the input variables was undertaken. This analysis provides additional insight into how different categories of input features influenced the forecasting outcomes across the residential clusters. Understanding the relative importance of input variables is essential in residential load forecasting, particularly when multiple sources of variability such as historical consumption patterns, and socio-demographic characteristics are incorporated into the forecasting framework. Although advanced post-hoc explainability techniques such as SHAP or LIME were not implemented in this study, feature importance was evaluated through a combination of statistical analysis and comparative model performance.

For the input variables derived from historical electricity consumption, Spearman rank correlation analysis was used to identify the most relevant lagged observations. This approach was selected because residential load data often exhibits non-linear relationships, and the Spearman coefficient can capture monotonic dependence without assuming linearity. By applying this analysis, only lagged features with the strongest correlation to the forecasting target were retained as model inputs. This reduced dimensionality while ensuring that the most informative temporal patterns were preserved within the forecasting model.

In addition to temporal features, the contribution of socio-demographic variables was assessed by comparing forecasting performance under different input combinations. Separate scenarios were developed to evaluate the influence of demographic inputs on forecasting accuracy. A further observation from the clustering analysis showed that the importance of socio-demographic features varied across clusters. Clusters with relatively low demographic variability achieved improved accuracy with only one or two demographic variables, whereas clusters with higher demographic diversity required a broader range of socio-demographic inputs to achieve similar improvement. This suggests that feature importance is not uniform across all household groups and depends strongly on the behavioural characteristics of each cluster.

Overall, the feature importance analysis demonstrated that the forecasting framework benefits from combining statistically selected temporal features with contextual household information. These findings also support the need for cluster-specific feature selection when modelling heterogeneous residential electricity demand.

This chapter provides a comprehensive explanation of the proposed methodology for TD hierarchical forecasting, detailing its approach and demonstrating its effectiveness through various scenarios. It highlights the model's high performance by analysing results from multiple case studies and comparing outcomes across different forecasting models. Additionally, the chapter offers practical guidelines on the potential benefits of incorporating socio-demographic features in forecasting models, particularly within the residential sector. It outlines specific scenarios where these attributes can enhance forecasting accuracy by capturing behavioural patterns and consumption trends, thereby improving the model's predictive capabilities and overall performance.

Chapter 4

Analysis and Modelling of Residential Load Profiles with Electric Vehicle Integration

4.1 Abstract

This chapter examines the impact of EV integration on residential electricity demand and evaluates how EV charging behaviour can be incorporated into the forecasting framework developed in Chapter 3. Since residential consumers typically exhibit highly variable consumption patterns, the addition of EV charging can further alter daily load profiles and influence forecasting accuracy. To assess this effect, residential demand is analysed before and after EV integration to establish a comparative baseline and quantify the additional load introduced by charging. The chapter also investigates the methodology used to generate additional EV charging profiles and assesses the resulting changes in forecast performance under different EV penetration scenarios.

4.2 Evaluation of Residential Load Profiles without Electric Vehicles

Residential load patterns vary considerably with lifestyle and occupancy behaviours, which often differ between weekdays and weekends. Previous studies [110] have shown that electricity consumption is influenced not only by location and demographic factors but also by the day of the week, which in turn affects EV charging behaviour. Accordingly, capturing the weekday and weekend differences in the baseline (non-EV) load profiles is a necessary first step for accurately evaluating how EV adoption alters demand under realistic operating conditions. Therefore, separate weekday and weekend profiles are generated for each household within each cluster, followed by an in-depth analysis of daily load patterns. This detailed analysis is essential for understanding the impact of EV integration on residential load profiles and the performance of forecasting model, which is the primary focus of this chapter. As discussed earlier, the dataset used in this study spans nine years (2013–2021) and comprises hourly electricity consumption data. To create representative load profiles, the data is categorized by days of a week, and consumption within each category is averaged.

Additionally, residential load profiles vary significantly depending on the day of the week. To capture these variations, separate weekday and weekend profiles are generated for each household within each cluster, followed by an in-depth analysis of daily load patterns. This detailed analysis is essential for understanding how EV integration alters load profiles and affects forecasting performance, which is the primary focus of this chapter. As discussed earlier, the dataset used in this study spans nine years (2013–2021) and comprises daily hourly electricity consumption data. To create representative load profiles, the data is categorized by day of the week, and consumption within each category is averaged.

In Chapter 3, a hierarchical clustering approach is applied to group 50 residential households into 10 clusters. Of these, three clusters, Cluster 0, Cluster 2, and Cluster 6 consist of homes without EVs, while the remaining seven clusters include households with EVs, as detailed in Table 4.1.

Table 4.1 No. of EVs in each cluster

Cluster	No. of Households	No. of EVs
C0	1	0
C1	4	1
C2	1	0
C3	3	2
C4	10	1
C5	2	1
C6	1	0
C7	13	5
C8	3	2
C9	12	6

To assess the impact of EV adoption on daily load profiles, the analysis in this chapter focuses specifically on those clusters with EV households. This detailed dataset-specific analysis provides crucial insights into baseline consumption behaviours, enabling a clear evaluation of how EV integration alters residential load profiles and, consequently, the forecasting model's accuracy. Furthermore, while the findings are derived from this specific dataset, the observed patterns and impacts are expected to be indicative of similar residential contexts where EV adoption trends follow comparable characteristics.

First, the daily load profiles of these households are analysed without EV charging included in an hourly total load. Subsequently, the same analysis is conducted with integrated EV charging, enabling a comparative assessment of the changes in daily load profiles due to EV charging. Additionally, each cluster's daily load profile is segmented into smaller time intervals, which are explained in the subsequent sections. This level of granularity is essential for understanding the variations in daily load patterns between houses with and without EVs.

Moreover, this section presents a detailed data analysis based on the 7 out of 10 identified clusters that have EVs , providing extensive descriptions of time slots within each cluster. This thorough investigation is crucial to justify the reason of analysing this specific dataset in such depth. By doing so, the study establishes a strong foundation for understanding importance of accounting EV integration to residential load forecasting models.

4.2.1 Cluster 1

A comparison of the average daily electricity consumption profiles for weekdays and weekends in a house of Cluster 1 is presented in Fig. 4.1. The green line represents weekday consumption, while the blue line corresponds to weekend consumption. Some key insights observed from the graph are discussed as below:

- Early morning (00:00 - 6:00): Electricity consumption is relatively low during the early hours of a day for both weekdays and weekends. During this period, weekend consumption is slightly higher than weekday levels, aligning with findings from residential load studies that report elevated electricity usage on weekends compared to weekdays [111].
- Morning (6:00 - 10:00): On weekdays, a small rise is observed at 6:00 hrs reflecting early morning household activities.. On weekends, the increase occurs more gradually but peaks at a higher level than on weekdays, consistent with findings from residential load studies that show weekend demand patterns often shift to later in the morning due to altered household routines [112].
- Afternoon (10:00 - 16:00): Weekend consumption remains consistently higher than weekdays throughout this period. This could be due to more people staying at home on weekends, using appliances, entertainment systems, and air conditioning.

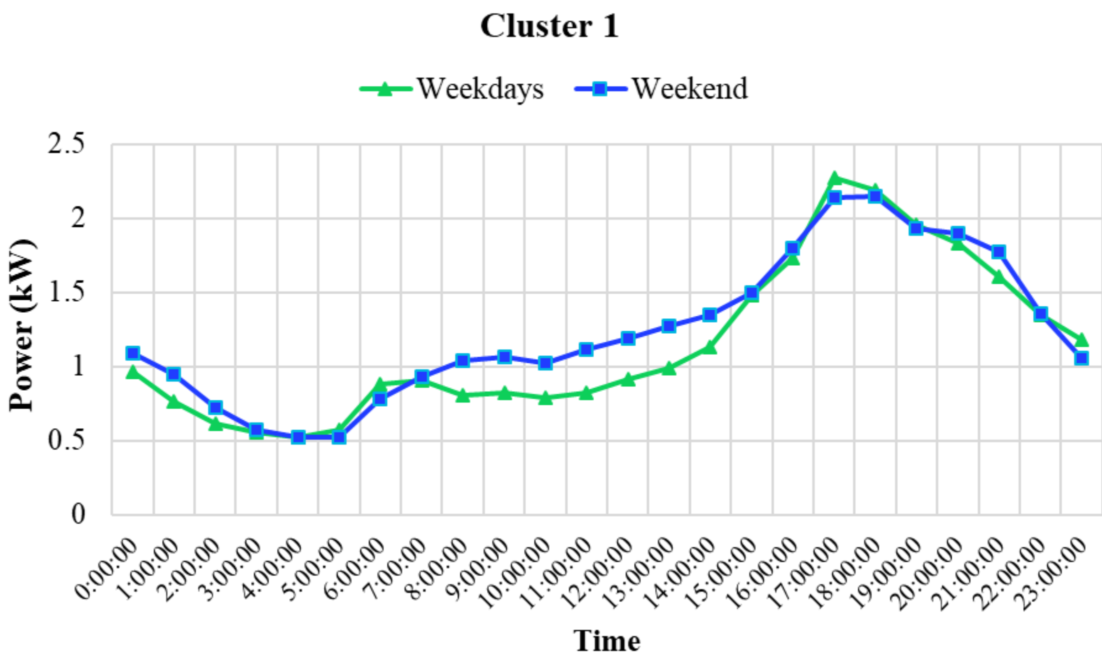


Fig. 4.1 Comparison of weekday and weekend profiles for Cluster 1

- Evening peak (16:00 - 21:00): A noticeable peak occurs in between 18:00 hrs and 20:00 hrs for both weekdays and weekends. This represents typical evening activities such as lighting and cooking. The peak for weekdays is slightly sharper, suggesting concentrated consumption after work hours, while weekends have a slightly more sustained peak.
- Night (21:00 - 23:00): After the peak, both weekday and weekend consumption declined steadily into the night. However, weekend consumption remains slightly elevated, reflecting extended leisure or other social activities.

The graph highlights notable differences in electricity usage between weekdays and weekends. Weekends show higher consumption levels during late nights, and the mornings, likely due to differing routines and activities compared to weekdays.

4.2.2 Cluster 3

Fig. 4.2 compares the weekday and weekend load profiles of two houses with IDs 1169 and 3482 within Cluster 3. Since both houses have EVs, this allows for a clearer comparison of the changes after incorporating EV charging, which will be discussed later.

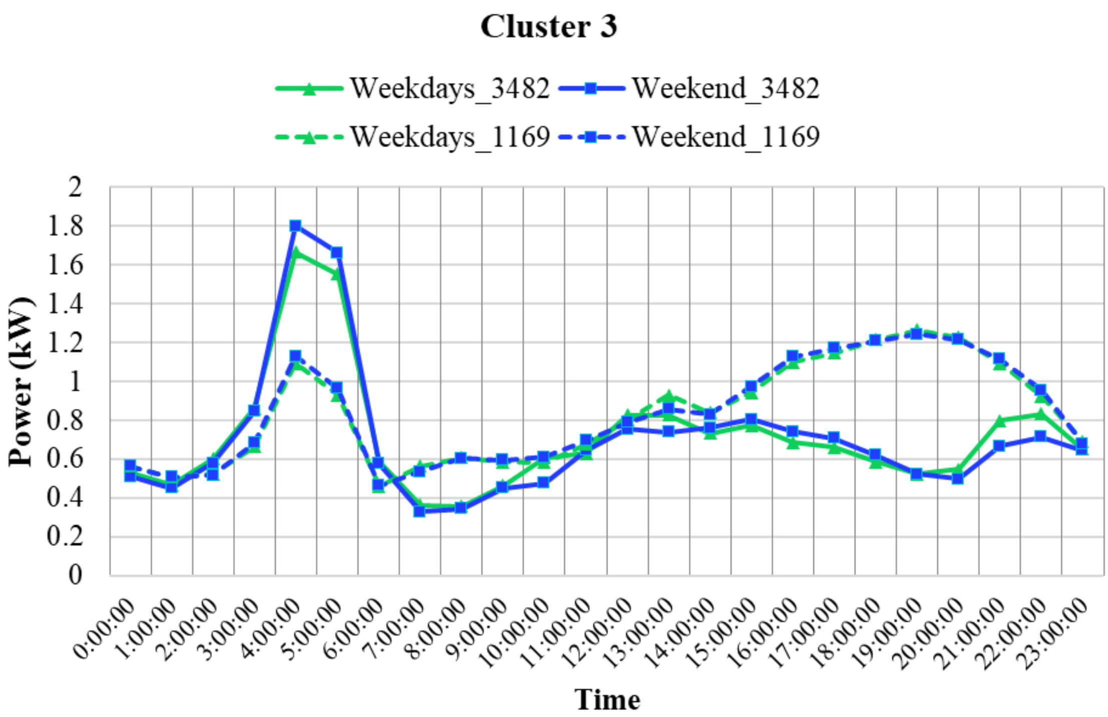


Fig. 4.2 Comparison of weekday and weekend profiles for Cluster 3

- Early morning (00:00 - 5:00): During the early morning period, House 1169 shows consistently low electricity consumption on both weekdays and weekends, with only small variations. A similar pattern is observed for House 3482 during weekdays; however, on weekends the same household exhibits a pronounced spike in consumption between 3:00 hrs and 5:00 hrs, significantly exceeding weekday levels.

  According to the household information available in the dataset, House 1169 consists of two residents and falls into the lower income category, whereas House 3482 comprises a single resident and belongs to the high income category. These socio-economic differences may help to explain the observed behaviour, as higher income households typically own a larger number of appliance intensive systems (e.g., entertainment devices or electric heating), the use of which is more likely to occur during late night or early morning hours on weekends.

- Morning (5:00 - 7:00) House 1169 exhibits a sharp rise in consumption around 5:00 for both weekdays and weekends, likely due to morning activities such as preparing breakfast and starting household appliances. Both house 1169 and 3482 have no significant variation in weekday and weekend profiles for this duration.

- Daytime (7:00 - 15:00): The profiles during these hours for House 1169 are nearly identical, with no significant variation between weekdays and weekends. This suggests that daytime consumption patterns, such as heating, cooling, or other routine uses, are consistent across both types of days. Whereas House 3482 has both weekday and weekend profiles showing a drop in consumption after the early morning spike, but the patterns remain consistent across both days, with slight fluctuations.
- Evening peak (15:00 - 21:00): Both weekdays and weekends display a clear rise in consumption during the evening, peaking in between 18:00 hrs and 19:00 hrs for House 1169. The peaks align closely, indicating that evening activities, such as cooking, entertainment, and lighting, are similar regardless of the day of the week.
- Night (21:00 - 23:00): The decline in consumption during these hours is almost identical for both profiles, reflecting similar end-of-day routines.

Therefore, it is concluded that House 1169 exhibits minimal differences in electricity usage between weekdays and weekends. The only notable variation occurs during the early morning peak. Overall, the load profiles remain closely aligned, suggesting that this household follows a consistent consumption pattern. This stability could be influenced by factors such as steady occupancy, automated appliances, or a regular daily routine. Such consistency provides a clear baseline for further analysis, including the impact of EV integration on load profiles. In contrast, House 3482 demonstrates consistently higher electricity usage during the early morning hours on weekends compared to weekdays, indicating specific activities or appliance usage during this period.

Although both houses belong to the same cluster, House 3482 exhibits distinct behaviour, particularly the early morning surge on weekends. This variability within the cluster may reflect individual lifestyle differences, such as staying up late or using specific appliances. However, for the rest of the day; daytime, evening, and nighttime, the load profiles of both houses remain largely similar, reinforcing the shared characteristics of the cluster.

4.2.3 Cluster 4

Fig. 4.3 shows the daily load profile of the single household in this cluster having an EV.

- Midnight to early morning (00:00 - 9:00): Both weekdays and weekends show lower consumption during these hours. Consumption is slightly higher on weekends, possibly due to altered sleep patterns.

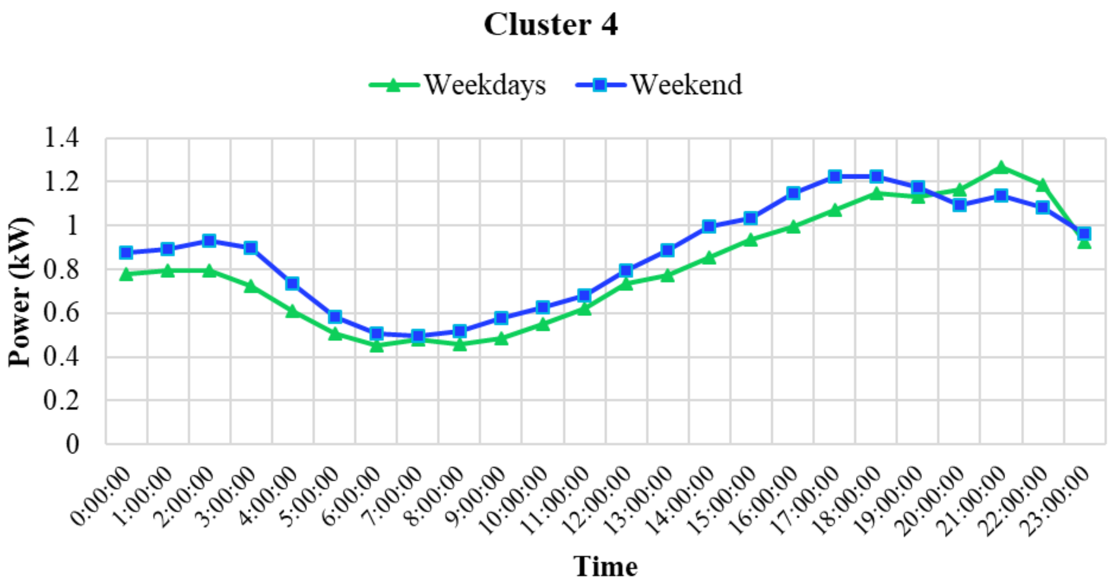


Fig. 4.3 Comparison of weekday and weekend profiles for Cluster 4

- Daytime (9:00 - 16:00): Weekdays show slightly more stable but lower usage, reflecting periods when many residents are at work or school. On the other hand, weekend consumption gradually rises, driven by home-based activities.
- Evening peak (16:00 - 22:00): Both profiles converge, with similar high consumption levels during this period, driven by activities like cooking, heating, lighting, and entertainment. However, weekday consumption rises higher than weekend consumption around 20:00, likely due to the completion of pending tasks in preparation for the following day, whereas weekends tend to be more relaxed.
- Late night (22:00 - 23:00): Usage starts to decline, with weekdays showing slightly sharper drops, likely due to stricter bedtime routines compared to weekends.

The load profile for this house exhibits a similar shape on both weekdays and weekends, with two distinct peaks in the morning and evening. However, the magnitude and timing of these peaks differ. This pattern underscores the importance of adjusting grid management strategies to account for weekday versus weekend variations, particularly in demand response programs.

4.2.4 Cluster 5

This section discusses the houses in cluster 5 that own EV.

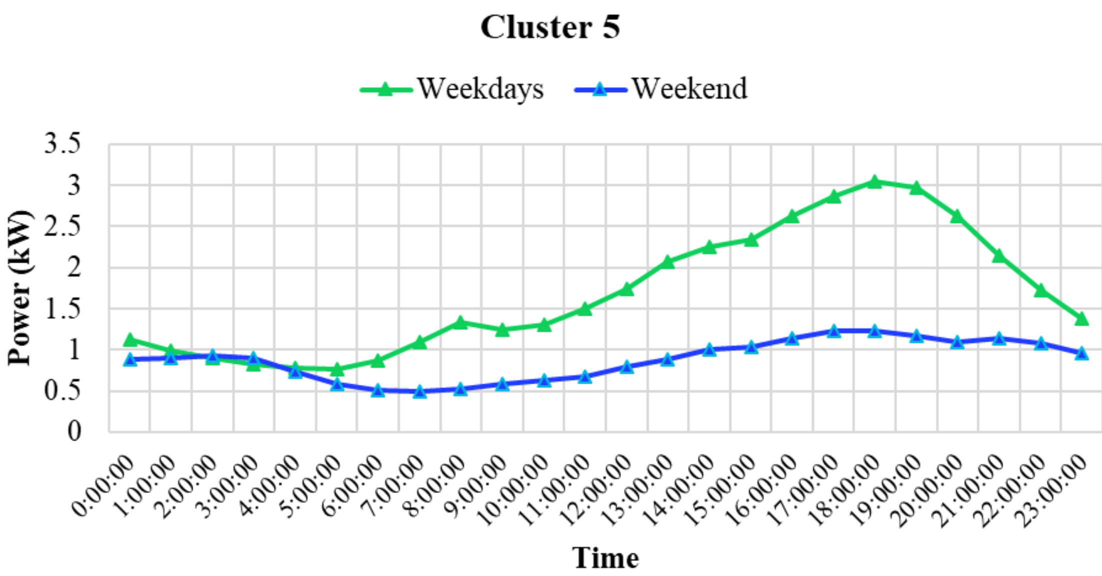


Fig. 4.4 Comparison of weekday and weekend profiles for Cluster 5

- Midnight to early morning (00:00 - 6:00): During weekdays, electricity usage starts at around 1.0 kW, with a slight decrease until 4:00. Whereas, weekend consumption remains consistently lower, around 0.5 kW, possibly reflecting reduced nighttime activity or more efficient use of appliances.

- Morning peak (6:00 - 9:00): There is a significant increase in weekdays usage, peaking around 1.5 kW by 9:00. This suggests a sharp rise due to typical weekday routines like cooking, heating, or preparing for work and school.

- Daytime (9:00 - 16:00): Weekdays have steady increase, with usage ramping up consistently from around 1.5 kW at 9:00 to over 2.5 kW by 16:00. This may indicate heating or cooling systems running in the absence of occupants or additional daytime activities at home including working from home. A flatter profile is observed for weekends, stabilizing between 0.5 and 1.0 kW throughout the day. This reflects fewer appliances being used or more consistent, low energy activities.

- Evening peak (16:00 - 21:00): An evening peak is observed around 18:00, reaching approximately 3.5 kW, before declining steadily. This is likely driven by high energy activities like cooking, heating, and entertainment. Weekends have smaller increase suggesting that evening energy usage is spread out more evenly compared to weekday spikes.

- Late night (21:00 - 23:00): During this period, a sharp decline in consumption is observed after 21:00, dropping to 1.0 kW by 23:00, consistent with people winding down for the day.

This house has stronger peaks during mornings and evenings on weekdays, which reflect structured routines driven by work and school schedules. The higher overall consumption suggests increased use of appliances such as HVAC systems or other high-energy devices during these periods. The weekend profile is significantly different from weekdays, with a flatter profile with fewer sharp increases, suggesting more flexible and evenly distributed energy use. Lower overall consumption could reflect more energy-conscious behaviour or reduced reliance on certain appliances.

The sharp weekday peaks could strain grid resources, highlighting the need for demand-side management strategies like time-of-use pricing or load shifting. Whereas weekends represent a more balanced load, providing opportunities for better integration of renewable energy.

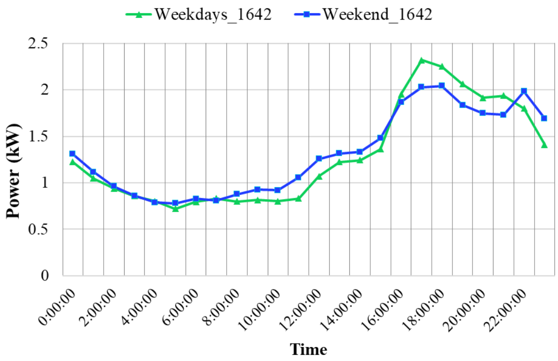
4.2.5 Cluster 7

This graph illustrated in Fig. 4.5 compares weekday and weekend profiles for five houses within the same cluster. Despite individual variations, the houses share comprehensive patterns reflective of their clustering, likely due to similarities in energy consumption behaviour, household size, appliance usage, or schedules. The details analysed and evaluated are discussed below:

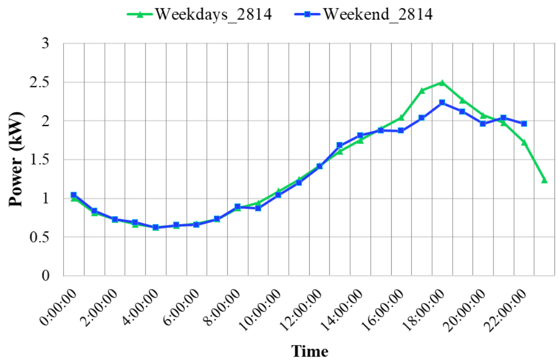
- Overall shape and profile: Both weekday and weekend load profiles generally exhibit a similar pattern, suggesting that the cluster comprises households with standard daily routines. Power consumption remains low from midnight to early morning (00:00 – 6:00). Two distinct peaks are observed: a morning peak and a more pronounced evening peak.

  1. Morning Peak (7:00 – 10:00): Corresponds to household activities such as cooking, heating, and preparing for the day.
  2. Evening Peak (18:00 – 22:00): It is more prominent in most households, reflecting evening routines, including cooking, entertainment, and appliance usage.

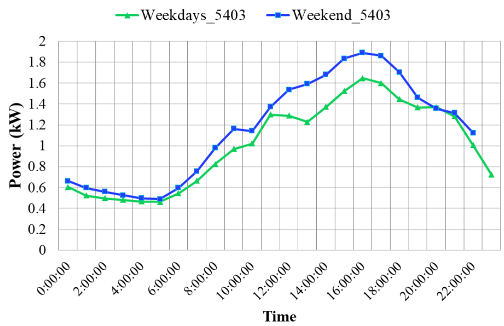
  Weekend consumption tends to be slightly higher than on weekdays, particularly in the afternoon and evening, indicating more flexible schedules and prolonged home occupancy.



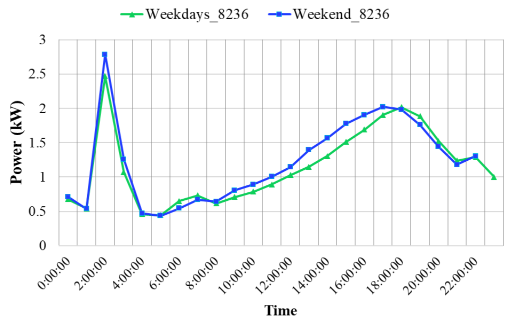
(a) House 1642



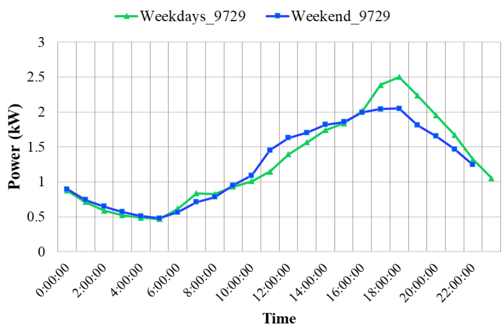
(b) House 2814



(c) House 5403



(d) House 8236



(e) House 9729

Fig. 4.5 Comparison of weekday and weekend profiles for Cluster 7

- House specific characteristics:
    1. House 1642 and 2814: Both weekday and weekend load profiles are largely similar, with a distinct evening peak. While minor variations exist, overall consumption remains consistent across both periods.
    2. House 5403 and 9729: Weekend consumption is slightly higher than weekday usage, particularly in the afternoon and evening. However, the overall curve shape remains consistent, reflecting predictable household routines.
    3. House 8236 (Anomaly): Unlike other households, house 8236 displays a sharp peak at midnight (00:00 – 2:00), surpassing the evening peak. This indicates an unusual consumption pattern, likely driven by late night appliance usage, such as electric heating or other high-power devices.
- Interpretation and implications: The overall similarity between weekday and weekend load profiles reinforces the idea that Cluster 7 comprises households with consistent daily routines, making it well suited for aggregated load forecasting. However, minor deviations, such as the unique behaviour of House 8236, emphasize the importance of accounting for anomalies in forecasting models. Incorporating outliers or employing flexible peak detection methods can help refine predictions and improve model accuracy.

In summary, this cluster largely follows a typical residential load pattern, characterized by low nighttime consumption and two main peaks in the morning and evening. The weekend consumption tends to be slightly higher, especially in the evening. However, House 8236 stands out with an unusual midnight peak, indicating distinct usage behaviour that should be considered in forecasting models. Overall, the consistency between weekday and weekend profiles highlights the cluster's homogeneity, making it well suited for aggregated demand modeling and forecasting.

4.2.6 Cluster 8

Fig. 4.6 compares the weekday and weekend residential load profiles for two houses (7989 and 9609) in this cluster. Both profiles exhibit cluster consistent patterns with key variations reflecting household specific energy consumption behaviours.

- Late night consumption (00:00 - 6:00): House 9609 (dashed lines) exhibits notably higher power consumption during late night hours, especially on weekends. In contrast, House 7989 shows a decreasing trend during this period, though its weekend consumption remains slightly higher than on weekdays.

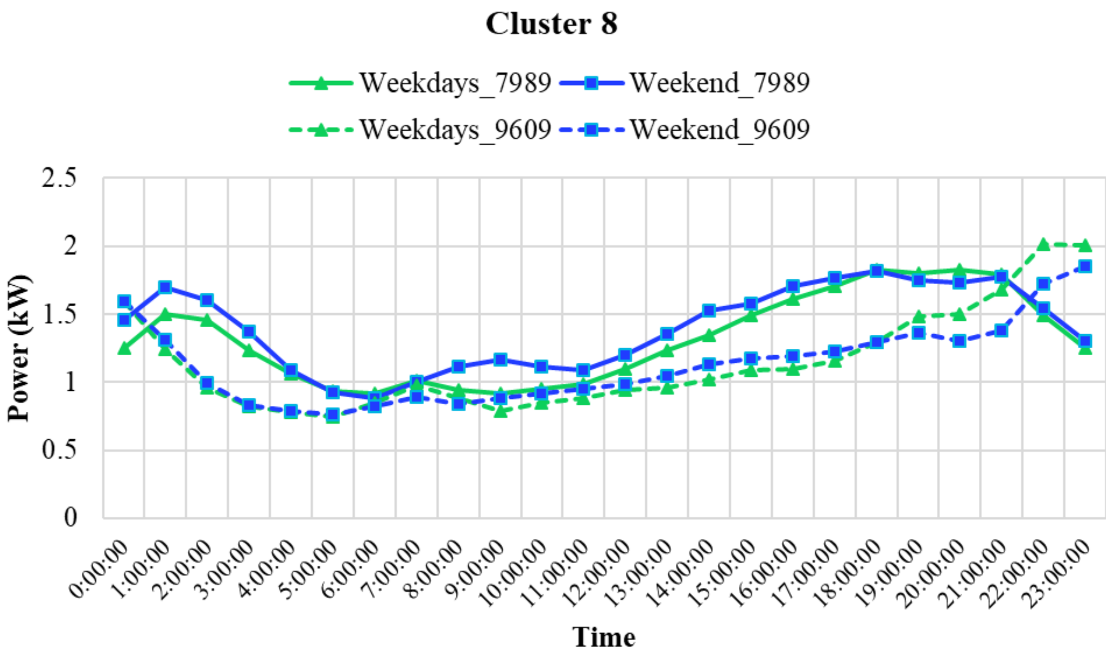


Fig. 4.6 Comparison of weekday and weekend profiles for Cluster 8

- Morning to midday period (6:00 – 14:00): During the late morning and early afternoon, power consumption stabilizes at a lower level for both houses. From the afternoon to evening (14:00 – 22:00), both houses experience a steady rise in power consumption, culminating in a distinct evening peak between 20:00 and 22:00. House 7989 reaches slightly higher peak values compared to House 9609. Weekend consumption exceeds weekday levels for both houses in the evening, reflecting increased household activity during weekends.

- Late night (22:00 – 00:00): Weekend power usage remains slightly higher than weekday usage, particularly for House 9609, which shows a late-night increase.

- Energy management: House 7989 could benefit from demand-side management targeting evening peak reduction on weekdays whereas House 9609, with its consistent weekend load, might be more adaptable to time-of-use pricing or renewable integration strategies.

- Forecasting: The consistent evening peak across both houses suggests strong predictability, useful for load forecasting models. The subdued weekend profile of House 9609 indicates a lower contribution to cluster-wide weekend variability.

4.2.7 Cluster 9

The graph in Fig. 4.7 illustrates the weekday and weekend load profiles for six houses in the same cluster. While individual variations exist, the overarching trends reflect the shared characteristics of the cluster, with energy usage dominated by morning and evening peaks.

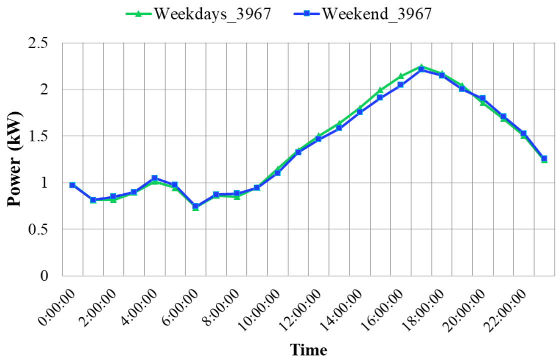
- Cluster wide trends: Between midnight and 6:00, all houses exhibit low power consumption, with minor fluctuations likely caused by standby appliances or occasional night time usage. A gradual increase in consumption is observed from early morning, starting around 6:00 and continuing until 10:00. On both weekdays and weekends, a pronounced peak occurs between 18:00 and 20:00, likely influenced by household activities such as cooking, heating, and entertainment.

- House specific observation:

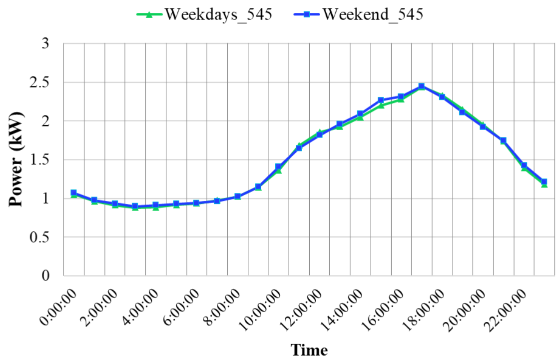
  1. House 3967 and House 545: Both houses exhibit highly similar load profiles on weekdays and weekends. The gradual increase in consumption from morning to evening, culminating in a peak between 18:00 and 22:00, indicates a stable and predictable usage pattern.
  2. House 1714 and House 2335: These two houses exhibit slightly higher evening consumption on weekends compared to weekdays. House 2335 shows a more pronounced evening peak between 20:00 and 22:00, likely driven by increased appliance usage or entertainment during this period.
  3. House 4998 and House 6139: These houses exhibit noticeable fluctuations in consumption throughout the day. House 4998 shows higher early morning usage between 2:00 and 6:00, suggesting possible night time appliance operation. In contrast, House 6139 displays a distinct evening peak from 18:00 to 22:00, similar to other houses, but with a more gradual increase in load.

- Correlations between Houses: The general similarity in profile shapes confirms the shared behavioural and demographic factors within the cluster. Variations in the magnitude of peaks likely originate from differences in household size, appliance ownership and usage patterns, or differences in heating or cooling needs.

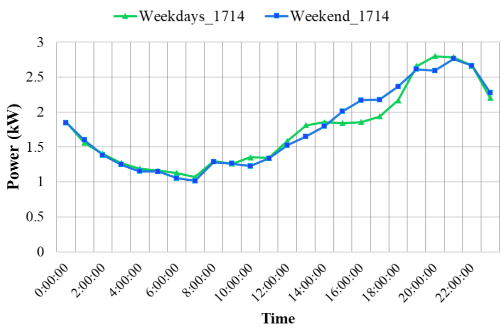
- Forecasting and modeling: The consistent morning and evening peaks across all houses strengthen the predictability of cluster wide energy demand. Houses with unique profiles add diversity to the dataset, enriching forecasting model robustness.



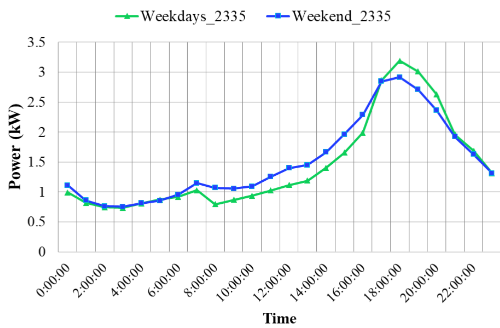
(a) House 3967



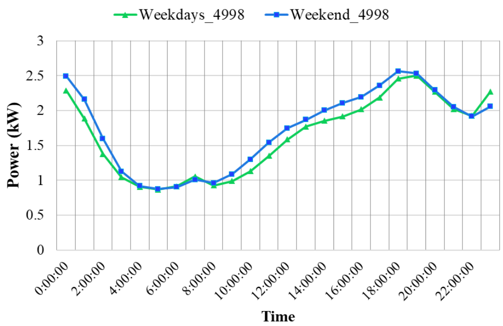
(b) House 545



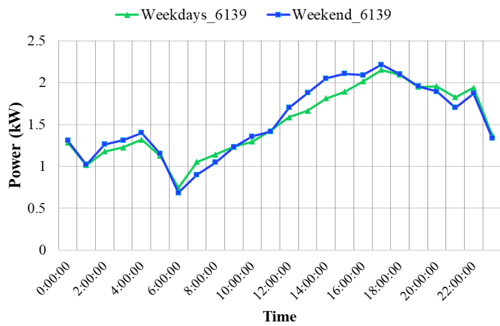
(c) House 1714



(d) House 2335



(e) House 4998



(f) House 6139

Fig. 4.7 Comparison of weekday and weekend profiles for Cluster 9

4.3 Impact of EVs on daily load profile

This section examines the impact of EV integration on the daily load profiles of residential consumers and categorises different EV charging levels. Understanding this impact on residential consumption patterns is essential, as it enables accurate assessment of electricity demand changes, peak load distribution, and overall consumption resulting from EV adoption. Such insights are critical for optimising grid management strategies, ensuring efficient energy distribution, and facilitating the seamless integration of EVs into residential power systems.

The analysis is based on households introduced in the previous section, where load profiles without EV charging were examined to establish a baseline. After establishing the baseline variability through the weekday and weekend analysis, the EV integration assessment shifted its focus to seasonal effects. Seasonal conditions have a direct and pronounced influence on both residential electricity consumption due to heating and cooling needs and EV charging requirements [113]. Consequently, seasonality becomes the dominant driver of load variability once EVs are introduced [114]. For this reason, the analysis prioritizes seasonal scenarios to provide a more realistic and meaningful evaluation of the EV impact on residential load profiles and the forecasting model. By comparing load profiles before and after EV integration, this study identifies how residential consumption behaviours are influenced by the EV charging loads.

To assess the impact of EV charging, daily EV charging data is first analysed to determine common charging power levels. This approach enables the identification of distinct charging categories, which are crucial for understanding the extent and nature of EV induced load changes. Although the clustering in Chapter 3 was conducted based solely on household load profiles without incorporating EV charging data, this does not affect the validity of the current analysis. On the contrary, it supports the core objective of this research, which is to evaluate how integrating EVs into existing residential consumption patterns influences forecast accuracy within these pre-established clusters.

In general, most households use level 2 charging, the most common residential method, which operates on AC power with levels ranging from 3.3 kW to 22 kW, depending on charger capacity and supply. In this study, however, majority of the households charge their EVs at 3.3 kW (categorised as low power AC charging), while a smaller portion charges at a medium power level of 7.2 kW. Only one EV charges at a higher power level, exceeding 7.2 kW and reaching up to 15 kW.

The dataset records EV charging consumption separately from the main household load, capturing actual charging behaviour rather than assuming maximum rated power use. Based on this data, charging sessions are categorised into three groups:

1. Trickle charging: This method refers to low power, long duration charging, typically using standard home sockets. It is the slowest form of EV charging and can take up to 24 hours to fully charge a battery, depending on its capacity [115]. Due to its low power output, trickle charging is generally used for overnight charging or when faster charging options are unavailable. It is mostly used for maintaining battery levels or slow overnight charging.

2. Regular charging: This typically refers to level 2 charging with moderate power levels, commonly used by residential EV owners [116]. It operates within a power range of approximately 1.5 kW to 3 kW, providing a balance between charging speed and energy efficiency. Regular charging is one of the most widely used methods, offering a practical solution for overnight or extended duration charging without placing excessive demand on the household electrical system.

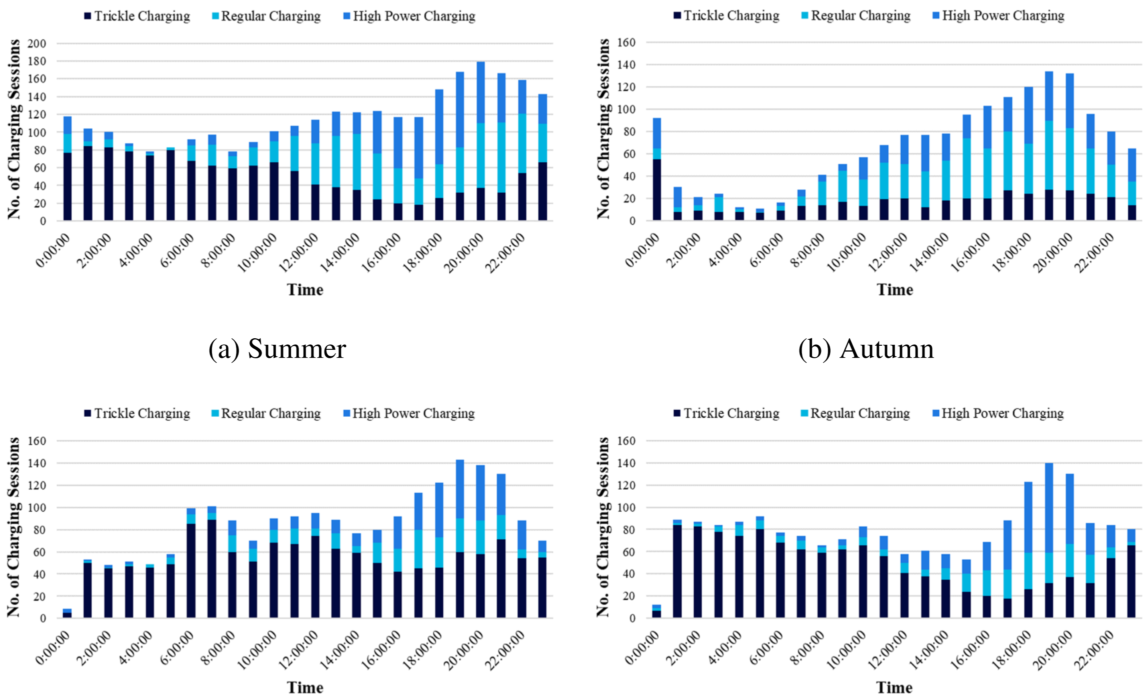
3. High power charging: In the residential sector, this category refers to charging sessions characterized by high power demand and elevated energy consumption, typically involving faster charging rates that exceed standard household charging levels. It involves charging at power levels exceeding 3 kW, enabling faster battery recharging compared to lower power methods. High power charging is suitable for users who require quicker turnaround times, though it may place a greater load on the electrical system and increase energy costs [115], [116].

As the dataset provides hourly EV consumption data rather than direct charging categories, a threshold based approach was applied to classify sessions. The annual EV consumption data was first divided into seasonal datasets to capture behavioural variations throughout the year. Charging consumption between 0.5–1.5 kW was classified as trickle charging, between 1.5–3 kW as regular charging, and above 3 kW as high power charging. After classification, the number of sessions per category was summed for each hour to analyse the distribution of charging behaviour throughout the day.

Each household within the clusters was evaluated based on these categories, enabling a detailed examination of the frequency and timing of different charging levels. This structured classification approach offers critical insights into how varying EV charging behaviours influence residential load profiles. By segmenting EV charging into distinct categories and analysing their respective impacts, the findings inform enhancements in load forecasting models and support effective energy management strategies in the context of increasing residential EV adoption.

4.3.1 Cluster 1

The house in Cluster 1 with an EV is identified by ID 6990, and this EV utilises all three charging types. Since EV charging is influenced by temperature variations, seasonal load profiles have been generated. Fig. 4.8 illustrates the different charging types across seasons, with each category analysed in detail for every season.



(a) Summer (b) Autumn

(c) Winter (d) Spring

Fig. 4.8 No. of charging sessions per type for House 6990

1. Trickle Charging: Trickle charging is consistently present throughout the day in all seasons, maintaining a relatively stable pattern with minor fluctuations. This suggests that the EV is often left plugged in for slow charging. In summer, trickle charging occurs throughout the day but contributes less compared to other charging types, indicating a preference for faster charging during warmer months. In autumn, it remains the least dominant charging type but still appears consistently. During winter, trickle charging becomes more prominent in the morning, particularly between 6:00 and 8:00, likely due to battery pre-conditioning for optimal efficiency. In spring, its presence is steady, similar to autumn, with slightly higher usage in the morning and late evening.

2. Regular Charging: Regular charging increases significantly during the evening hours across all seasons, acting as an intermediary between slow and high power charging. It is likely to be used when the EV does not require an urgent top up but needs to be ready for the next day. In summer, regular charging is most prominent in the afternoon and evening, suggesting that the car is used more frequently and requires recharging before night. During autumn, there is a gradual increase throughout the day, peaking between 18:00 and 22:00, indicating that end of day charging is common. In winter, it is less dominant in the early hours but becomes more noticeable in the evening, aligning with trickle charging being more frequent in the morning. In spring, the pattern is similar to autumn, with an evening peak but a slightly more consistent presence throughout the day.

3. High Power Charging: High power charging is primarily utilised in the evening between 18:00 and 22:00 across all seasons, suggesting that the household prefers quickly recharging the EV after daily use. In summer, the number of high power charging sessions is at its peak, particularly in the evening, possibly due to longer trips. During autumn, usage remains significant but slightly lower than in summer, while the evening peak remains dominant. In winter, high power charging is less frequent compared to summer and autumn, likely due to reduced battery efficiency in cold temperatures, which may encourage slower charging strategies. In spring, the pattern is similar to autumn but with a slightly lower magnitude.

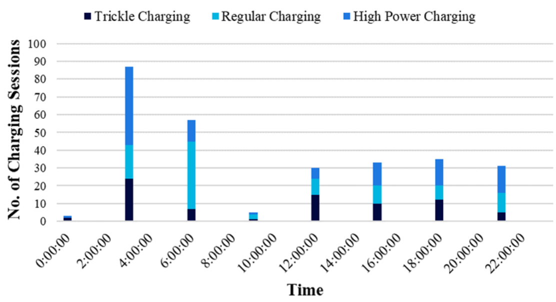
4.3.2 Cluster 3

Both houses (1169 and 3482) in Cluster 3 exhibit similar charging behaviours, yet they differ notably in the frequency and timing of their charging sessions, as illustrated in Fig. 4.9 and Fig. 4.10.

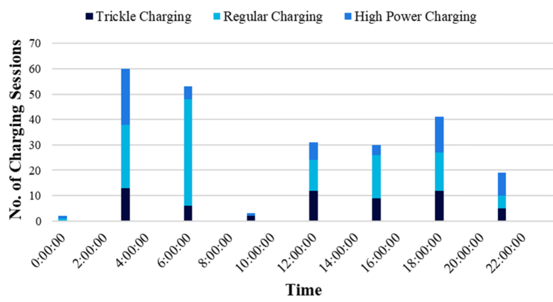
Both houses experience a peak in charging sessions during the early morning hours (2:00–6:00) across all seasons, indicating a reliance on overnight charging, likely influenced by time-of-use tariffs or preferred charging habits. They utilise trickle, regular, and high power charging throughout the year. High power charging is primarily concentrated in the evening, while trickle charging remains steady throughout the day. Autumn and spring display similar patterns, with lower but consistent charging activity compared to summer.

House 3482 records significantly more charging sessions than House 1169, particularly in summer and autumn, suggesting higher EV usage or more frequent recharging. This difference is most evident in the early morning peaks, where House 3482 registers nearly twice as many charging sessions as House 1169.

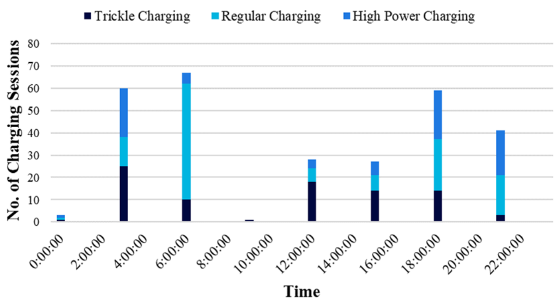
Despite both houses following a similar early morning charging pattern, House 3482 exhibits a more pronounced concentration of sessions between 4:00 – 6:00, whereas House 1169 displays a more even distribution of charging events throughout the day. Additionally, House 1169 maintains a notable level of charging activity in the evening (18:00 – 22:00), whereas House 3482 experiences a sharp decline after 18:00. This suggests that House 1169 may rely more on high power charging later in the day, while House 3482 prefers to complete charging primarily during early morning hours.



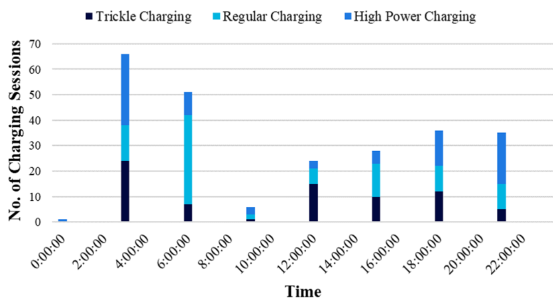
(a) Summer



(b) Autumn



(c) Winter



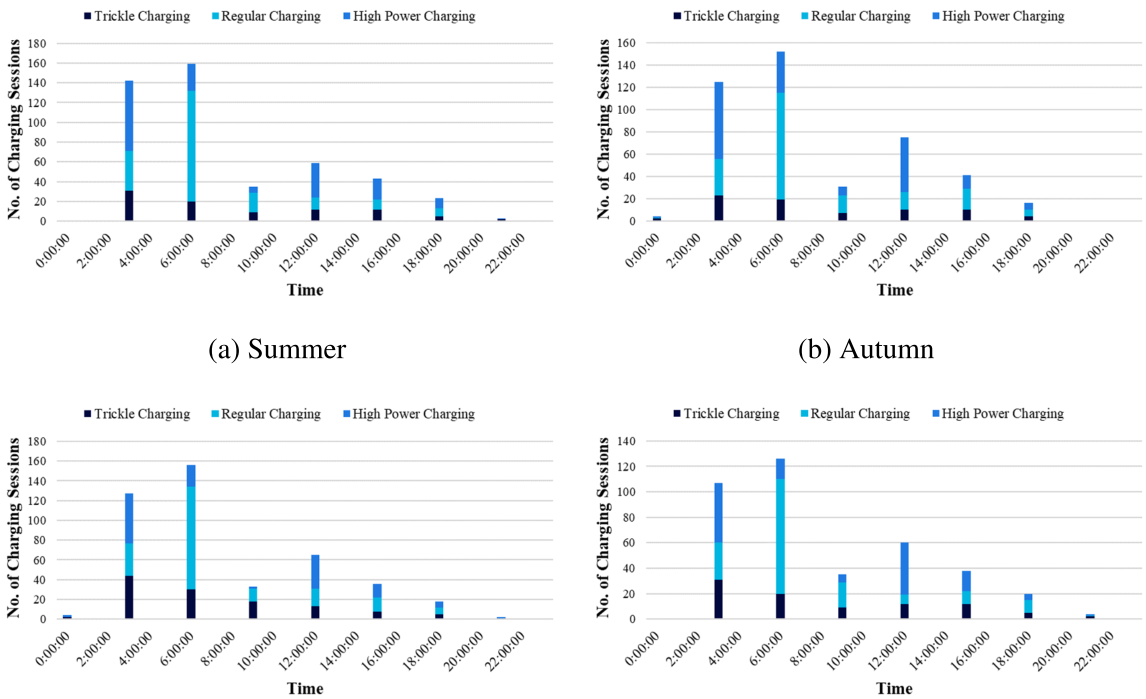
(d) Spring

Fig. 4.9 No. of charging sessions per type for House 1169

4.3.3 Cluster 4

The graph in Fig. 4.11 represents the number of charging sessions per type (trickle, regular, and high-power charging) for a specific household across different seasons.

Across all seasons, charging activity peaks significantly between 2:00 and 4:00, indicating a strong preference for overnight charging. This pattern is likely to be influenced by lower electricity tariffs or the convenience of charging when the vehicle is not in use. Trickle, regular, and high power charging occur throughout the year, reflecting a mix of charging



(a) Summer (b) Autumn

(c) Winter (d) Spring

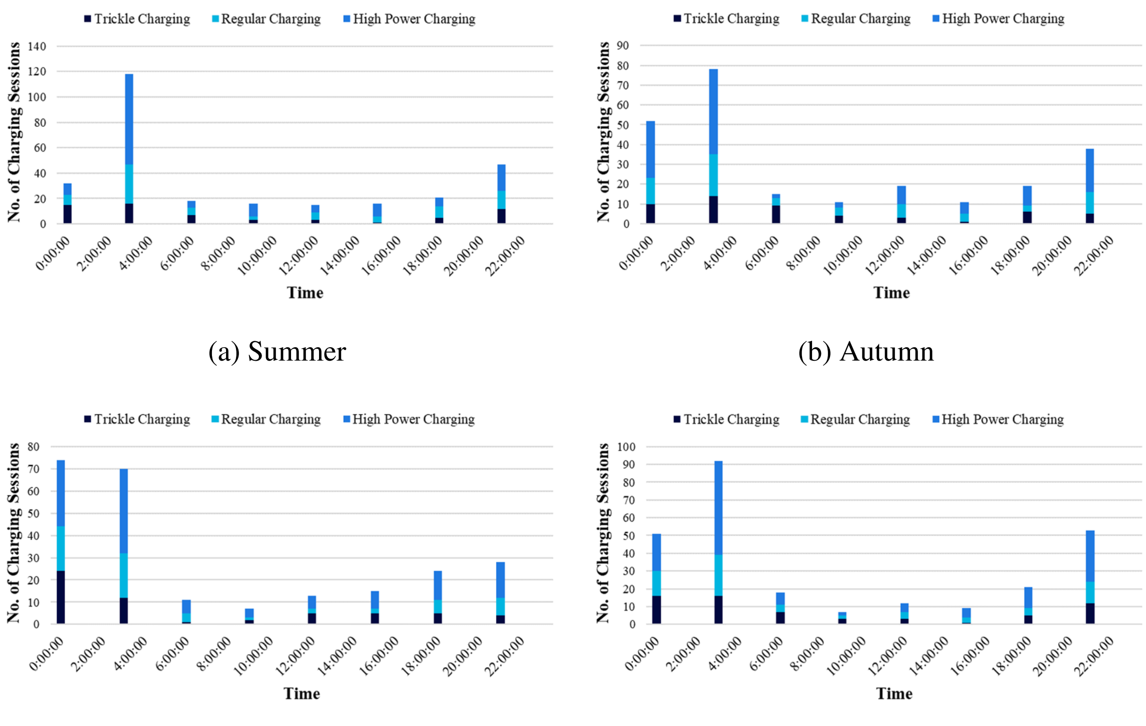
Fig. 4.10 No. of charging sessions per type for House 3482

strategies. High power charging is particularly common in the evening and during peak morning hours.

A secondary peak is noticeable around 21:00, though it is less pronounced than the early morning surge. This suggests that some level of recharging takes place after daily usage, likely to ensure sufficient battery levels for the next day.

During summer, high power charging is most prominent in the early morning, which may indicate frequent vehicle use and a need for rapid recharging, possibly due to longer summer trips. In autumn, all three charging types are present, but high power charging remains dominant. Similar to summer, overnight charging is common, though a slight decline in total sessions suggests a reduced travel frequency. In winter, trickle and regular charging become more prevalent, while high power charging decreases. This shift could be attributed to lower travel demand in colder weather, with trickle charging potentially used for battery pre-conditioning. In spring, high power charging patterns resemble those seen in autumn. As temperatures rise, vehicle usage increases, leading to a similar charging behaviour. Additionally, the evening charging peak is more prominent compared to winter.

Overall, the household primarily relies on overnight charging, with occasional evening sessions. High power charging is dominant in summer and spring, while winter sees a greater



(a) Summer (b) Autumn

(c) Winter (d) Spring

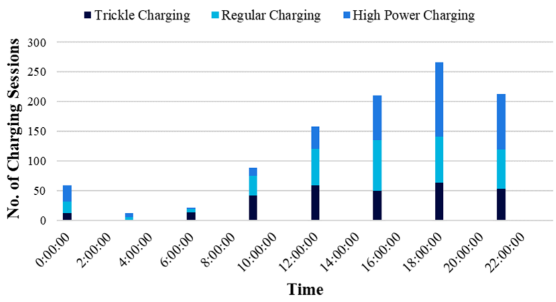
Fig. 4.11 No. of charging sessions per type for House 2470

reliance on trickle and regular charging. These seasonal variations in charging behaviour likely reflect changes in travel needs, the impact of temperature on battery efficiency, and electricity pricing strategies.

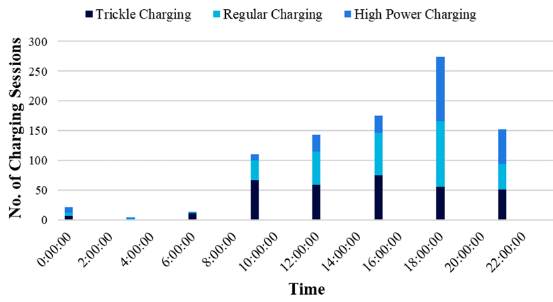
4.3.4 Cluster 5

The charging sessions of a house in Cluster 5 with EV is illustrated in Fig. 4.12. The charging activity for this EV is predominantly concentrated in the evening, between 16:00 and 22:00. Unlike the EVs in Cluster 4, where early morning charging from 2:00 to 4:00 was dominant, this dataset shows peak charging occurring in the late afternoon and evening, with the most significant surge between 18:00 and 20:00. This pattern likely aligns with vehicle users returning home from work and plugging in their EVs for recharging.

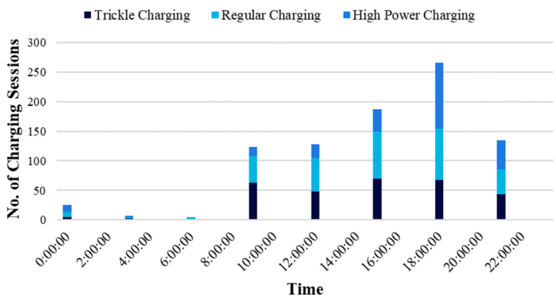
In this case, charging in early morning (00:00–6:00) remains minimal, suggesting that overnight charging is not a common practice in this dataset. Several factors could contribute to this trend, including tariff structures that do not incentivize night time charging, user preferences, or limited access to overnight charging infrastructure. High power charging is the most prominent during evening peaks, indicating a preference for quick recharges



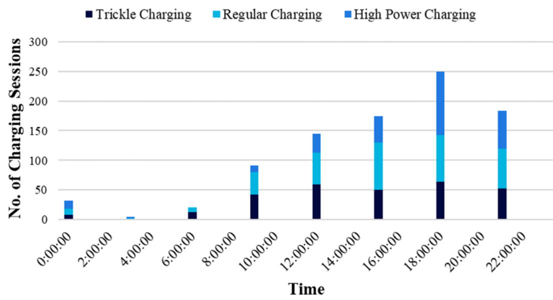
(a) Summer



(b) Autumn



(c) Winter



(d) Spring

Fig. 4.12 No. of charging sessions per type for House 4373

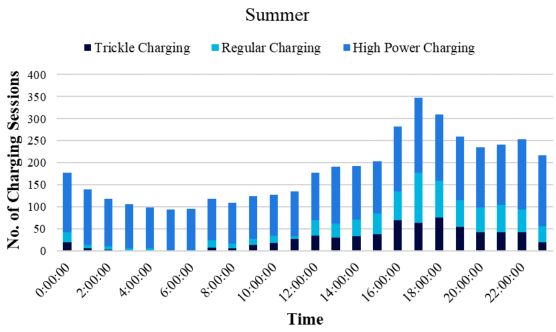
after daily use. In contrast, trickle charging appears infrequently, suggesting that slow, long duration charging is less favored. Additionally, a notable increase in charging activity is observed in the late morning (10:00–11:00) and early evening (18:00–21:00). This suggests that some users may follow more flexible daytime charging routines, possibly due to remote work schedules or midday vehicle use. This behaviour stands in contrast to the overnight heavy charging patterns observed in other clusters.

The distribution of trickle and regular charging sessions throughout the day indicates a steady but moderate charging approach, complementing the high demand evening periods. Rather than relying heavily on overnight charging, users in this dataset appear to engage in opportunistic charging throughout the day, particularly during the evening rush hours and midday breaks.

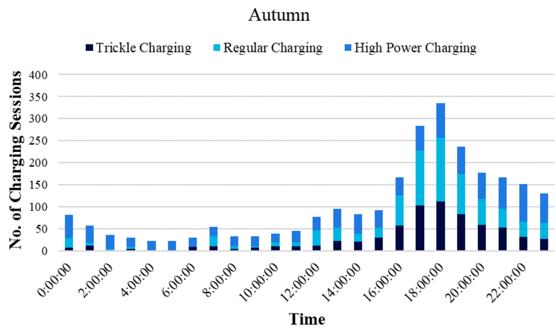
4.3.5 Cluster 7

The charging pattern of House 1642 is characterized by two distinct peak periods: early morning (1:00 - 7:00) and evening (17:00 – 23:00), illustrated in Fig. 4.13. Substantial charging sessions dominate energy consumption, particularly overnight and during the evening peak, likely influenced by time-of-use electricity tariffs. Regular charging remains moderate yet consistent, primarily occurring in the evening (17:00 - 22:00), suggesting routine after work top-ups. In contrast, level 1 trickle charging has a minimal contribution but becomes noticeable between 7:00 – 22:00, potentially for low mileage trips or battery maintenance. During the daytime (7:00 – 16:00), charging activity drops significantly, implying that the vehicle is either in use or away from home.

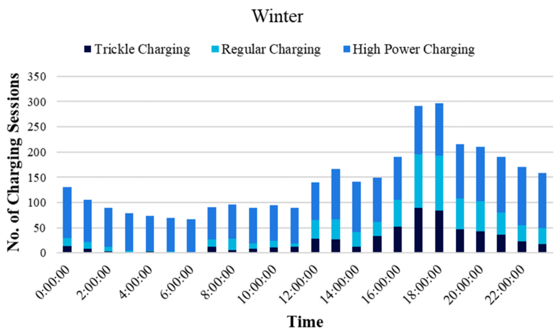
The overall load profile follows a bi-modal pattern, with demand concentrated in the early morning and evening hours, reflecting a structured and routine based charging behaviour. The evening peak (17:00 - 22:00) remains consistent across all seasons, reinforcing a strong preference for post work charging. Winter exhibits the highest early morning charging, likely due to cold temperatures and pre-conditioning requirements, whereas autumn shows the lowest daytime charging activity. In contrast, summer and spring display more midday charging sessions. High power charging dominates peak hours, while trickle charging is used sparingly, mostly in the evening. These seasonal variations suggest that charging behaviour is influenced by time-of-use tariffs, work schedules, and climate conditions.



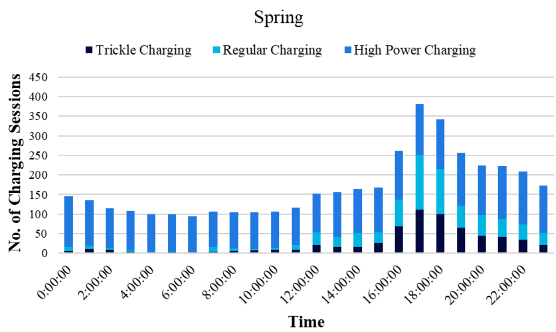
(a) Summer



(b) Autumn

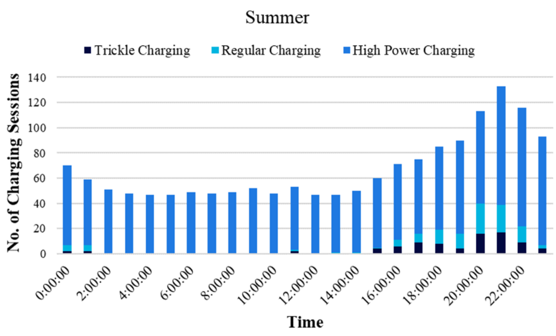


(c) Winter

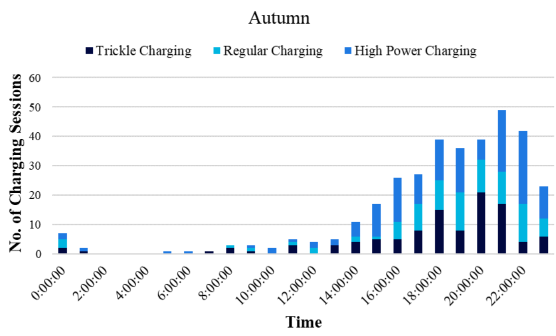


(d) Spring

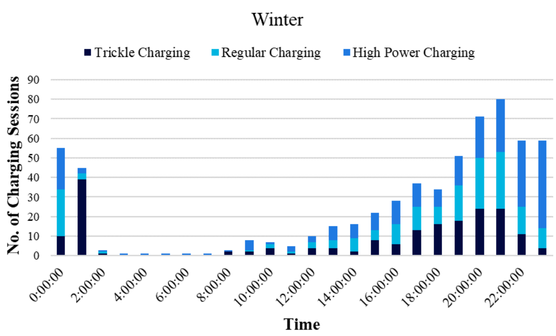
Fig. 4.13 No. of charging sessions per type for House 1642



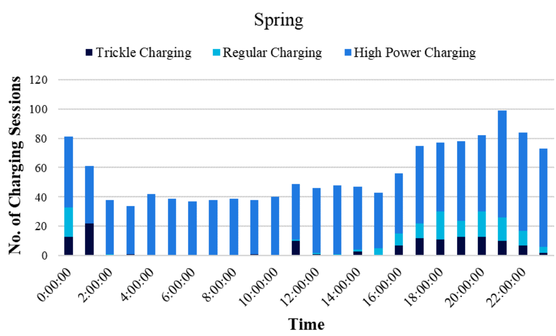
(a) Summer



(b) Autumn



(c) Winter

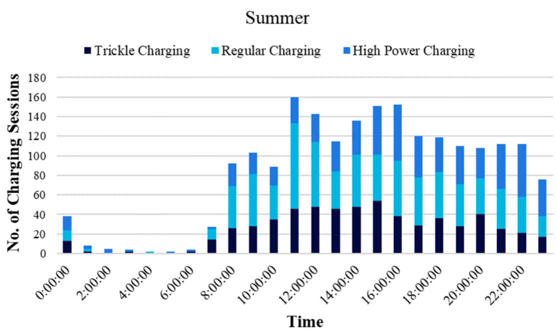


(d) Spring

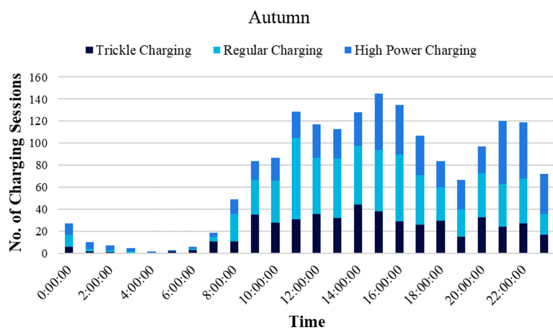
Fig. 4.14 No. of charging sessions per type for House 2814

The charging distribution for House 2814 reveals distinct patterns across different charging types. Level 1 trickle charging exhibits small peaks during the evening hours, particularly between 20:00 and 23:00. Regular charging sessions are minimal, sparsely distributed, and do not contribute significantly to overall energy consumption. In contrast, substantial charging sessions are heavily concentrated in the early morning, around 1:00, and see a sharp increase during the evening hours from 18:00 to 00:00, shown in Fig. 4.14. Key observations highlight that substantial charging dominates the load profile, especially in the evening, while there is a noticeable gap in charging activity during the middle of the day, suggesting limited vehicle presence or usage during work hours.

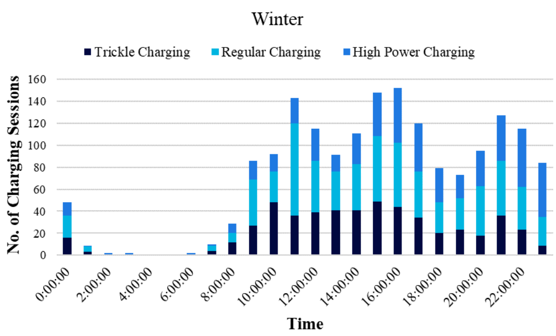
The charging distribution for House 5403 as shown in Fig. 4.15 reflects a more balanced charging behaviour compared to other households. Level 1 trickle charging is spread evenly throughout the day, with noticeable peaks occurring during midday and late evening. Regular charging sessions are prominent, with a sharp peak at 11:00 and moderate activity persisting through the evening hours. While substantial charging sessions are less dominant than in House 2814, they still occur primarily in the evening and are scattered throughout the



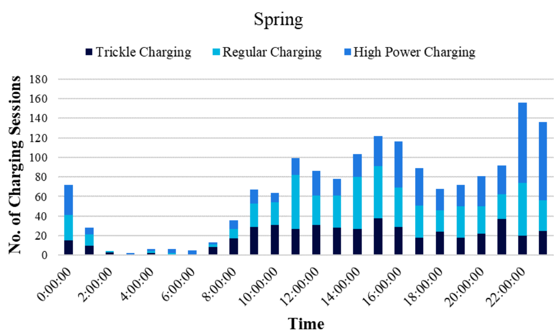
(a) Summer



(b) Autumn



(c) Winter



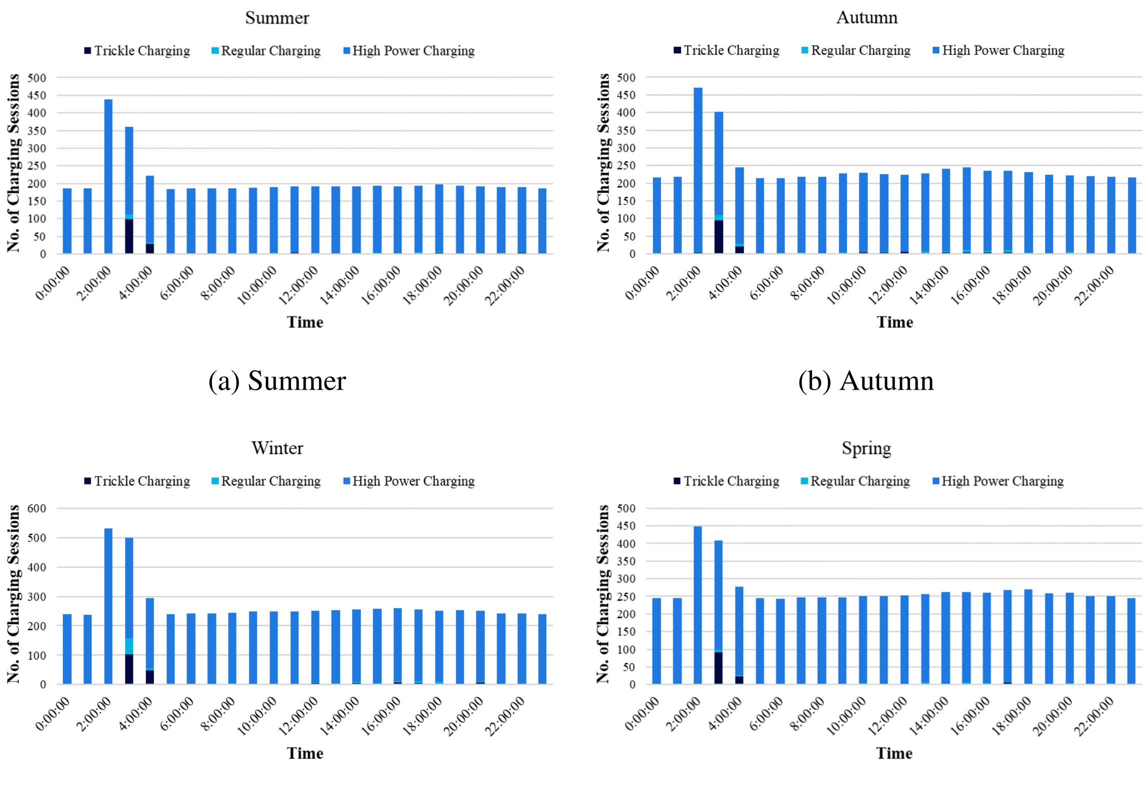
(d) Spring

Fig. 4.15 No. of charging sessions per type for House 5403

day. Key observations suggest that this household relies more on regular charging, with a significant spike at 11:00, possibly indicating a habitual or one-time midday charging event.

The charging distribution for House 8236 is characterized by a distinct early morning charging pattern, illustrated in Fig. 4.16. Level 1 trickle charging is concentrated between 3:00 – 5:00, with almost no activity observed throughout the rest of the day. Regular charging sessions are minimal and sporadic, contributing little to the overall load. In contrast, substantial charging sessions exhibit an extremely high load at 3:00, followed by a consistent but lower background activity throughout the day. Key observations suggest that the household relies predominantly on scheduled overnight charging, with minimal engagement in other charging types. This behaviour likely reflects a deliberate strategy to take advantage of off-peak electricity rates or a fixed charging routine.

The charging pattern for House 9729, shown in Fig. 4.17 reveals distinct trends across different types of charging sessions. Level 1 trickle charging, characterized by low power and long durations, remains minimal but shows an unusual spike at 7:00, possibly due to a scheduled or automated task. Regular charging sessions, which likely use medium power, exhibit a steady increase from midday, peaking between 12:00 and 19:00, suggesting align-



(a) Summer (b) Autumn

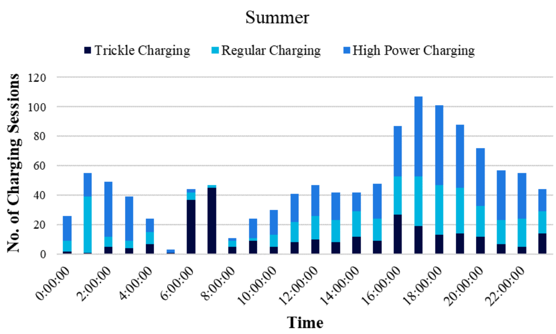
(c) Winter (d) Spring

Fig. 4.16 No. of charging sessions per type for House 8236

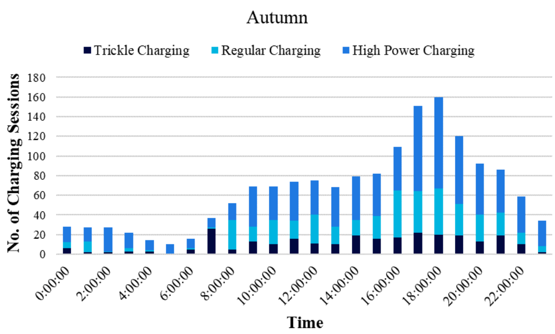
ment with daytime usage patterns. Substantial charging, involving high power consumption, peaks significantly between 18:00 and 20:00, likely driven by evening routines or high energy demand during this period.

Low usage periods are observed between 1:00 and 6:00, reflecting typical overnight low demand behaviour. The dominance of evening charging, 18:00 – 21:00, suggests a structured routine, potentially related to post-work vehicle charging or other energy-intensive activities. These trends highlight potential stress on the energy infrastructure during peak evening hours, emphasizing the need for demand redistribution to optimize load management and reduce strain on the system.

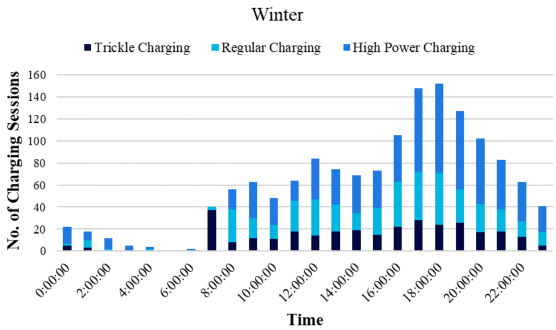
The charging behaviours of the three houses exhibit notable diversity despite being part of the same cluster. House 2814 predominantly charges in the evening, House 5403 follows a more balanced pattern with a distinct midday charging peak, and House 8236 is heavily skewed toward early morning charging. These variations have important implications for load management. The evening peak load from House 2814 could contribute to grid stress, while the midday charging in House 5403 may align well with solar energy generation if available. Meanwhile, House 8236's early morning charging could take advantage of off-peak



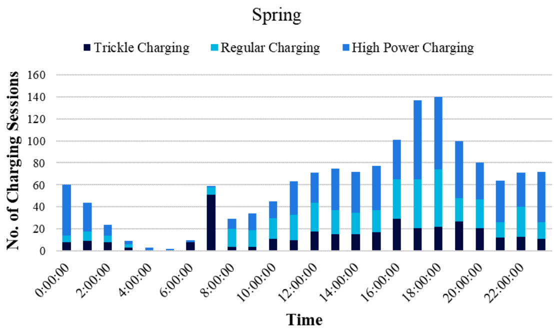
(a) Summer



(b) Autumn



(c) Winter



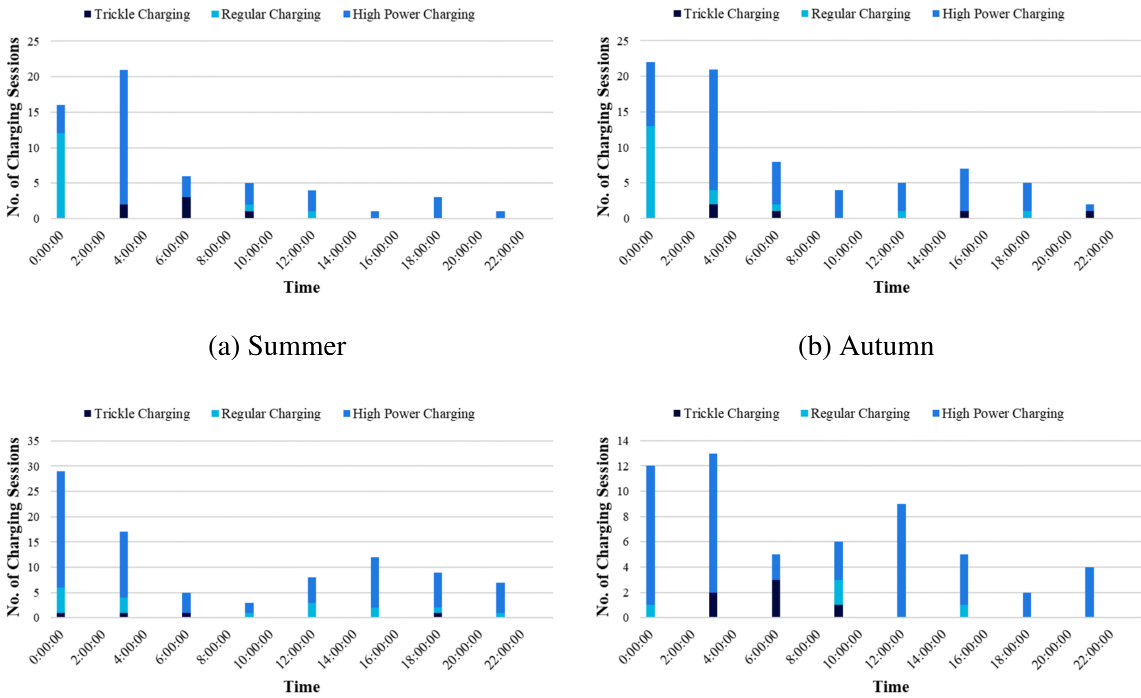
(d) Spring

Fig. 4.17 No. of charging sessions per type for House 9729

electricity tariffs, optimizing cost and grid efficiency. Given this variability, demand-side management strategies must be tailored to accommodate these different charging patterns, ensuring a balanced grid load and more efficient energy distribution.

4.3.6 Cluster 8

The charging behaviours of House 7989 and House 9609, illustrated in Fig. 4.18 and 4.19 respectively, exhibit distinct patterns, reflecting different usage habits and potential impacts on the grid. House 7989 demonstrates a more distributed charging profile, with sessions occurring throughout the day, particularly between 00:00 - 6:00 and sporadically in the afternoon and evening. This pattern suggests a more flexible charging schedule, likely influenced by varying daily routines or dynamic electricity pricing. In contrast, House 9609 shows an extremely concentrated charging pattern, with the majority of sessions occurring between 00:00 - 2:00 and a secondary peak at 21:00. This behaviour indicates a rigid, possibly automated charging routine, likely set to take advantage of off-peak electricity tariffs.



(a) Summer

(b) Autumn

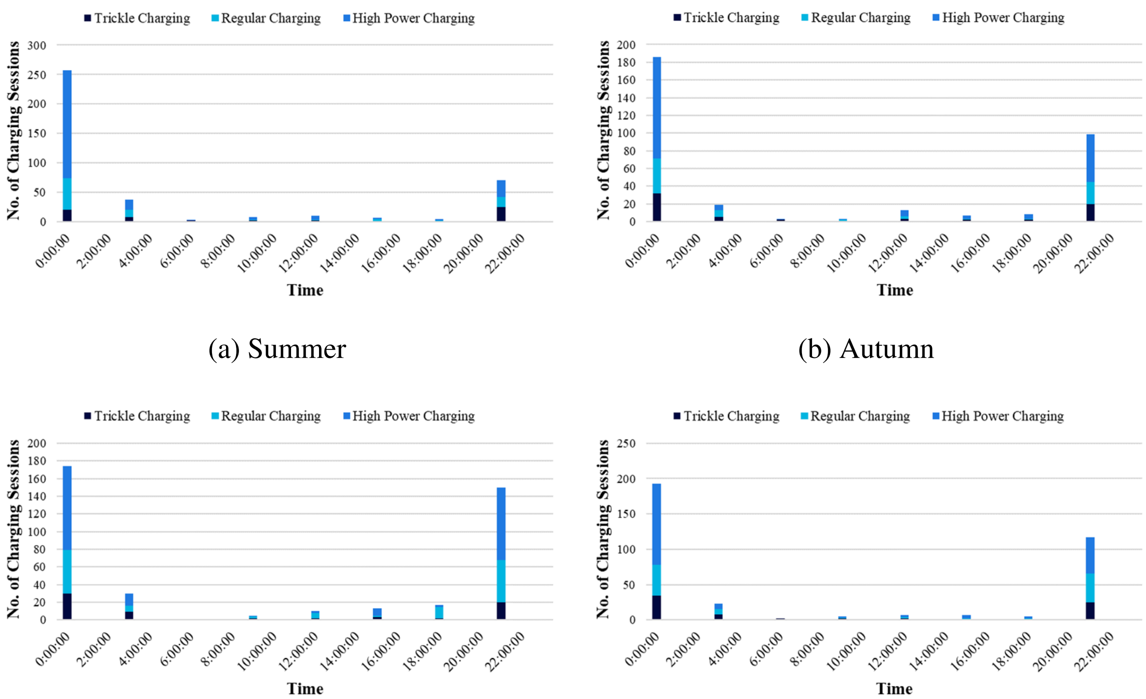
(c) Winter

(d) Spring

Fig. 4.18 No. of charging sessions per type for House 7989

In terms of charging types, regular charging is the dominant mode in both houses, but House 7989 exhibits more variation, incorporating high power and trickle charging at different times. House 9609, however, relies heavily on regular charging with little variation in charging type or timing. This rigid schedule in House 9609 could pose a greater challenge to grid stability, as the clustering of charging sessions around midnight may contribute to peak demand stress. On the other hand, House 7989's spread out charging sessions may help alleviate demand spikes, leading to a more balanced grid load.

The underlying reasons for these differences could originate from different household routines, EV usage patterns, or financial incentives such as time-of-use tariffs. House 9609's charging habits strongly suggest a fixed overnight charging strategy, while House 7989 appears to follow a more adaptive and varied approach. Understanding these behavioural patterns is crucial for designing demand-side management strategies that encourage optimal charging times, ensuring grid stability while accommodating user convenience.



(a) Summer (b) Autumn

(c) Winter (d) Spring

Fig. 4.19 No. of charging sessions per type for House 9609

4.3.7 Cluster 9

The houses within this cluster exhibit distinct yet overlapping charging behaviours, with implications for grid management and energy optimization. House 3967 displays a notable early morning peak in substantial charging between 5:00 – 6:00, likely indicating early commutes or programmed overnight charging. This is followed by an evening surge (16:00–19:00), aligning with common post work charging patterns. In contrast, House 545 sees a strong midday increase in both trickle and substantial charging from 12:00, peaking around 15:00 - 16:00, while evening charging remains present but less dominant. These differences suggest varied user schedules; House 3967 relies on structured early morning and evening charging, whereas House 545 may be leveraging solar energy or midday availability for charging.

All other three houses in this cluster; House 1714, 2335 and 4998 exhibit a significant increase in charging activity during late evening (20:00 – 00:00), in line with typical home charging behaviour. Houses 1714 and 2335 maintain consistent evening charging peaks, though House 4998 stands out with an exceptionally high level of substantial charging, particularly during off-peak hours (00:00 – 4:00). This house appears to rely heavily on high capacity charging, possibly utilising scheduled overnight sessions or an energy management system. While trickle charging remains minimal across all three houses, regular charging is a key contributor to evening demand.

House 6139 presents a unique charging profile with an extreme spike in regular charging at 6:00, reaching nearly 700 units far exceeding the cluster average. This may indicate scheduled EV charging, a high power appliance, or an automated energy task. Additionally, substantial charging occurs predominantly in the early morning (3:00 - 5:00), with a secondary peak at 23:00, suggesting structured energy use at night. Unlike other houses, this house experiences consistently low charging activity from 7:00–22:00, with only minor trickle charging spread throughout the day. The unusual 6:00 spike differentiates this house from the rest of the cluster and may require load redistribution strategies. Some of the cluster insights discussed as below:

- Shared Trends: Most houses exhibit substantial charging during evening hours, typically between 16:00 and 00:00. Trickle charging tends to increase steadily through midday and evening, possibly for appliances or slow EV charging.
- Key Differences: House 3967 exhibits substantial early morning charging activity, likely indicating early departures or an automated charging schedule. In contrast, House 545 shows a pronounced midday charging peak, potentially leveraging solar energy for efficiency. House 4998 stands out with the highest levels of substantial charging, particularly concentrated overnight, suggesting a deliberate shift toward off-peak charging. Meanwhile, House 6139 displays an unusual spike in regular charging at 6:00, which could be attributed to a programmed event or a specific high energy demand at that hour.
- Load Management & Optimization: The combined peak demand between 12:00 and 20:00 poses a potential strain on local infrastructure, which could be alleviated by staggering high energy activities across different time slots. Houses with midday peaks, such as House 545, may benefit from solar energy storage to maximize self consumption and reduce grid dependence. Implementing smart charging systems could help distribute substantial charging more evenly, minimizing congestion during peak evening hours. Additionally, introducing incentives for off-peak charging, particularly for houses like 4998 and 6139, could enhance grid stability while optimizing energy costs.

A detailed analysis of residential load profiles with and without EV integration highlights the significant impact of electric vehicle charging on overall electricity demand. In many cases, EV integration primarily affects the magnitude of the load, often intensifying the evening peak beyond typical levels. If a large proportion of households in a given area own EVs and choose to charge them simultaneously, particularly during peak evening hours; this could place considerable strain on the grid. Such a scenario may necessitate infrastructure upgrades, including transformer reinforcements, to accommodate the increased demand. Given the potential shifts in load patterns caused by widespread EV adoption, it becomes crucial to assess whether the designed load forecasting model remain accurate when EV charging profiles are incorporated. Ensuring reliable forecasting under these conditions is essential for effective grid planning, demand-side management, and maintaining overall system stability.

With a clear understanding of how EV charging affects the load profiles of these clusters particularly the impact of different charging categories and power levels, it is essential to evaluate whether the developed forecasting model can accurately predict load consumption when EV charging is incorporated, or whether its performance deteriorates under these conditions. To conduct this evaluation, additional EV charging load profiles are simulated using the Monte Carlo method to create scenarios with different EV penetration levels within the residential clusters. The following sections describe the methodology for generating simulated EV charging profiles, integrating them into the forecasting framework, and presenting the results that assess the model's accuracy and robustness under varying levels of EV integration.

4.4 Methodology to incorporate EV charging profile in Forecast Model

The increasing penetration of EVs and their charging at residential premises significantly alters daily load profiles, making it essential to incorporate EV charging effects into residential load forecasting models. However, the accuracy of such models is heavily dependent on the availability of high quality EV charging data, which remains scarce. This lack of reliable, real world data presents a major challenge in developing precise and robust forecasting models. Without accurate datasets, predicting EV charging behaviour and its impact on the grid becomes difficult, necessitating alternative methodologies to bridge this data gap.

In this study, Monte Carlo Simulations (MCS) are utilised to address this limitation by generating additional synthetic 24-hour EV charging profiles. These simulated profiles are used to create different EV penetration scenarios within the residential clusters, enabling comprehensive evaluation of the forecasting model under varying levels of EV integration.

Therefore, a review of Monte Carlo (MC) use cases is included in this section to establish its suitability for this application.

The MC method is a powerful statistical technique that relies on random sampling to model complex systems and predict their behaviour. Given that EV charging demand is influenced by multiple uncertain factors such as driver behaviour, trip characteristics, and the availability of charging infrastructure availability, the MC approach is particularly well suited for simulating realistic charging patterns.

By incorporating probabilistic elements, MCS enable researchers and grid operators to analyse a wide range of possible charging scenarios and assess their impact on residential load profiles. This flexibility is crucial for evaluating worst case, best case, and average load conditions, thereby enhancing the robustness of forecasting models. The methodology has been widely applied in studies focused on EV load profile generation, allowing for more accurate predictions of energy demand fluctuations and supporting better grid planning and demand-side management strategies.

This section reviews key studies that have leveraged the MC approach to model and analyse EV charging load profiles. This review establishes the effectiveness of MCS in addressing data limitations and capturing the inherent uncertainties of EV charging behaviour, thereby justifying its application within the methodology of this thesis.

4.4.1 Monte Carlo Simulation Use Cases

Before implementing the MC approach to generate additional EV load profiles, it is essential to first explore and understand the various use cases. In [73], the authors presented a study that introduces a methodology for generating EV load profiles using probability density functions (PDFs) integrated with the MC method to simulate realistic charging behaviours. PDFs are developed for key parameters, including arrival times, which are derived from real-world travel patterns, state of charge (SOC) reflecting initial and desired charge levels, and charging power that varies with charger types and battery characteristics. Once the PDFs are generated, MCSs are performed to randomly sample from these distributions, generating numerous potential charging scenarios. Following this approach, load profiles are generated and these profiles exhibit temporal variability, emphasizing the influence of charging patterns on peak demand. The method offers flexibility to adapt PDFs for diverse datasets, enabling application across different geographic or demographic contexts. This study demonstrates the capability of the MC method to replicate the stochastic nature of EV charging, providing valuable insights for planning and forecasting grid impacts.

In another study [74], the authors focused on predicting EV charging loads by leveraging the MC method to capture the inherent variability and randomness in charging patterns. The proposed methodology optimally utilised input parameters such as travel patterns, which influence arrival times at charging stations; state of charge (SOC) distributions, which reflect the initial and target charge levels; and charging infrastructure availability, including charger types and their accessibility. This approach was followed by Monte Carlo simulations, which performed randomized iterations to simulate diverse charging scenarios and create aggregate load profiles that effectively captured variations in peak loads and their distribution. The study concluded that these simulations highlighted peak charging periods and their implications for grid infrastructure. Overall, this research demonstrated the utility of MCSs in forecasting charging loads under various scenarios, providing a valuable tool for utility companies and urban planners.

The authors in [117] present a MC-based approach for user profiling and forecasting spatiotemporal charging demands. The methodology follows mainly two steps: user profiling for identification of user behaviour, travel patterns, and charging preferences using statistical data, and spatiotemporal forecasting, that employs MCSs to estimate charging demand distributions across different locations and times. The model effectively captures spatial and temporal variations in charging demands. This study highlights the importance of combining user profiling with MCSs to forecast localized charging needs, enabling efficient resource allocation.

In another paper [118], the authors evaluate the impact of EV integration on the power grid and explore optimal charging schemes under uncertainty using MC methods. Their methodology involves simulating EV charging scenarios through scenario analysis, which considers uncertainties in load demand, user behaviour, and charging infrastructure. Based on these simulations, they develop optimal charging strategies that aim to minimize grid impacts while ensuring user satisfaction. The findings reveal that uncontrolled charging significantly increases peak loads, whereas implementing optimal charging schemes substantially reduces grid stress. This study demonstrates the effectiveness of MCSs in assessing grid impacts and guiding the development of efficient charging strategies.

In [119], an investigation is conducted to find the hosting capacity of distribution networks under static and dynamic thermal ratings for controlled and uncontrolled EV charging scenarios. This study also utilises the MC approach by running simulations for models charging scenarios under both controlled, i.e., smart charging, and uncontrolled conditions. The thermal rating is included that considers static and dynamic thermal limits of network components. It was found that dynamic ratings significantly improve hosting capacity compared to static ratings. Whereas controlled charging mitigates peak demand, enhancing grid reliability. This study underscores the role of smart charging and advanced thermal management in maximizing grid integration of EVs.

The research in [120] focuses on simulating EV load profiles for smart charging strategies, incorporating driving behaviours and vehicle performance characteristics. In this research, driving behaviour analysis and smart charging strategies are included, where driving behaviour uses MC simulations to model variability in trip lengths, departure times, and SOC levels. Smart charging strategies optimize charging schedules based on grid demand and vehicle requirements. It was found that smart charging reduces grid peaks and improves load balancing and that driving behaviour significantly impacts load profile variability. This study demonstrates the integration of driving behaviour into load profile simulations, highlighting the potential of smart charging for efficient grid management.

In another literature [121], the authors highlight the application of MCS in generating synthetic load profiles to support asset planning for low-voltage electricity grids. There are numerous uncertainties involved in a distribution network, such as customer load variability and EV charging patterns, and this literature utilises probabilistic modeling for these uncertainties. Whereas the paper [122] focuses on forecasting EV-related load demand using MCS, emphasizing its value for accurate predictions in the context of EV integration.

Studying these research articles, following important points are found.

- Commonalities: All studies leverage the MC method to address uncertainties in EV charging, incorporating stochastic behaviours and variable parameters.
- Distinct Contributions: The first two studies emphasize general load profile generation and forecasting.
- Grid Impact Assessments: These studies concentrate on infrastructure planning and the development of optimal charging strategies.
- Hosting Capacity and Smart Charging: Research in this area emphasizes grid reliability and load balancing

The reviewed studies collectively demonstrate the versatility of the MC method in modeling and analysing EV charging loads. From scenario generation and spatiotemporal forecasting to grid impact assessments and optimal charging strategies, these approaches provide critical insights into managing EV integration into power grids, emphasizing the importance of accounting for stochastic behaviours in charging patterns.

4.4.2 Importance of Monte Carlo Approach

Based on the use cases, it has been identified that MC approach is quite useful for the following scenarios [121]:

1. Probabilistic Modeling: MCS allows the incorporation of uncertainties inherent in load profiles, such as customer behaviour, EV charging patterns, and distributed generation. This probabilistic modeling captures a wide range of possible future scenarios, enhancing the robustness of grid planning.

2. Scenario Diversity: By generating multiple random realizations, MCS provides a diverse set of load profiles. These profiles help planners identify edge cases, e.g., peak loads that deterministic methods may overlook.

3. Scalability and Flexibility: The approach can be adapted to different types of loads, grid configurations, and emerging technologies, making it a versatile tool for planners.

4. Insight into Asset Utilisation: The detailed load profiles generated via MCS improve predictions of asset usage, operational constraints, and potential failures, leading to optimized investments in grid upgrades.

4.5 Monte Carlo Approach for Generating EV load Profile

Monte Carlo simulations have become a widely adopted method in the energy sector for addressing uncertainties in load forecasting and grid planning. Given the limited availability of real-world EV charging data, this thesis employs the MC approach to generate additional EV load profiles. These generated profiles are then integrated with the existing EV load profiles of the dataset's residential houses. By integrating additional EV load profiles, multiple scenarios are simulated to assess the forecasting model's performance under different levels of EV penetration. This evaluation helps to determine whether the model can maintain its accuracy despite fluctuations in EV adoption and charging behaviours. Since the developed load forecasting model relies on historical 24-hour consumption data, the MC approach used in this study specifically generates 24-hour EV load profiles to align with the forecasting framework. This ensures a comprehensive assessment of the model's robustness in the presence of increased EV adoption and diverse charging behaviours.

4.5.1 Methodology used for Monte Carlo Simulation

The methodology employed for MCS in this thesis is depicted in Fig. 4.20. The subsequent sections provide a detailed explanation of each major component of the methodology.

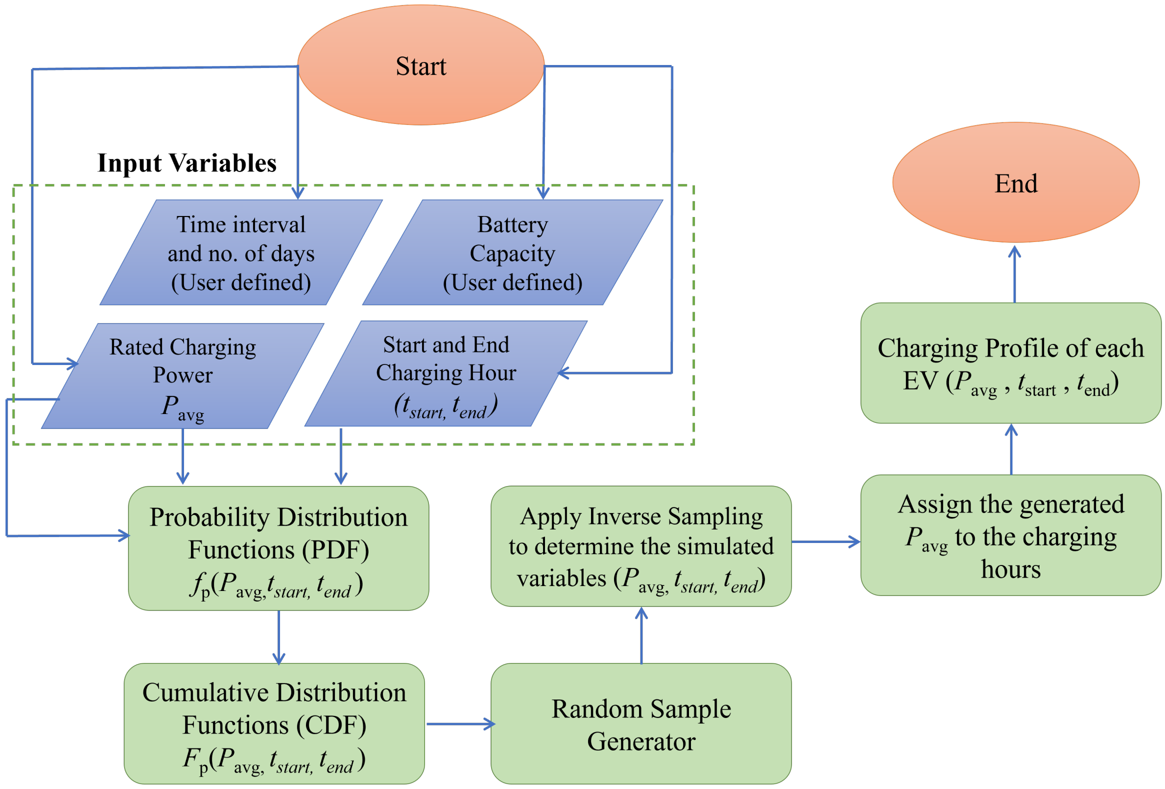


Fig. 4.20 Monte Carlo Methodology for Creating EV Charging Profiles

Input Data

Extensive literature studies have consistently demonstrated that the accuracy of MCS is highly dependent on the quality of input data. A fundamental step in this process is identifying the most influential factors that affect the simulation output specifically, in this case, the EV charging load profile.

To develop a realistic and reliable simulation framework, it is essential to carefully select and incorporate key parameters that shape EV load profiles. These parameters not only enhance the accuracy of the generated profiles but also ensure that the simulation reflects real world charging behaviours and grid interactions. The following factors are critical when generating EV load profiles using MCS:

1. EV Characteristics: The characteristics of EVs significantly influence the charging demand and load profile. The primary parameters include [123], [124], [125]:

   - Battery Capacity (kWh): Determines the total energy storage capacity of an EV, influencing the frequency and duration of charging sessions. Larger battery capacities allow for longer driving ranges, reducing the frequency of charging events. Conversely, smaller battery capacities require more frequent recharges, impacting the overall load profile.

- Rated Charging Power: Defines the maximum power at which an EV can be charged, affecting the instantaneous demand on the grid.
- Daily Energy Consumption: Represents the average energy usage per day, which varies based on driving habits and vehicle efficiency.
- State of Charge (SOC): It represents the remaining battery energy as a percentage of the total battery capacity and influences charging frequency, duration, and power demand.

2. Charging Behaviour: Understanding the charging behaviour of EV users is crucial for modeling realistic load profiles. The key factors include:

    - Start Charging Time: The time at which EV users initiate charging significantly impacts the load curve. Peaks often occur in the evening when users return home from work, but workplace and public charging introduce additional variations.
    - Charging Duration: The length of a charging session depends on battery SOC, charging power, and user preferences. Longer sessions may lead to sustained load periods, whereas short duration fast charging increases peak demand.

3. EV Population: The number and penetration level of EVs in a given area affect aggregate charging demand and grid impact. Essential parameters include:

    - Number of EVs in the Area: A higher number of EVs contributes to increased overall electricity demand, which must be accounted for in load forecasting and grid planning.
    - EV Penetration Levels: Estimations of current and projected EV adoption rates, helping model future grid load scenarios.

4. Grid or Location Data: The local grid infrastructure and demand characteristics play a vital role in shaping EV load profiles. The relevant factors include:

    - Available Charging Infrastructure: The presence of home, public, and fast charging stations affects where and when EVs are charged. Insufficient infrastructure may lead to clustered demand spikes.
    - Location Specific Load Profiles: Regional variations in electricity demand, renewable energy integration, and grid constraints must be considered to ensure that EV charging aligns with the existing load curve.

5. External Factors: Various external influences affect EV charging behaviour and energy demand patterns. Important considerations include:

   - Weather Conditions: Extreme temperatures impact battery performance and efficiency, leading to variations in charging demand. Cold weather, for instance, increases energy consumption for heating, reducing driving range and requiring more frequent charging.
   - Policy Incentives: Government incentives, time-of-use tariffs, and demand response programs influence charging patterns by encouraging users to charge at off-peak hours or utilise renewable energy sources.

By incorporating these key parameters into MCS, a comprehensive and realistic EV load profile can be generated, enabling better forecasting, demand management, and grid integration strategies. These factors collectively ensure the accurate reflection of the stochastic nature of EV charging and provide insights in the development of robust energy planning and infrastructure investments.

The dataset used in this research does not include all the desired input features due to the lack of information. However, the most relevant available features are selected, specifically those related to battery capacity and charging behaviour. Given that this study focuses on residential consumers, with the assumption that all EVs are charged at home, charging infrastructure and location are treated as uniform across all EVs and are not considered as separate input parameters. Additionally, external factors are not included in this initial assessment. The PECAN dataset used in this thesis provides EV charging data, including rated average charging power P_{avg} , daily energy consumption (E_i), battery capacity (C_i), and charging start times (t_{start}). The primary input parameter, battery capacity (C_i) is selected by the user. Another user defined input feature is the time interval and the number of days. Since the goal is to generate a daily load profile, the time interval is set to 24 hours. The main simulation assumptions and their expected influence on the resulting EV load profiles are summarised in Table 4.2.

Probability Distribution Functions

MCSs are widely used to model uncertainties in EV load profiles by representing key parameters as probability distributions. To generate additional EV charging profiles, available data is used to identify PDFs for the key variables P_{avg}, t_{start} and t_{end}.

PDF describes the likelihood of different values occurring for a given variable, helping to capture the statistical variability in EV charging behaviour. By analysing historical data, the PDF is estimated for the key charging parameters, which are then used to simulate diverse

Table 4.2 Monte Carlo assumptions and their expected influence on EV load profiles

Parameter	Assumption	Expected influence
Battery capacity (C_i)	Defined by the user according to the battery capacity categories represented in the dataset	Larger battery capacities increase charging duration and total daily energy demand.
Charging power (P_{avg})	Derived from the historical probability distribution function	Higher charging power increases peak magnitude while reducing charging duration.
Charging start time (t_{start})	Sampled from the historical charging time distribution	Earlier charging shifts additional demand into the residential evening peak period.
Charging location	All EV charging assumed to occur at home	Concentrates EV demand within the residential household load profile.

EV charging scenarios. Once the PDF is established, the next step is to derive the cumulative distribution function (CDF).

Cumulative Distribution Function

CDF provides the probability that a variable, such as EV charging load, does not exceed a certain value. It is obtained by integrating the PDF and is particularly useful for evaluating load exceedance probabilities, which are essential for grid stability analysis and demand-side management. Mathematically, the CDF is expressed as:

$$F(x) = P(X \leq x) = \int_{-\infty}^{x} f(t)\,dt \tag{4.1}$$

where, $f(t)$ represents the PDF of random variable x and $F(x)$ is the corresponding CDF.

Sampling Using the Inverse Transform Method

Once the CDF is established, Monte Carlo sampling is performed to generate EV charging load profiles. In this process, a random value is first drawn from a uniform distribution. This is required by the inverse transform sampling method because the CDF always lies in the interval [0, 1], and the uniform value serves purely as a probability input. The inverse transform is then applied to map this value to a sample from the empirical distribution of the charging parameters, specifically obtaining P_{avg}, t_{start} and t_{end} in this case. The charging start and end times are therefore selected based on the empirical distribution derived from the existing dataset, ensuring that the random sampling reflects patterns observed in the real data. This procedure generates a daily charging profile for a single EV, incorporating factors such as rated average charging power and charging duration, and is subsequently repeated to create charging profiles for the desired number of days.

Simulating EV Charging Profiles

Following this process, the daily charging profile of an individual EV is simulated, including the start and end times of the charging event, the average charging power at which charging occurs. By leveraging PDFs and CDFs within MCS, realistic EV charging behaviours can be modeled, enabling more accurate load forecasting and grid impact assessments.

Aggregate Profiles for the Population

Aggregate the individual EV load profiles to generate a total load profile for the entire EV population. This process includes summing the individual profiles of all EVs at each time step (e.g., hourly resolution) and repeating the aggregation across all simulation runs. Once a number of EV profiles are generated using MCS then they are combined with existing charging profiles in the dataset to create various scenarios that are evaluated to check performance of the built load forecast model.

4.6 Electric Vehicle Load Profiles Generated via Monte Carlo Simulation

The clusters created using the PECAN dataset contain EVs in 7 out of 10 clusters. To generate EV load profiles using MCS, data from these EVs has been utilised. Table 4.3 provides details of the EV models and their corresponding battery capacities. When simulating EV charging load profiles, battery capacity can either be modeled as a distribution function or selected by the user. In this thesis, battery capacity is user defined. All of the EVs charge at a maximum power rating of either 3.3 kW or 7.2 kW, with actual charging power varying below these limits based on the capacity of the household electrical circuit and the battery's SOC. To generate samples, historical data on average charging power has been used, following the inverse transform sampling method explained earlier in the methodology. The historical data is selected based on the desired battery capacity for the simulation.

Table 4.3 EV Models and battery capacity

EV Model	Battery Capacity (kWh)
Tesla Model X	75
Tesla Model 3	50
Nissan Leaf	40
Chev V	18

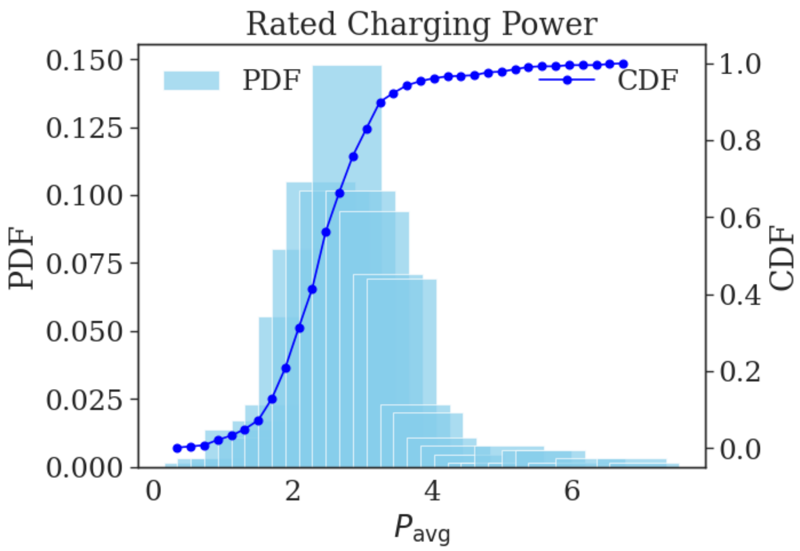


Fig. 4.21 PDF and CDF of rated average charging power of an EV with battery size of 18 kWh

4.6.1 Simulated EV Charging Profile of an EV with 18 kWh Battery

Based on the available data, Fig. 4.21 depicts the PDF and the corresponding CDF of an EV with a battery capacity of 18k kWh. The blue bars represent the PDF, illustrating the likelihood of different P_{avg} values occurring. It peaks around 2–3 kW, indicating that most charging power values fall within this range. Meanwhile, the CDF starts at 0 and gradually approaches 1, ensuring that all P_{avg} values are captured within the distribution. Beyond 4 kW, the PDF flattens, signifying a lower occurrence of higher charging power values.

Fig. 4.22 presents both the PDF and CDF of the hours when charging begins. The highest peak is observed between 6:00 and 7:00, indicating a concentration of charging sessions during this early time window. While the distribution suggests that the majority of charging sessions are concentrated in the morning, the data also reveals a relatively uniform spread of charging activity from midday through to the late evening. This pattern suggests that

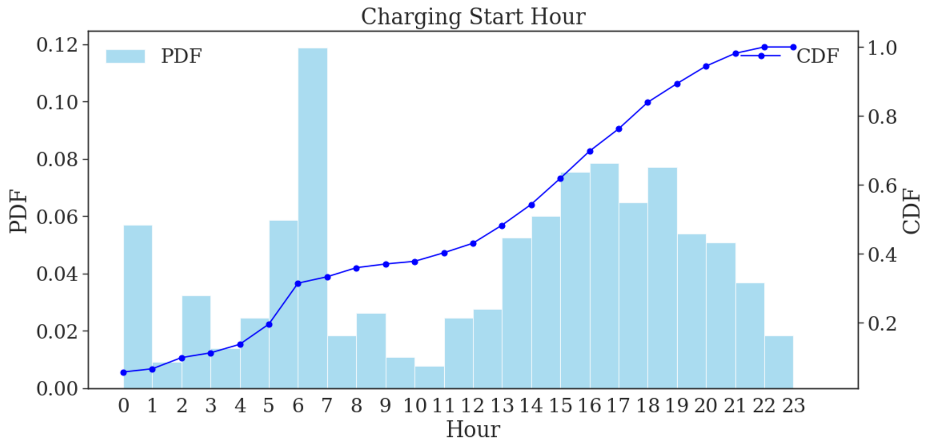


Fig. 4.22 PDF and CDF of start of charging hour of an EV with a battery size of 18kWh

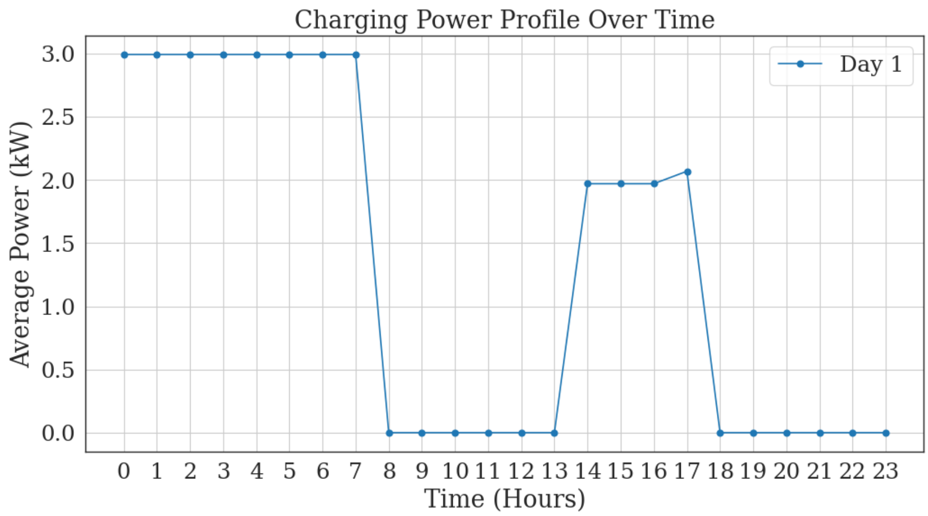


Fig. 4.23 Simulated daily charging profile of EV with a battery size of 18 kWh

charging occurs consistently throughout the day, with no significant periods of inactivity, reflecting a continuous demand for charging over a 24-hour period.

The simulated daily load profile for the same EV is presented in Fig. 4.23. As shown, the charging pattern closely mirrors the distribution of the start charging hours, highlighting a clear alignment between the two. Furthermore, the rated average power also follows a similar distribution, with power values predominantly ranging between 2 and 3 kW. This suggests a consistent charging behaviour, where both the timing and power consumption are in line with the observed patterns in the start charging hours, indicating that the simulation accurately reflects real world charging trends for the EV.

4.6.2 Simulated EV Charging Profile of an EV with 75 kWh Battery

As an example, a separate simulation was conducted for an EV with a larger battery capacity of 75 kWh. Fig. 4.24 presents the corresponding PDF and CDF for this EV. From the figure, it is evident that the larger battery requires higher charging power compared to the smaller one, as expected due to its increased capacity. The rated average power is concentrated within the range of 8 to 13 kW, reflecting the greater energy demand. The simulated daily load profile for this EV, shown in Fig. 4.25, illustrates the charging pattern that aligns with the higher power requirements, further reinforcing the relationship between battery size and charging power demand.

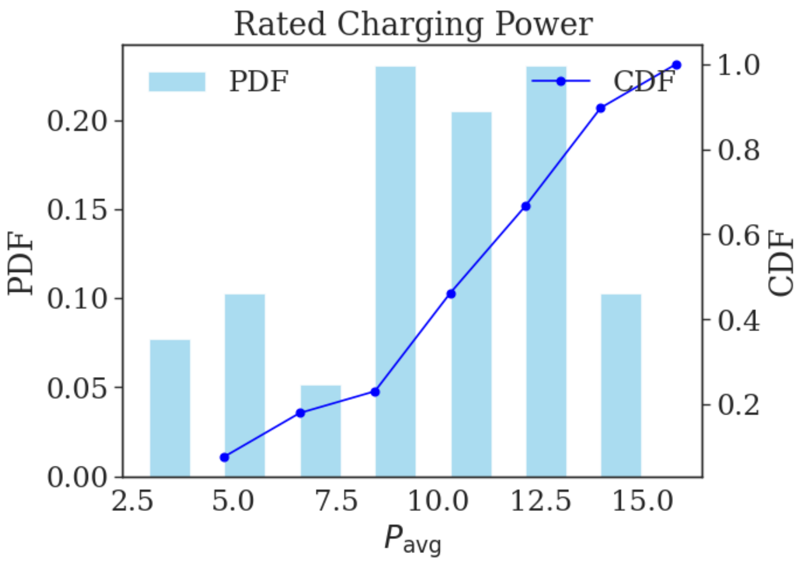


Fig. 4.24 PDF and CDF of rated average charging power of an EV with battery size of 75 kWh

4.7 Assessment of forecast model with EV load profiles

The primary objective is to assess the forecasting model's performance under different levels of EV penetration and to evaluate how the inclusion of EVs influences forecast accuracy. For this purpose, clusters that contain EVs are selected, and their consumption profiles are modified by incorporating EV charging data. A 24-hour EV charging profile is also added as an additional input feature to the forecast model, and the model is retrained accordingly.

It is important to note that the original forecast model was developed and trained using nine years of historical data. However, for evaluating the impact of EV penetration, only one

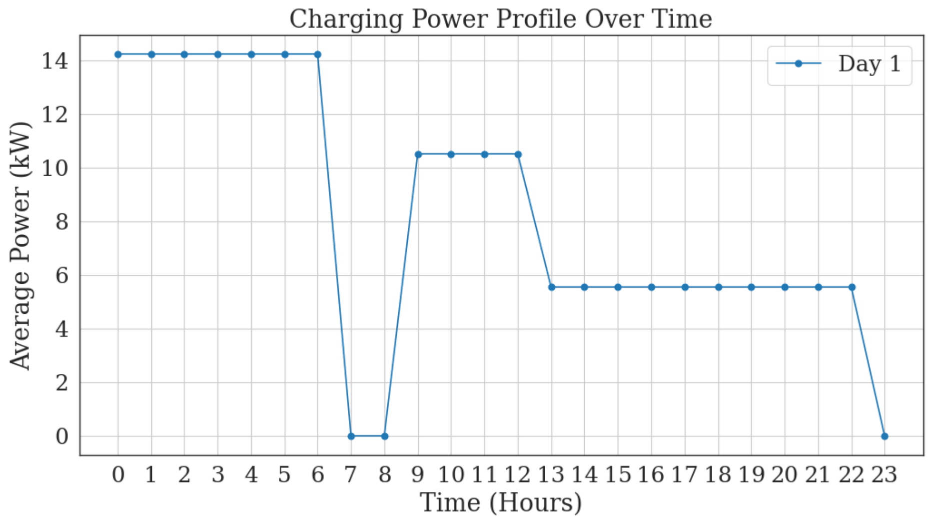


Fig. 4.25 Simulated daily charging profile of EV with a battery size of 75 kWh

year of data is used. This difference in training and evaluation data span may also influence the model's predictive accuracy.

4.7.1 Different EV charging scenarios

Table 4.4 EV Penetration in Each Cluster

Cluster	No. of houses	Low Penetration	Medium Penetration	High Penetration
C1	4	25%	50%	75%
C3	3	0%	33%	67%
C4	10	10%	20%	60%
C5	2	0%	50%	100%
C7	13	23%	38%	62%
C8	3	0%	33%	67%
C9	12	17%	50%	67%

The evaluation is conducted across three levels of EV penetration. The first level represents low or no penetration, where up to 25% of households have EVs. The second level corresponds to medium penetration, involving 25% to 50% of households with EVs. The third level represents high penetration, where more than 50% of households own EVs. For each penetration level, two charging behaviour scenarios are evaluated: random charging and night (overnight) charging. These scenarios have been selected intentionally to reflect two representative and commonly cited behavioural patterns in the literature:

1. Random charging represents an uncontrolled or user-driven behaviour, where EV owners charge at arbitrary times based purely on their individual convenience (e.g., after returning home, during the afternoon, or whenever the battery level is low). This captures the worst-case volatility in demand and reflects driving profiles in which no explicit price signals or incentives are considered.

2. Night/overnight charging reflects a more typical and incentivised behaviour, where EV owners plug in their vehicles in the evening and charge them overnight so that they are fully charged and available for use the following morning. This scenario also aligns with the majority of time-of-use (TOU) tariff structures, which encourage night charging to reduce grid congestion and take advantage of lower electricity prices.

These two scenarios therefore represent two extreme but realistic patterns from completely uncoordinated (random) to incentive-aligned (overnight) which together allow the assessment of how the chosen forecasting model performs under different charging behaviours across all EV penetration levels. This results in two case studies being evaluated for each level of EV penetration. These case studies were selected based on current user behaviour, which typically involves either unscheduled charging or overnight charging. Therefore, these two scenarios were chosen for evaluation to reflect realistic charging practices.

Only seven clusters with existing EV data are used in this analysis. In situations where real EV data is insufficient, synthetic EV charging profiles generated using a MCS approach are employed. The cluster details and corresponding penetration levels are summarized in Table 4.4.

The forecast model is retrained for each of the defined case studies, and the corresponding results are presented in Table 4.5. While the previously discussed forecasting performance across all clusters showed an error of less than 5%, the current evaluation uses a significantly smaller training dataset. As a result, the acceptable threshold for forecasting error has been relaxed to approximately 10%.

Examining the results, it is observed that the MAPE remains below 10% for all clusters under the random charging scenario, except for Cluster 8. In contrast, there are several instances where the MAPE exceeds 10% when EVs are charged overnight. This difference in performance can be attributed to the nature of the charging patterns, as in the random charging scenario, the load is more evenly distributed throughout the day, resulting in a smoother load profile. However, in the overnight charging scenario, EV load is concentrated within a narrow time window, leading to a pronounced peak in demand across all EVs in the cluster. This abrupt shift in peak load introduces additional complexity and variability, making it more challenging for the forecast model to accurately learn the underlying patterns.

Table 4.5 Forecasting Accuracy for Different Penetration Levels Using MAPE

Cluster	Low Penetration		Medium Penetration		High Penetration	
	Random	Overnight	Random	Overnight	Random	Overnight
C1	9.62	16.15	5.02	11.19	5.72	7.47
C3	N/A	N/A	8.24	10.24	15.3	10.07
C4	6.19	5.01	4.71	5.43	5.46	6.81
C5	N/A	N/A	8.25	9.07	8.02	7.46
C7	4.84	5.87	5.34	8.83	10.57	6.32
C8	N/A	N/A	14.22	14.8	17.3	17.73
C9	4.16	4.29	4.16	6.35	5.99	9.21

Fig. 4.26, 4.27, and 4.28 illustrate the load profiles of random and overnight EV charging for Cluster 1 under low, medium, and high EV penetration levels, respectively. In all three scenarios, it is evident that random charging results in a more evenly distributed load profile throughout the day, leading to a smoother overall demand curve.

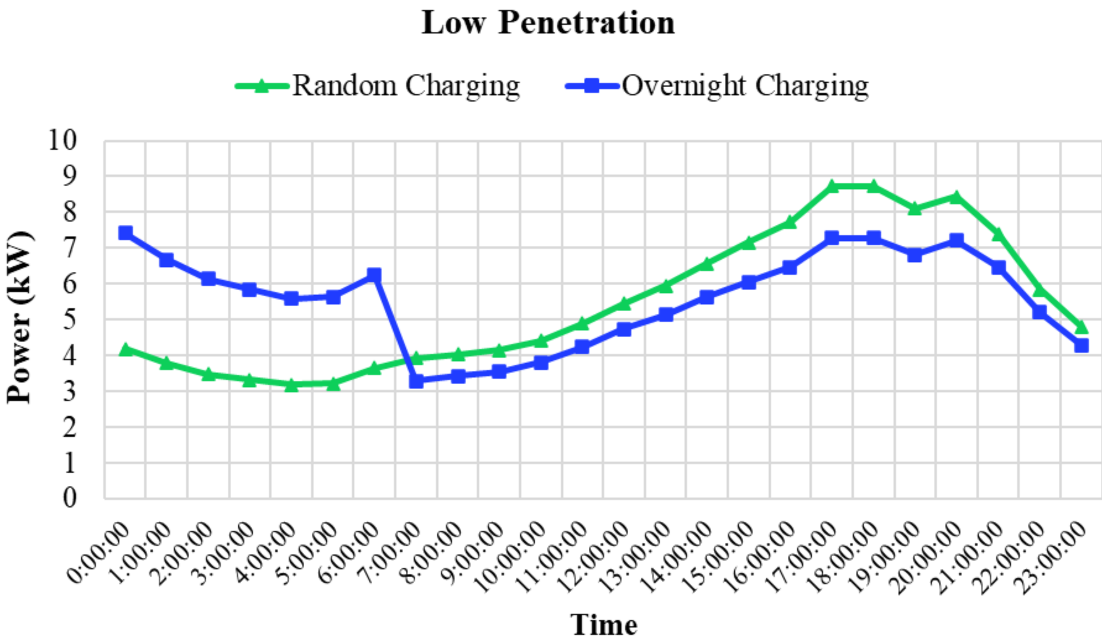


Fig. 4.26 Comparison between random and overnight charging under low EV penetration

In contrast, overnight charging produces a sharp, concentrated increase in demand during nighttime hours, resulting in a pronounced peak. This abrupt surge in load creates a more volatile and less predictable pattern, which places greater strain on the forecasting model.

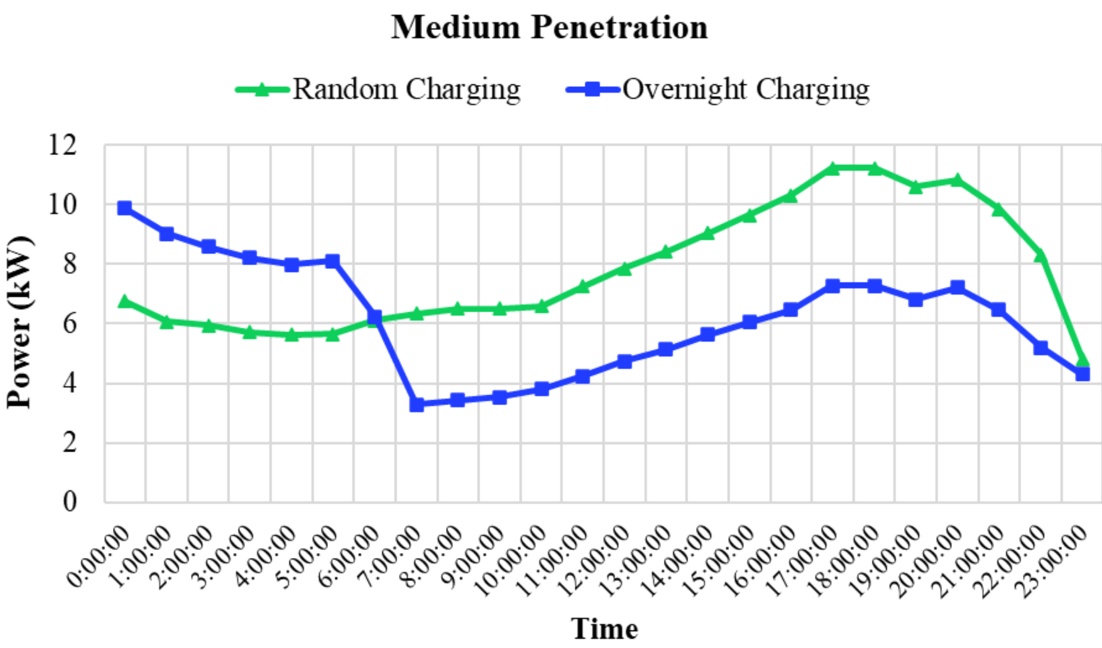


Fig. 4.27 Comparison between random and overnight charging under medium EV penetration

Such concentrated load behaviour can be more difficult for the model to learn and generalize, particularly if similar patterns are underrepresented in the training data. This further emphasizes the importance of incorporating charging behaviour characteristics into the model design to improve forecasting accuracy under structured EV charging scenarios.

This suggests that overnight charging imposes greater stress on the forecasting model, and in such cases, further refinement such as hyperparameter tuning or model adaptation might improve performance. Nonetheless, since the focus here is on evaluating the originally designed forecast model under different levels of EV penetration rather than optimizing it, no additional tuning is carried out at this stage.

4.7.2 Discussion

The evaluation of the forecast model under different EV penetration levels and charging scenarios reveals important insights about the model's robustness and limitations. In this study, the original forecast model previously trained on historical data was retrained to account for the influence of electric vehicles by incorporating a 24-hour EV charging profile as an additional input feature. This retraining step was essential to reflect the altered load dynamics introduced by EV charging. The results show that MAPE remains below 10% for most clusters under the random charging scenario, indicating that the retrained model

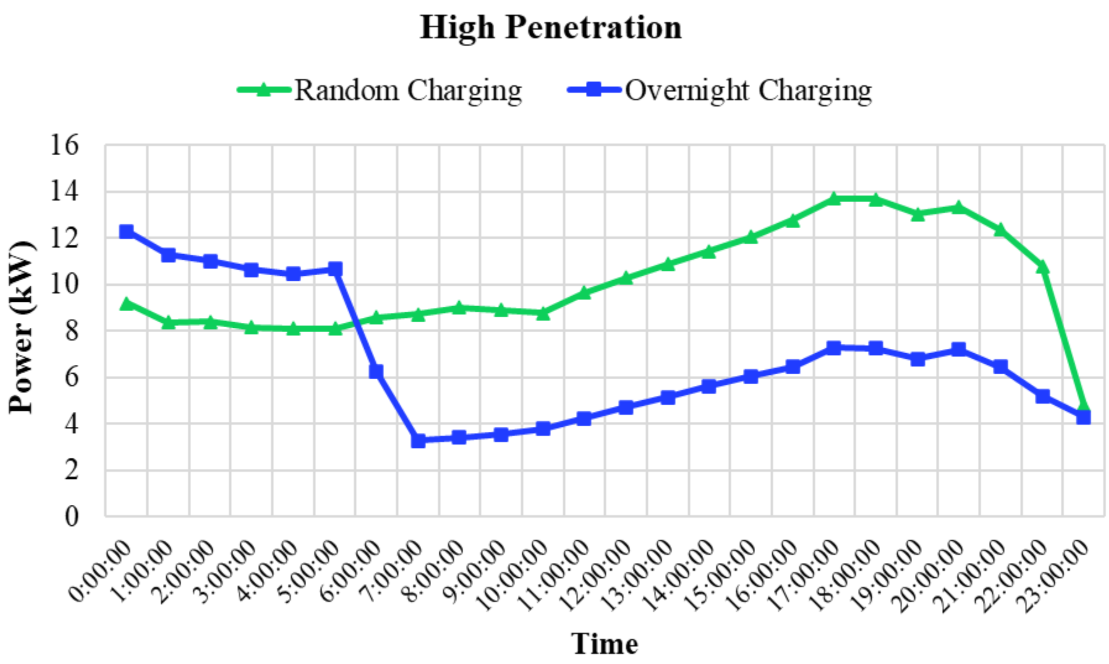


Fig. 4.28 Comparison between random and overnight charging under high EV penetration

is capable of capturing the increased variability in household load profiles when charging behaviour is dispersed across the day. However, forecasting accuracy declines in specific cases under overnight charging, with MAPE exceeding 10% in several clusters, most notably Cluster 8. This can be attributed to the high concentration of EV load during a narrow nighttime window, which significantly alters the peak demand pattern.

While the inclusion of EV charging as an input improved the model's ability to adapt to new load conditions, the synchronized nature of overnight charging presents a more complex challenge. The resulting sharp peaks are less represented in the original training data, the model struggles to fully generalize under these abrupt load changes. These findings imply that while retraining with EV related features improves performance, further enhancements may be necessary for scenarios with structured or peak heavy charging patterns.

However, it is important to note that the goal of this study was to assess the effectiveness of the retrained forecast model, not to optimize or fine tune it further for each specific case. The consistent approach across clusters and scenarios ensures a fair evaluation of model robustness in the face of increasing EV integration.

In conclusion, the retrained model demonstrates reasonable forecasting accuracy under varying levels of EV penetration, particularly when charging is uncoordinated. However, the decline in forecasting accuracy under overnight charging underscores the need for more adaptive forecasting strategies capable of capturing the increasingly non-linear and synchronized load spikes associated with overnight EV charging in high penetration residential environments.

Chapter 5

Impact of EV Charging Price Variations on Forecasting Models

5.1 Abstract

This chapter examines the relationship between residential EV charging prices and short-term load forecasting within the proposed forecasting framework. It investigates how different charging tariff structures and smart charging strategies can influence household charging behaviour and alter residential demand patterns. Building on the forecasting models developed in earlier chapters, the chapter evaluates how forecasted household demand can support more coordinated EV charging decisions, reduce peak demand, and improve the efficiency of residential energy management. The analysis also considers the implications of charging price signals for consumers, aggregators, and network operators, highlighting their role in supporting reliable and economically efficient EV integration.

5.2 Static Charging Price

Static or flat-rate charging price refers to a fixed pricing strategy in which the cost of electricity for EV charging remains constant, regardless of factors such as the time of day, grid load, or overall electricity demand [126]. Under this model, a uniform price is applied at all times, without any dynamic adjustments. For consumers, this approach offers convenience and simplicity, allowing them to charge their vehicles at their convenience without worrying about fluctuating costs. However, from the perspective of electricity providers, static pricing presents challenges, particularly during peak demand periods, as it does not incentivize load shifting or support grid balancing [127]. Although static pricing is commonly applied in residential settings due to its ease of implementation, it can contribute to increased stress on the power network, especially as EV adoption continues to increase. To ensure the optimal integration of EVs and maintain grid stability, relying on static charging prices alone is insufficient. Instead, there is a need to have more dynamic and adaptive solutions such as smart charging strategies.

5.3 Smart Charging Strategies

Smart charging strategies are developed to optimize EV charging such that it serves the interests of the involved stakeholders, including the power grid, charging aggregators, and end users. These approaches aim to balance electricity demand, lower overall costs, and facilitate the integration of renewable energy sources. A common principle underlying many of these strategies is the use of pricing mechanisms to influence consumer behaviour, encouraging them to adjust their charging patterns in response to cost incentives [128]. Below are the different types of pricing schemes and the different charging strategies for each pricing category. The outlined strategies focus on optimising pricing to achieve outcomes that benefit both utility providers and consumers. Studying these different pricing strategies is essential to identify which approaches are most suitable for various consumer groups, with particular emphasis on determining the optimal strategies for the residential sector.

5.3.1 Stochastic Pricing

Stochastic pricing is a form of dynamic pricing in which the cost of charging an EV fluctuates based on inherent uncertainties within the power system [129]. Unlike deterministic pricing models, where prices follow a fixed or predefined pattern, stochastic pricing accounts for random or unpredictable variables such as fluctuating renewable energy generation, market volatility, existing load, grid congestion, etc. These random factors introduce variability in supply and demand conditions, causing electricity prices to change dynamically and often unpredictably. As a result, charging decisions under stochastic pricing must adapt to uncertain and evolving conditions, making it more complex but potentially more efficient, especially in systems with high renewable penetration. This approach can be modeled using probabilistic methods or scenarios to simulate various outcomes and support more responsive and resilient EV charging strategies. Some types of stochastic pricing are discussed as below.

Emission Based Charging:

This strategy prioritizes EV charging during periods of low CO_2 emissions, aiming to reduce the environmental impact of EV usage [130]. There are two commonly employed approaches. The first involves charging the EV at full power during time windows when predicted CO_2 emissions are at their lowest, thereby aligning charging demand with periods of cleaner energy availability [131]. This method is relatively straightforward to implement but relies on accurate forecasts of carbon intensity. The second is a more dynamic method in which the charging power is continuously adjusted based on real time or forecasted emission levels. By adjusting the charging rate in response to fluctuations in renewable generation or grid conditions, this method achieves a finer balance between user requirements and emission reduction, though it requires more advanced control and communication infrastructure [130].

In the dynamic approach, the charging rate is directly influenced by the predicted CO_2 intensity of electricity generation. The maximum charging power is reserved for periods with the lowest emission levels, while higher emission periods result in proportionally reduced charging power or even a temporary halt to charging. This gradual modulation helps avoid short bursts of high-power charging that may coincide with periods of high-emission. Overall, the strategy encourages a smoother charging profile and supports cleaner grid operation by aligning EV energy consumption with low-carbon electricity availability. This type of charging is more commonly used in the commercial sector than among residential consumers.

Self-Consumption Charging:

This strategy is tailored for households equipped with photovoltaic (PV) systems, where EV charging is coordinated to align with solar energy production [132]. One approach is reactive, in which, charging is initiated only when there is sufficient surplus PV generation available. If the PV output drops below a certain threshold, charging is paused to avoid drawing electricity from the grid. An alternative approach is predictive, whereby charging is scheduled during periods of high expected solar irradiance, typically around midday when PV generation peaks [133]. By synchronizing EV charging with these periods of maximum solar output, the strategy enhances self-consumption of renewable energy, reduces dependency on grid electricity, and fosters more sustainable charging practices. For instance, Sykiotis et al. [133] demonstrate that an EV charging approach optimized via deep reinforcement learning to coincide with solar peaks can achieve an average PV utilisation exceeding 88%, while reducing consumer electricity costs by over 11%.

Priority or Forecast Based Charging:

Priority or forecast-based charging strategies determine EV charging schedules by integrating user-specific preferences or anticipated travel needs, such as desired departure times and target SOC. These approaches enable a personalized and efficient charging experience by synchronizing energy use with individual routines. However, they often rely on user input or behavioural data adding complexity to their deployment. In forecasting models, such strategies can be represented by including user-defined demand profiles or SOC targets. Within simulation frameworks, this integration can be executed by adjusting charging schedules to shift demand away from peak periods, applying dynamic price signals within Monte Carlo simulations to mimic price-driven behaviours, and incorporating probabilistic elements to capture variability in user behaviour during smart charging.

This concept aligns directly with the framework proposed by Li et al. [134], who introduce a driver-centered, resource-aware EV charging recommendation system. Their model balances user preferences i.e., when and where to charge with external rewards such as minimizing wait times or travel distance, effectively embodying a priority-based charging methodology.

5.3.2 Dynamic Pricing

Dynamic pricing is a flexible pricing mechanism in which the cost of charging an EV adjusts according to specific, known variables within the electricity system [135]. These variables may include real time grid conditions, TOU schedules, demand levels, and electricity market rates. By aligning prices with current system status, dynamic pricing encourages consumers to shift their charging behaviour to off-peak periods, thereby helping utility providers manage grid load more effectively and reduce the risk of congestion. For consumers, this strategy offers the potential for lower charging costs through timely response to price signals. Unlike stochastic pricing which is driven by uncertain or random factors such as unpredictable renewable generation, dynamic pricing is based on measurable conditions, making it more structured and predictable in nature.

This charging strategy is designed to take advantage of variations in electricity prices by scheduling EV charging during the most cost-effective hours. This approach typically relies on known electricity pricing schemes, such as spot market prices or TOU tariffs, which reflect fluctuations in demand and supply throughout the day. A predefined cost threshold is calculated based on user preferences or optimization objectives, and the EV is programmed to charge only when electricity prices fall below or match this threshold. This ensures that charging occurs during economically favorable periods, minimizing the overall energy cost to the consumer while still meeting the required state of charge by a given deadline.

Time-Of-Use Tariffs:

In a TOU tariff strategy, electricity prices are predetermined and vary according to specific periods within the day [136]. The day is typically divided into peak, off-peak, and sometimes mid-peak hours. Each time block is assigned with a different tariff rate. Under this pricing scheme, consumed electricity during off-peak hours, usually late at night or early in the morning costs significantly less than that of during peak demand periods, such as early evenings when residential consumption is at its highest. For instance, a consumer might be charged with a reduced rate of electricity between 23:00 hrs and 8:00 hrs, while facing higher rates between 17:00 hrs and 19:00 hrs at the elevated grid demand. This strategy encourages users to shift their energy usage, including EV charging, to times when the grid is under less strain, thereby promoting grid efficiency by flattening demand curve and lowering overall electricity costs for the users. However, it is not adaptive to real-time grid conditions and works well in scenarios where TOU tariffs are available.

Beyond cost savings, this strategy contributes to better grid management by encouraging load shifting away from peak demand periods. When implemented at scale, price-based charging can reduce grid congestion, improve system reliability, and support the integration of renewable energy sources by aligning charging behaviour with periods of high renewable generation. Additionally, this method offers flexibility for both utility providers and consumers, forming a critical component of demand-side management in smart grid environments [137].

5.3.3 Menu Based Pricing

Menu based pricing offers consumers a selection of predefined charging options, each with its own pricing structure and associated service conditions [138]. Instead of adhering to a single pricing model, users can choose from a menu of pricing based on their preferences, such as charging speed, flexibility, time of day usage, or environmental impact. These options may combine elements of different pricing schemes, for example, flat rates, TOU tariffs, or dynamic pricing, allowing for greater personalization and adaptability. This approach allows consumers to select the charging plan that best suits their lifestyle, driving habits, and cost saving goals, while also enabling utility providers to segment and manage demand more effectively.

The various smart charging strategies demonstrate that it is indeed possible to effectively regulate EV charging prices in a way that minimizes grid congestion and reduces charging costs compared to conventional, uncontrolled charging. Importantly, these benefits can be achieved without compromising user convenience ensuring that the vehicle reaches the desired SOC by the specified time, ready for the next trip [139].

5.4 EV Charging Mechanism in the Residential Sector

Different pricing schemes are adopted by various groups of consumers, depending on their specific needs and contexts. In the residential sector, this diversity is further shaped by the variety of dwelling types ranging from standalone houses to shared community buildings with common parking facilities. These different housing configurations influence the modes of EV charging available to residents. While some homeowners benefit from private, at-home charging setups, others, particularly those in shared or constrained parking environments, depend on communal charging stations. Such shared access often leads to limited availability and uncertain charging opportunities, presenting unique challenges for consistent EV charging.

In these scenarios, dynamic and stochastic charging strategies become particularly relevant. These approaches facilitate intelligent scheduling of charging sessions, offering multiple advantages; they alleviate peak load stress for grid operators, enable consumers to benefit from off-peak electricity prices, and give aggregators flexibility to design pricing schemes that optimize both grid performance and economic outcomes.

For instance, the study [140] introduces a menu based pricing mechanism, allowing EV users to select from a set of prices based on their desired charging completion deadlines. This strategy incentivizes users with greater flexibility to defer charging to low demand periods, reducing grid stress and improving cost efficiency. By monetizing deadline flexibility, this decentralized approach enhances grid reliability while empowering consumers with greater choice.

Similarly, the authors in [141] present an optimization framework for managing EV charging through real-time dynamic pricing. By sending time sensitive price signals that reflect grid conditions, the model shapes user behaviour to achieve load balancing across the network. This supports the argument that dynamic pricing can be an effective tool for managing distributed EV loads in residential areas.

A broader perspective is offered in [135], which categorizes key pricing models such as real-time pricing (RTP), time-of-use (TOU), critical peak pricing (CPP), and day ahead pricing. The review highlights how these mechanisms influence user charging patterns, encourage off-peak consumption, and support integration of renewable energy. It also addresses the challenges of implementing dynamic pricing, such as demand forecasting accuracy, consumer responsiveness, and designing incentive-compatible frameworks.

Dynamic pricing also shows promise in older residential buildings with shared charging infrastructure, where traditional charging schedules may not be feasible. In [142], the authors propose an adaptive TOU pricing scheme that is updated daily based on the previous day's load. This enables users to plan charging during lower demand periods, enhancing both user savings and grid efficiency.

Moreover, coordinated charging strategies are shown to be beneficial for all stakeholders. In particular, valley-filling charging during low-demand, low-cost periods helps reduce peak load stress. While aggregators may face reduced profit margins in these periods, the study [143] introduces an incentive mechanism to encourage aggregators to promote consumer behaviour change in favor of grid stability.

Coordinated charging has been recognized as an effective strategy for the optimal integration of EVs in the residential sector. As EVs represent a new category of flexible, yet often unpredictable, electrical loads, their inclusion along with other new loads introduce additional uncertainty into residential demand patterns, highlighting the need for accurate and responsive forecasting models. Given the significant influence of charging prices on user behaviour, it is essential to explore how pricing strategies affect residential load forecasting models. Integrating smart charging into forecasting frameworks enhances both their precision and applicability, particularly when assessing the impact of policy measures such as incentivized off-peak tariffs or vehicle-to-grid (V2G) initiatives. As EV adoption continues to rise, embedding pricing mechanisms within forecasting models becomes increasingly important for managing demand in a transitioning, decarbonized energy system. Therefore, understanding the role of dynamic charging strategies under TOU tariffs is crucial in evaluating how different pricing approaches influence the accuracy and effectiveness of residential load forecasting models. The following section discusses the impact of charging prices on forecast model performance.

5.5 Impact of Electric Vehicle Charging Price on Load Forecast Model

Most electricity retailers offer different tariff rates depending on consumer type. In the residential sector, static pricing or TOU pricing structures are predominantly used, with TOU tariffs being the most common form of dynamic pricing available to households. Under TOU schemes, electricity prices vary between peak and off-peak periods. Typically, peak hours occur in the morning from 7:00 to 11:00 and in the evening from 17:00 to 19:00, while the remaining hours are classified as off-peak.

Given that this thesis focuses on the residential sector, it is assumed that EV owners charge their vehicles at home, meaning their charging costs directly reflect household electricity tariffs. While advanced dynamic pricing mechanisms such as real time pricing are often discussed in research, their practical implementation in the residential sector remains limited, with TOU remaining the most widely adopted due to its simplicity and ease of integration for consumers.

Table 5.1 Electricity Rates

Time	Price ($/kWh)
Peak hours	0.0908
Off-peak hours	0.0108

In addition, shared EV charging facilities, such as those installed in apartment complexes or community housing with communal parking areas, are classified ambiguously within existing tariff structures. While these chargers are physically located within residential premises, they are often managed by body corporates or third-party providers and may operate under commercial or embedded network tariffs rather than standard residential rates. This is because the electricity consumed at these shared chargers is typically metered separately from individual household consumption and billed through commercial agreements or user pays systems.

Therefore, this study focuses on evaluating the impact of TOU tariffs on EV charging behaviour and residential load forecasting models. Table 5.1 presents the peak and off-peak electricity prices sourced from Wellington Electricity.

The pricing data reveals a distinct cost differential between peak and off-peak periods, emphasizing the financial advantage of scheduling EV charging during off-peak hours when electricity prices are considerably lower. By shifting demand to these low-tariff periods, households can achieve substantial cost savings, making off-peak charging a practical and economically attractive strategy. This cost-saving potential highlights the importance of evaluating forecast model performance under such scenarios, as it helps determine whether specific charging periods can be both accurately represented in forecasts and effectively adopted to balance economic benefits with system reliability

In a nutshell, this chapter solely focuses on EVs charged at home using private home chargers, where the charging costs directly align with household electricity tariffs. Limiting the scope in this way ensures that the analysis remains consistent with the TOU pricing structures typically adopted in the residential sector, without the added variability introduced by commercially managed shared charging facilities.

5.5.1 Methodology

To study the impact of pricing mechanisms on the proposed forecasting model, two evaluation strategies were considered. The first is a direct approach, in which explicit information on EV charging tariffs is incorporated into the forecasting model as an additional input variable and its performance is examined under various pricing conditions. The second is an indirect approach, which assumes that charging behaviour changes in response to price signals which includes shifting demand from peak to off-peak hours, and evaluates the model's performance under these alternative behavioural scenarios. As the dataset utilised in this work does not include detailed information on time-varying electricity tariffs, the indirect approach is adopted, based on realistic and widely used assumptions regarding typical TOU tariff structures i.e., higher prices during peak hours and lower prices during off-peak hours. Although this approach does not allow formal validation of the absolute accuracy of the price induced forecasting impact, it provides a meaningful comparative assessment of how the forecasting model responds to changes in charging behaviour that are consistent with price incentives. This is a common approach when tariff data are unavailable.

Based on the findings from the previous chapter, a medium EV penetration level (25–50%) is selected for the residential cluster under consideration, as this represents a realistic near-term adoption scenario in which pricing signals may influence charging decisions. Under this assumption, the forecasting model is first evaluated assuming that EVs are charged during peak hours in between 18:00 hrs and 22:00 hrs, representing a convenience-driven charging pattern. Subsequently, an off-peak overnight charging scenario i.e., charging after 22:00 hrs is considered to reflect a price-responsive behaviour that users may adopt in order to take advantage of lower tariffs. Following a similar methodology to the earlier chapter, EV load profiles are integrated under both charging patterns, and the model is tested for accuracy. A comparison of the forecasting accuracy obtained under these two charging scenarios enables an indirect assessment of the impact of pricing on residential EV load forecasting performance.

5.5.2 Results

To evaluate the effect of price-induced behavioural changes on the performance of the proposed load-forecasting model, two charging scenarios peak and off-peak are considered, as outlined in the previous section. These scenarios are designed to reflect convenience-based and price-responsive charging behaviours, respectively, under a medium level of EV penetration. By comparing the forecasting error obtained under each scenario, the impact of shifting EV charging away from the system peak can be assessed.

The forecasting performance, expressed in terms of MAPE, for EV charging during peak and off-peak hours are presented in Table 5.2. The results indicate that forecasting accuracy generally improves under off-peak charging conditions compared to peak-hour charging across most clusters. For instance, MAPE in Cluster 1 drops sharply from 32.48% during peak hours to 11.19% under off-peak charging, while improvements are also evident in Clusters 4, 7, and 9. This can be explained by the reduced variability of household demand during late-night periods, where EV charging becomes the dominant contributor to the load, making patterns more predictable for the forecasting model. In contrast, peak-hour charging coincides with already high and diverse household activities, such as cooking, heating, and appliance use, leading to more complex load profiles and increased forecast error. Certain clusters (e.g., Cluster 3, 5, and 8) show marginal or no improvement, reflecting persistent variability in some households even during night hours. It indicates that EV charging during peak hours not only poses operational challenges for the power system, such as increased congestion, but also compromises forecasting accuracy due to the model's inability to capture the sudden spike. Therefore, it becomes essential to adapt and fine tune the forecasting models to account for these new peak patterns, ensuring reliable predictions under EV penetration. Overall, these results demonstrate that off-peak charging is not only economically advantageous due to lower tariffs but also tends to yield higher forecasting accuracy, reinforcing the value of incorporating pricing considerations into forecasting studies.

Table 5.2 Forecasting Accuracy (MAPE) During Peak and Off-Peak EV Charging Periods

Cluster	Peak Hours	Off-Peak Hours
C1	32.48	11.19
C3	9.06	10.24
C4	11.52	5.43
C5	8.45	9.07
C7	13.05	8.83
C8	14.9	14.8
C9	18.01	6.35

While these results provide general insights, they do not fully capture the most critical operational conditions faced by the power system namely, the annual peak day, when demand is at its highest and the system is already under stress. Analysing the impact of EV charging on this specific day offers a more thorough understanding of how consumer charging behaviour, particularly in response to price signals, could exacerbate or alleviate system stress. Since electricity prices are typically highest during peak periods and lowest during off-peak periods, the annual peak day serves as an appropriate case study to investigate the implications of charging during high- versus low-price windows. Accordingly, EV charging profiles were superimposed onto the day with the highest recorded load within the year to evaluate the effects. Peak charging hours were defined from 18:00 hrs to 22:00 hrs, while off-peak charging was assumed to occur overnight from 00:00 hrs to 6:00 hrs. It is assumed that the battery's SOC, charging power, and charging duration remain identical for both scenarios; that is, the same charging power is drawn and the same number of hours is required to fully charge the battery regardless of whether charging takes place during peak or off-peak hours.

Fig. 5.1 illustrates how the timing of EV charging for directly relates to electricity price variation for Cluster 1. When EVs are charged during peak hours in between 18:00 hrs and 22:00 hrs, the resulting load profile i.e., the green curve coincides with the period of highest electricity prices. This amplifies the evening peak, increases overall system costs, and introduces sharp demand spikes that the forecasting model struggles to capture, thereby reducing accuracy. In contrast, off-peak charging (00:00– 6:00) occurs during low-price periods shown by the blue curve, where the additional EV demand remains below the natural evening peak. This not only lowers consumer charging costs but also preserves the stability of the load profile, enabling the forecasting model to maintain higher predictive accuracy. Thus, the relationship between charging time, price signals, and model performance is evident: peak-hour charging elevates both financial and operational risks, while off-peak charging aligns economic incentives with improved forecasting reliability.

Fig. 5.2 presents the same comparison for Cluster 3. As each cluster has a distinct load profile, the impact of EV integration also differs accordingly. In this case, under the medium penetration scenario, Cluster 3 includes only a single EV, and on the peak day, the charging duration is limited to one hour in both charging scenarios. During peak hours, the EV is plugged in at 21:00, resulting in a minor increase in overall load consumption that remains below the existing evening peak, which occurs around 18:00. For off-peak charging, although there is a noticeable rise in overnight load due to EV charging, it still remains below the evening peak. Consequently, in both charging scenarios, the additional EV load does not surpass the traditional peak, indicating that no upgrades or modifications to the existing infrastructure are required.

The impact of EV charging on Clusters 4 and 8 is illustrated in Fig. 5.3 and Fig. 5.4. In both clusters, EV charging results in an increase in load consumption; however, this additional load does not exceed the existing peak demand, regardless of whether charging occurs during peak or off-peak hours.

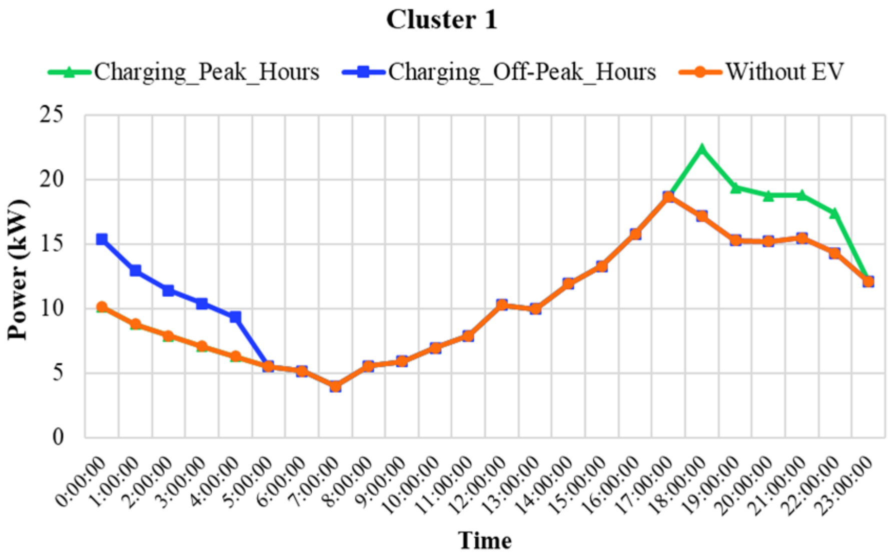


Fig. 5.1 Load profile of Cluster 1 under peak and off-peak EV charging scenarios

For Clusters 5,7 and 9, shown in Fig. 5.5, Fig. 5.6 and Fig. 5.7, EV integration leads to an increase in the overall load only when EVs are charged during peak hours. In these cases, the additional EV charging load coincides with the traditional evening peak, resulting in a combined peak that surpasses the existing one. Conversely, when EVs are charged during off-peak hours, the load remains below the evening peak in both clusters.

Given that electricity prices are typically lower during off-peak hours, charging EVs overnight not only reduces load congestion and avoids creating new demand peaks but is also a more economical option. Therefore, encouraging off-peak charging can support grid stability while eliminating the need for costly infrastructure upgrades.

5.6 Discussion

The findings highlight that differences in charging prices, and consequently in EV charging times, have a significant impact on forecasting model performance. When EVs are charged during off-peak hours, the forecasting accuracy remains high, suggesting that the load profile retains its typical structure, enabling the model to capture patterns effectively. This indicates that off-peak charging not only reduces grid congestion but also aligns well with the historical consumption data used to train forecasting models.

In contrast, peak hour EV charging significantly reduces forecasting accuracy. This is attributed to the overlap between EV charging demand and the existing evening residential peak, resulting in an amplified peak load that deviates from the model's learned patterns.

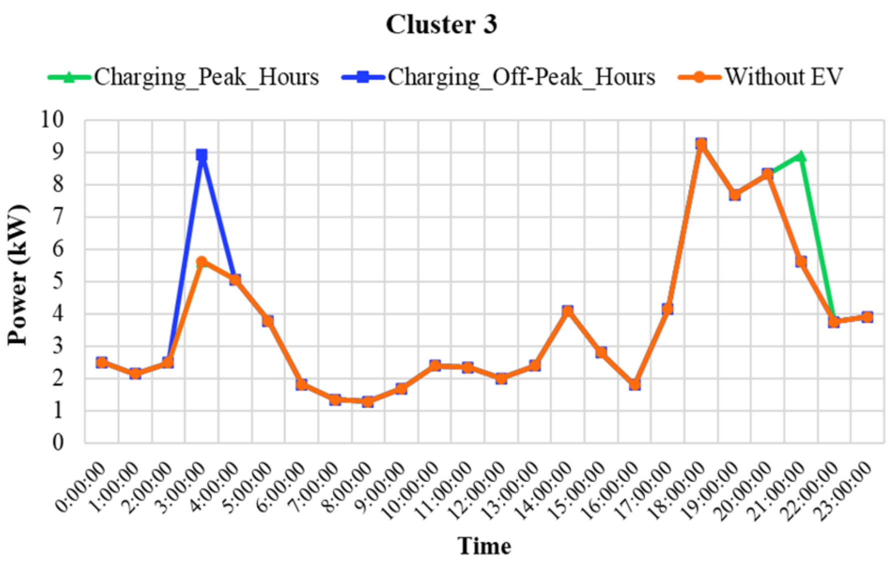


Fig. 5.2 Load profile of Cluster 3 under peak and off-peak EV charging scenarios

Essentially, the combined peak acts as an outlier relative to historical load profiles, which impacts model performance.

These findings underscore two critical considerations. First, from a power system operational perspective, peak hour EV charging increases the risk of grid congestion, voltage drops, and transformer overloading. Second, from a forecasting perspective, current models trained on traditional load profiles without significant EV integration are not adequately equipped to predict such structural changes in demand.

To address this, forecasting models must be adapted to incorporate EV charging behaviour explicitly, either through the inclusion of charging related features, retraining with integrated EV data, or adopting hybrid approaches that combine behavioural models with traditional forecasting techniques. Furthermore, implementing smart charging strategies that incentivise off-peak charging can benefit both system stability and forecast model accuracy, ensuring reliable grid operation under growing EV adoption.

Overall, these results emphasise the importance of aligning charging strategies, pricing schemes, and forecasting model design to achieve optimal outcomes in future decarbonised and electrified residential sectors.

In summary, this chapter examined the impact of EV charging prices on residential load forecasting models. The results demonstrated that charging behaviour influenced by pricing structures, such as peak versus off-peak charging, significantly affects forecast accuracy. In particular, EV charging during peak hours introduces substantial deviations in the load

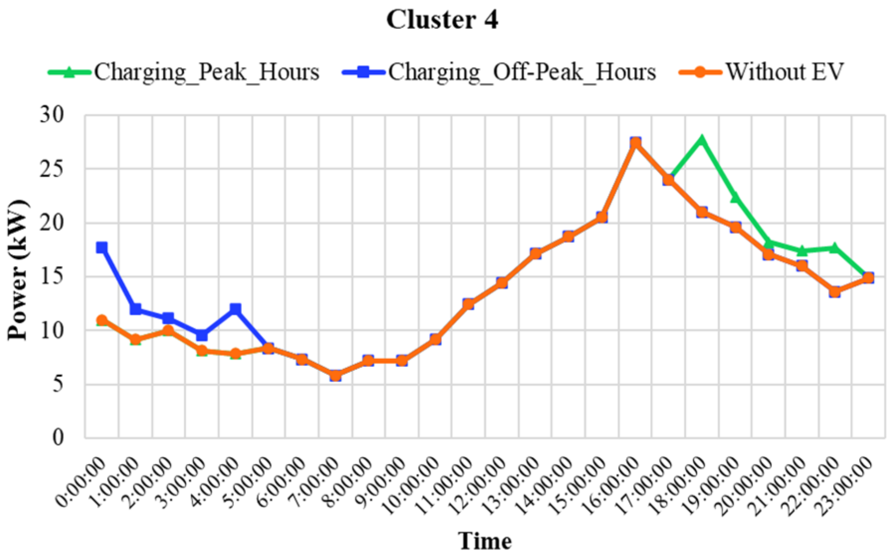


Fig. 5.3 Load profile of Cluster 4 under peak and off-peak EV charging scenarios

profile, reducing model performance, whereas off-peak charging aligns more closely with existing demand patterns, maintaining forecast reliability.

These findings highlight the need to integrate charging price considerations within forecasting frameworks, as pricing directly shapes user charging behaviour and, consequently, residential electricity demand. Developing models that account for such behavioural responses is essential for ensuring accurate forecasts in future power systems with widespread EV adoption and dynamic pricing mechanisms.

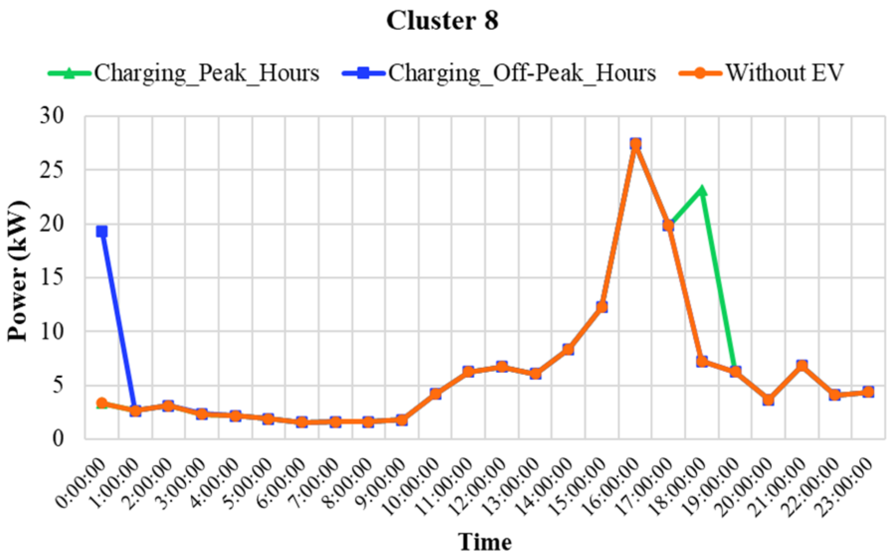


Fig. 5.4 Load profile of Cluster 8 under peak and off-peak EV charging scenarios

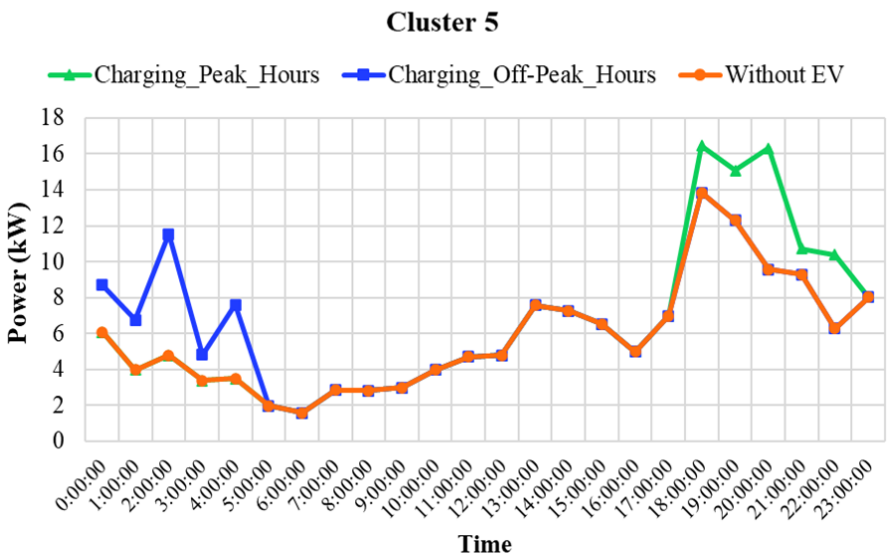


Fig. 5.5 Load profile of Cluster 5 under peak and off-peak EV charging scenarios

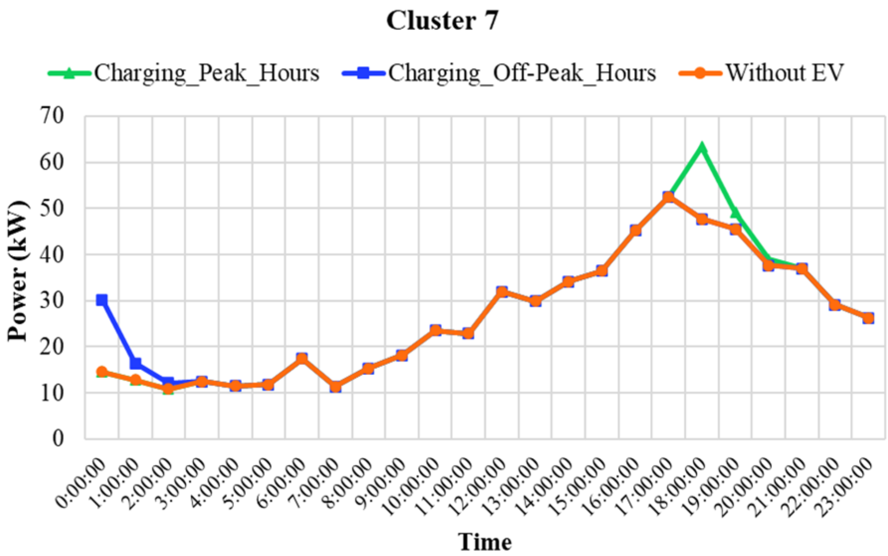


Fig. 5.6 Load profile of Cluster 7 under peak and off-peak EV charging scenarios

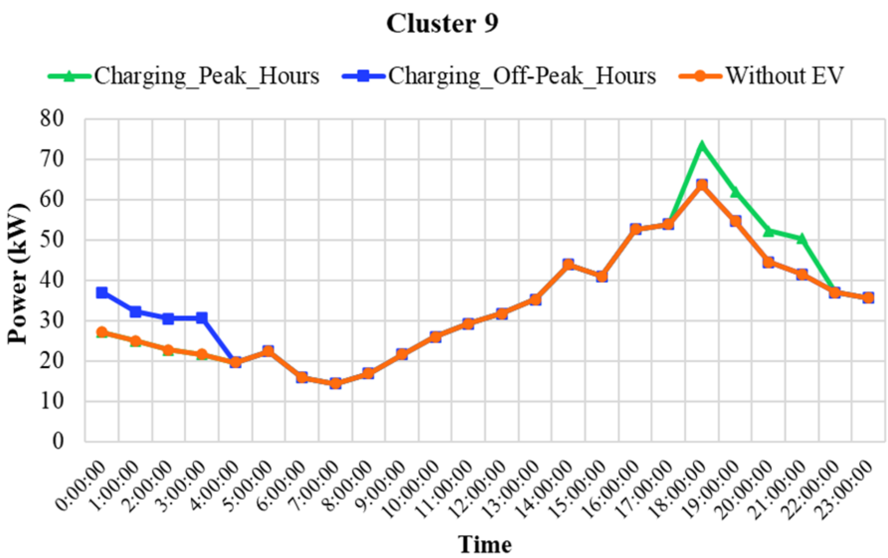


Fig. 5.7 Load profile of Cluster 9 under peak and off-peak EV charging scenarios

Chapter 6

Conclusion and Future Work

This chapter presents the concluding remarks of the research undertaken in this PhD study. It provides a concise summary of the key objectives, methodologies, and findings discussed in the preceding chapters. The chapter also reflects on the contributions made to the field of residential load forecasting and evaluates the impact of non-linear attributes onto the accuracy of forecasting performance. In addition, it highlights the main limitations encountered during the study and discusses future research opportunities that could further advance the development of intelligent forecasting frameworks.

6.1 Synopsis and Conclusion

Load forecasting plays a vital role in modern power systems by enabling optimal planning and efficient operation. Accurate short-term, hourly forecasts are essential for improving system efficiency and resilience. With the growing integration of renewable energy sources and the adaptation of non-linear loads such as EVs, load patterns particularly within the residential sector have become increasingly dynamic and complex. These changes have significantly altered the load profiles, posing new challenges for accurate forecasting. In response, this thesis presents the development of a novel hierarchical load forecasting model specifically tailored for the residential sector, offering insights across various levels of consumer aggregation.

6.1.1 Novel Hierarchical Forecast Model

In this research, a novel hierarchical load forecasting model was developed based on the principles of the top-down (TD) approach. The proposed model is designed to provide forecasts at multiple levels of the hierarchy from smaller consumer clusters to the aggregated sector level making it highly applicable for both operational planning and maintenance scheduling within modern power systems.

Traditionally, hierarchical forecasting has relied on the bottom-up (BU) approach, which involves training separate models for each disaggregated level and summing the results to obtain higher level forecasts. While this method often yields accurate results, it is computationally intensive and requires detailed fine grained data for each node at the lower level, which may not always be readily available.

In contrast, the TD approach has seen limited application, largely due to the perception that disaggregating forecasts from higher levels introduces error and reduces accuracy. This thesis challenges that notion by proposing two variations of TD-based hierarchical forecasting models, which offer a streamlined alternative requiring fewer models and input completely based on smart meter consumption data, which is easily available these days.

Both proposed TD models were evaluated against conventional statistical forecasting techniques such as ARIMA and support vector regression (SVR), as well as against the BU hierarchical approach. The results demonstrated that the TD-based models not only reduced computational overhead but also consistently outperformed the baseline models across all levels of the hierarchy in terms of forecasting accuracy.

This novel approach thus offers a scalable and efficient forecasting framework well-suited for the evolving dynamics of residential electricity demand, especially in the presence of increasingly heterogeneous load patterns driven by technologies like EVs.

6.1.2 Exploring Impact of Socio-demographics and Electric Vehicle Charging onto the Forecast Model

Given that residential electricity consumption is inherently variable and unpredictable, accurate load forecasting in this sector requires a thorough understanding of the factors driving this volatility. Among the many influences, two stand out as particularly relevant to residential consumers: the diversity in socio-demographic characteristics and the growing presence of EVs. This research therefore evaluated how both these aspects affect the performance of the proposed TD hierarchical forecasting model.

From a socio-demographic perspective, the study found that the variability within clusters plays a key role in determining forecast accuracy. Clusters exhibiting low demographic variability benefited from the inclusion of only a few demographic features as model inputs, which was sufficient to improve forecast performance. In contrast, clusters with high demographic diversity required a more extensive set of demographic features to achieve similar accuracy improvements. These findings underline the importance of tailoring model inputs to the demographic composition of consumer groups when forecasting at the cluster level.

In addition to socio-demographic impacts, the thesis also explored the effect of EV charging behaviours on residential load profiles. As detailed in Chapter 4, the study began by analysing baseline load patterns and clustering households based on their temporal consumption characteristics. EV charging demand was then modelled using a Monte Carlo simulation approach, which effectively captured the stochastic nature of real-world EV charging including uncertainties in arrival times, charging durations, and power levels.

Integrating these simulated EV loads into the baseline profiles revealed significant changes in consumption patterns, particularly under peak-hour charging scenarios. Most notably, load profiles displayed increased evening peaks, reflecting the common practice of charging vehicles after work hours. These shifts in load dynamics had a notable impact on cluster-level forecasting performance, highlighting the necessity of accounting for emerging non-linear loads such as EVs when designing predictive models.

Overall, the findings confirm that both socio-demographic diversity and EV charging behaviours introduce important variability into residential load profiles, and must be considered when developing accurate and robust forecasting frameworks. By explicitly incorporating these factors, the proposed TD-based forecasting model achieved improved accuracy and better adaptability to real-world residential consumption trends.

6.1.3 Correlation between Electric Charging Price and Charging Time with Impact Analysis onto the Forecast Model

The adoption of EVs is strongly influenced by the affordability and convenience of charging, with residential charging being the most preferred option due to its accessibility and cost-effectiveness. Most residential consumers tend to charge their EVs after returning home from work, a period that typically aligns with the evening peak in electricity demand. This peak period also corresponds with higher electricity tariffs, as energy retailers often implement TOU pricing structures that increase rates during high demand hours.

In this context, the thesis evaluates how shifting EV charging from peak to off-peak periods affects forecasting accuracy. By simulating different charging behaviours under varying pricing scenarios, the study analyses the extent to which price driven charging patterns impact the residential load profile and, in turn, the performance of the proposed forecasting model.

This analysis contributes to the development of a forecasting framework that is not only novel in its hierarchical structure but also specifically tailored to the unique characteristics of residential consumers. The model incorporates key behavioural drivers such as socio-demographic diversity, EV penetration, and charging behaviour influenced by TOU pricing. Through this comprehensive approach, the model captures realistic consumption trends, enhancing its applicability in modern residential energy systems.

6.2 Practical Implications

The proposed forecasting framework can provide practical value beyond improving predictive accuracy. The generated load forecasts can support operational planning, tariff design, infrastructure investment, and policy development across different parts of the electricity sector. The forecasting results can assist stakeholders in making more informed planning decisions. Table 6.1 summarises the potential use of the model outputs by different stakeholders.

Table 6.1 Potential Application for Stakeholders

Stakeholder	Potential application
Distribution network operators	Assess feeder-level load growth, identify EV-driven peak risks, plan network reinforcement
Electricity retailers	Develop dynamic tariffs, manage customer load profiles, forecast energy procurement needs.
System planners	For long-term infrastructure investment decisions
Researchers	To validate the model and improve future forecasting results

6.3 Limitations

While this study achieved its objectives, several limitations remain:

1. The residential load hierarchy in this work was built using clustering techniques applied to historical smart meter data. However, the clustering structure is static, meaning once a household is assigned to a cluster, it remains fixed. In reality, residential consumption patterns can evolve—for instance, when a new family moves in or household routines change. A promising extension would be to explore dynamic or adaptive clustering mechanisms that periodically reassess and reassign consumers to clusters based on their updated load profiles. Similarly, for newly connected consumers, automated cluster

allocation based on early consumption behaviour could improve model adaptability and scalability.

2. The forecasting models were developed and validated using data from specific geographic regions and household datasets. Although the results demonstrate strong performance within these contexts, the general applicability of the model across regions with varying consumption habits remains to be validated. Future work could test the model on diverse datasets to assess its robustness and adaptability.

6.4 Recommendations for Future Work

The current work in this thesis adopts a static clustering approach, where households are assigned to clusters based on their load consumption patterns. However, residential consumption profiles are not necessarily fixed and may evolve over time due to factors such as changes in household occupancy, installation of rooftop PV systems, or increased EV ownership. Such changes can significantly alter load behaviour, potentially making the initially assigned cluster less representative of the household's updated consumption pattern. Therefore, future research should investigate dynamic clustering approaches to determine their effectiveness in adapting to evolving load profiles. In addition, dynamic clustering could enable the automatic assignment of new households into appropriate clusters within the hierarchy, improving the practical applicability of the framework.

Furthermore, model generalisation could be strengthened by evaluating the proposed forecasting approach using datasets from different geographical regions and operating conditions. This would provide a more robust assessment of its transferability across diverse residential environments. Finally, with recent advancements in forecasting methodologies, attention-based architectures such as Transformers present a promising direction for future study. These methods could potentially enhance forecasting accuracy by enabling the model to focus on the most relevant temporal dependencies and input features within the data. To build upon the findings of this thesis, future studies could:

1. develop an online learning-based clustering system that automatically reassigns households to clusters based on streaming load data and profile drift detection.

2. create a hybrid framework that combines static clustering for stability and dynamic re-clustering for adaptability, with user defined thresholds for change.

3. evaluate model performance using real-world data from regions with different regulatory environments, climate zones, or electrification levels to test universality.

4. formulate an approach for dynamically classifying new consumers into existing clusters by analysing their initial usage patterns.

5. incorporate policy scenarios or V2G technologies to explore how bidirectional EV charging could affect both load patterns and forecast accuracy.

References

[1] U.S. Energy Information Administration. Today in energy: U.s. electric vehicle sales increased in 2018, 2019. Accessed: 17-Jul-2025.

[2] International Energy Agency (IEA). Approximately 100 million households rely on rooftop solar PV by 2030. Analysis, part of *Technology and innovation pathways for zero-carbon-ready buildings by 2030* technology report, September 2022. Licence: CC BY 4.0.

[3] Michael Zipf and Dominik Möst. Impacts of volatile and uncertain renewable energy sources on the german electricity system. In *2013 10th International Conference on the European Energy Market (EEM)*, pages 1–8. IEEE, 2013.

[4] Filipe Rodrigues, Carlos Cardeira, João MF Calado, and Rui Melicio. Short-term load forecasting of electricity demand for the residential sector based on modelling techniques: a systematic review. *Energies*, 16(10):4098, 2023.

[5] R. V. Jones, A. Fuertes, and K. J. Lomas. The socio-economic, dwelling and appliance related factors affecting electricity consumption in domestic buildings. *Renewable and Sustainable Energy Reviews*, 43:901–917, 2015.

[6] F. McLoughlin, A. Duffy, and M. Conlon. Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An irish case study. *Energy and Buildings*, 48:240–248, 2012.

[7] Khrisydel Rhea M. Supapo, Lorafe Lozano, Ian Dominic F. Tabañag, and Edward M. Querikiol. Untangling the impact of socio-demographic factors on energy consumption: Why is energy access difficult to achieve in off-grid island communities? *Energy for Sustainable Development*, 70:32–44, 2022.

[8] Wei Guan, Kenneth Chung, Kwok W Cheung, Xiaorong Sun, Peter B Luh, Laurent D Michel, and Stephen Corbo. Advanced load forecast with hierarchical forecasting capability. In *2013 IEEE Power & Energy Society General Meeting*, pages 1–5. IEEE, 2013.

[9] Rob J Hyndman, Roman A Ahmed, George Athanasopoulos, and Han Lin Shang. Optimal combination forecasts for hierarchical time series. *Computational statistics & data analysis*, 55(9):2579–2589, 2011.

[10] Seyedeh Narjes Fallah, Ravinesh Chand Deo, Mohammad Shojafar, Mauro Conti, and Shahaboddin Shamshirband. Computational intelligence approaches for energy load

forecasting in smart energy management grids: state of the art, future challenges, and research directions. *Energies*, 11(3):596, 2018.

[11] Shouxiang Wang, Xinyu Deng, Haiwen Chen, Qingyuan Shi, and Di Xu. A bottom-up short-term residential load forecasting approach based on appliance characteristic analysis and multi-task learning. *Electric Power Systems Research*, 196:107233, 2021.

[12] Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. Hierarchical structure based energy consumption forecasting in top-down approach. In *2022 7th Asia Conference on Power and Electrical Engineering (ACPEE)*, pages 1732–1737. IEEE, 2022.

[13] Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. End-to-end top-down load forecasting model for residential consumers. *Energies*, 17(11):2550, 2024.

[14] Barkha Parkash, Tek Tjing Lie, Weihua Li, and Shafiqur Rahman Tito. Ai-based electrical load forecasting for residential sector using smart meter data. In *Engineering Applications of AI for Demand Forecasting*, pages 230–254. CRC Press.

[15] L Budach, M Feuerpfeil, N Ihde, A Nathansen, N Noack, H Patzlaff, H Harmouch, and F Naumann. The effects of data quality on ml-model performance. arxiv, 2022.

[16] Xiaorong Sun and Chenhao Jin. Impacts of solar penetration on short-term net load forecasting at the distribution level. In *2021 IEEE 4th International Electrical and Energy Conference (CIEEC)*, pages 1–6. IEEE, 2021.

[17] Fankun Bu, Kaveh Dehghanpour, Yuxuan Yuan, Zhaoyu Wang, and Yifei Guo. Disaggregating customer-level behind-the-meter pv generation using smart meter data and solar exemplars. *IEEE Transactions on Power Systems*, 36(6):5417–5427, 2021.

[18] Baran Yildiz, Jose I Bilbao, Jonathon Dore, and Alistair B Sproul. Short-term forecasting of individual household electricity loads with investigating impact of data resolution and forecast horizon. *Renewable Energy and Environmental Sustainability*, 3:3, 2018.

[19] Margaux Brégère and Malo Huard. Online hierarchical forecasting for power consumption data. *International Journal of Forecasting*, 38(1):339–351, 2022.

[20] Mobolaji Shobanke, Mehul Bhatt, and Ekundayo Shittu. Advancements and future outlook of artificial intelligence in energy and climate change modeling. *Advances in Applied Energy*, page 100211, 2025.

[21] Farhan Amir Fardush Sham, Ahmed El-Shafie, Wan Zurina Wan Jaafar, Mohsen Sherif, Al Mahfoodh Ali Najah Ahmed, et al. Advances in ai-based rainfall forecasting: A comprehensive review of past, present, and future directions with intelligent data fusion and climate change models. *Results in Engineering*, page 105774, 2025.

[22] Isaac Kofi Nti, Moses Teimeh, Owusu Nyarko-Boateng, and Adebayo Felix Adekoya. Electricity load forecasting: a systematic review. *Journal of Electrical Systems and Information Technology*, 7(1):13, 2020.

[23] Saima Akhtar, Sulman Shahzad, Asad Zaheer, Hafiz Sami Ullah, Heybet Kilic, Radomir Gono, Michał Jasiński, and Zbigniew Leonowicz. Short-term load forecasting models: A review of challenges, progress, and the road ahead. *Energies*, 16(10):4060, 2023.

[24] Xiaosheng Peng, Diyuan Deng, Jinyu Wen, Lei Xiong, Shuanglei Feng, and Bo Wang. A very short term wind power forecasting approach based on numerical weather prediction and error correction method. In *2016 China International Conference on Electricity Distribution (CICED)*, pages 1–4. IEEE, 2016.

[25] Archee Gupta, Kailash Chand Sharma, Archita Vijayvargia, and Rohit Bhakar. Very short term wind power prediction using hybrid univariate arima-garch model. In *2019 8th International Conference on Power Systems (ICPS)*, pages 1–6. IEEE, 2019.

[26] Lian Tan, Jing Han, and Hongtao Zhang. Ultra-short-term wind power prediction by salp swarm algorithm-based optimizing extreme learning machine. *IEEE Access*, 8:44470–44484, 2020.

[27] Yubo Tao, Yafei Zhang, Bo Chen, and Jing Shi. A combined approach for very short term wind power probability forecast. In *2018 International Conference on Power System Technology (POWERCON)*, pages 874–880. IEEE, 2018.

[28] Jie Shi, Zhaohao Ding, Wei-Jen Lee, Yongping Yang, Yongqian Liu, and Mingming Zhang. Hybrid forecasting model for very-short term wind power forecasting based on grey relational analysis and wind speed distribution features. *IEEE Transactions on Smart Grid*, 5(1):521–526, 2013.

[29] Lu Qiuyu, CAI Qiuna, LIU Sijie, YANG Yun, Yan Binjie, Wang Yang, and Zhou Xinsheng. Short-term load forecasting based on load decomposition and numerical weather forecast. In *2017 IEEE Conference on Energy Internet and Energy System Integration (EI2)*, pages 1–5. IEEE, 2017.

[30] Yan Liu, Ruijuan Zheng, Muhua Liu, Junlong Zhu, Xuhui Zhao, and Mingchuan Zhang. Short-term load forecasting model based on time series clustering and transformer in smart grid. *Electronics*, 14(2):230, 2025.

[31] Michael Negnevitsky, Paras Mandal, and Anurag K Srivastava. An overview of forecasting problems and techniques in power systems. In *2009 IEEE Power & Energy Society General Meeting*, pages 1–4. IEEE, 2009.

[32] Arunesh Kumar Singh, S Khatoon, Md Muazzam, Devendra Kumar Chaturvedi, et al. Load forecasting techniques and methodologies: A review. In *2012 2nd international conference on power, control and embedded systems*, pages 1–10. IEEE, 2012.

[33] N Phuangpornpitak and W Prommee. A study of load demand forecasting models in electric power system operation and planning. *GMSARN International Journal*, 10(2016):19–24, 2016.

[34] Milind Kolambe and Sandhya Arora. Forecasting the future: A comprehensive review of time series prediction techniques. *Journal of Electrical Systems*, 20(2s):575–586, 2024.

[35] Giancarlo Aquila, Lucas Barros Scianni Morais, Victor Augusto Durães de Faria, José Wanderley Marangon Lima, Luana Medeiros Marangon Lima, and Anderson Rodrigo de Queiroz. An overview of short-term load forecasting for electricity systems operational planning: Machine learning methods and the brazilian experience. *Energies*, 16(21):7444, 2023.

[36] Arunesh Kumar Singh, S Khatoon Ibraheem, Md Muazzam, and DK Chaturvedi. An overview of electricity demand forecasting techniques. *Network and complex systems*, 3(3):38–48, 2013.

[37] Rob Hyndman, Anne Koehler, Keith Ord, and Ralph Snyder. *Forecasting with exponential smoothing: the state space approach*. Springer, 2008.

[38] George E. P. Box, Gwilym M. Jenkins, Gregory C. Reinsel, and Greta M. Ljung. *Time Series Analysis: Forecasting and Control*. John Wiley & Sons, Hoboken, NJ, 5 edition, 2015.

[39] Leo Breiman, Jerome Friedman, Richard A Olshen, and Charles J Stone. *Classification and regression trees*. Chapman and Hall/CRC, 2017.

[40] Evangelos Spiliotis et al. Decision trees for time-series forecasting. *Foresight*, 1:30–44, 2022.

[41] Geoffrey K. F. Tso and Kelvin K. W. Yau. Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. *Energy*, 32(9):1761–1768, September 2007.

[42] A. Abdulsalam et al. Electric power load forecast using decision tree algorithms. Unpublished manuscript or technical report, 2015. Includes comparison of CART, REPTree, and Decision Stump algorithms using WEKA.

[43] Jiashen Fu. A review of load forecasting technology based on artificial intelligence. *Applied and Computational Engineering*, 90(1):89–92, October 2024.

[44] Leo Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

[45] Ali Lahouar and Jaleleddine Ben Hadj Slama. Random forests model for one day ahead load forecasting. In *Proceedings of the 6th International Renewable Energy Congress (IREC)*, Sousse, Tunisia, March 2015. IEEE.

[46] Mohammad Belal Aziz and Syed Wajahat Abbas Rizvi. Comparative analysis of machine learning algorithms for heart disease prediction. *International Journal of Computer Applications*, 187(5):62–65, May 2025.

[47] Vladimir Cherkassky and Yunqian Ma. Practical selection of svm parameters and noise estimation for svm regression. *Neural networks*, 17(1):113–126, 2004.

[48] Chellai Fatih. Forecasting models based on fuzzy logic: An application on international coffee prices. *Econometrics. Ekonometria. Advances in Applied Data Analytics*, 26(4):1–16, 2022.

[49] Luis Palomero, Vicente Garcia, and José Salvador Sánchez. Fuzzy-based time series forecasting and modelling: a bibliometric analysis. *Applied Sciences*, 12(14):6894, 2022.

[50] Konstantinos Plakas, Ioannis Karampinis, Panayiotis Alefragis, Alexios Birbas, Michael Birbas, and Alex Papalexopoulos. A predictive fuzzy logic model for forecasting electricity day-ahead market prices for scheduling industrial applications. *Energies*, 16(10):4085, 2023.

[51] Vladimir Urošević. Short-term electrical load forecast using fuzzy logic in python. Medium article, 2024. Demonstrates using scikit-fuzzy (skfuzzy) in Python for forecasting short-term electrical load using historical consumption and weather data from Serbia (2016–2022).

[52] Mahmoud Khamaira and Saleem Altaeb. A fuzzy logic model for short-term load forecasting in the libyan power network. *University of Zawia Journal of Engineering Sciences and Technology*, 2(2):146–157, 2024.

[53] D. Ali, M. Yohanna, M. I. Puwu, and B. M. Garkida. Long-term load forecast modelling using a fuzzy logic approach. *Pacific Science Review A: Natural Science and Engineering*, 18:123–127, 2016.

[54] Krzysztof Drachal and Michał Pawłowski. A review of the applications of genetic algorithms to forecasting prices of commodities. *Economies*, 9(1):6, 2021.

[55] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521(7553):436–444, 2015.

[56] Cao Thi Nhien, Dang Ngoc Hung, and Vu Thi Thanh Bình. Using random forest and artificial neural network to detect fraudulent financial reporting: Data from listed companies in vietnam. *Calitatea*, 25(202):160–173, 2024.

[57] Raunaq Vohra, Kratarth Goel, and Jajati Keshari Sahoo. Modeling temporal dependencies in data using a dbn-lstm. In *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, pages 1–4. IEEE, 2015.

[58] Bon-Gil Koo, Min-Seok Kim, Kyu-Han Kim, Hee-Tae Lee, June-Ho Park, and Cheol-Hong Kim. Short-term electric load forecasting using data mining technique. In *2013 7th International Conference on Intelligent Systems and Control (ISCO)*, pages 153–157. IEEE, 2013.

[59] Huaiguang Jiang, Yingchen Zhang, Eduard Muljadi, Jun Jason Zhang, and David Wenzhong Gao. A short-term and high-resolution distribution system load forecasting approach using support vector regression with hybrid parameters optimization. *IEEE Transactions on Smart Grid*, 9(4):3341–3350, 2016.

[60] Joe H Chow, Felix F Wu, and James A Momoh. Applied mathematics for restructured electric power systems. In *Applied Mathematics for Restructured Electric Power Systems: Optimization, Control, and Computational Intelligence*, pages 1–9. Springer, 2005.

[61] João Pedro Gouveia and Júlia Seixas. Unraveling electricity consumption profiles in households through clusters: Combining smart meters and door-to-door surveys. *Energy and buildings*, 116:666–676, 2016.

[62] Chengjin Ye, Yi Ding, Peng Wang, and Zhenzhi Lin. A data-driven bottom-up approach for spatial and temporal electric load forecasting. *IEEE Transactions on Power Systems*, 34(3):1966–1979, 2019.

[63] Rob J Hyndman and George Athanasopoulos. *Forecasting: principles and practice*. OTexts, 2018.

[64] Franklin L Quilumba, Wei-Jen Lee, Heng Huang, David Y Wang, and Robert L Szabados. Using smart meter data to improve the accuracy of intraday load forecasting considering customer behavior similarities. *IEEE transactions on smart grid*, 6(2):911–918, 2014.

[65] Tao Hong and Shu Fan. Probabilistic electric load forecasting: A tutorial review. *International Journal of Forecasting*, 32(3):914–938, 2016.

[66] Rui Xu and Don Wunsch. *Clustering*. John Wiley & Sons, 2008.

[67] Amit Saxena, Mukesh Prasad, Akshansh Gupta, Neha Bharill, Om Prakash Patel, Aruna Tiwari, Meng Joo Er, Weiping Ding, and Chin-Teng Lin. A review of clustering techniques and developments. *Neurocomputing*, 267:664–681, 2017.

[68] Gianfranco Chicco, Roberto Napoli, Federico Piglione, Petru Postolache, Mircea Scutariu, and Cornel Toader. Emergent electricity customer classification. *IEE Proceedings-Generation, Transmission and Distribution*, 152(2):164–172, 2005.

[69] Vladimir Urošević and Andrej M. Savić. Temporal clustering for accurate short-term load forecasting using bayesian multiple linear regression. *Applied Intelligence*, 55(1), November 2024.

[70] Wenhui Zeng, Jiarui Li, Changchun Sun, Lin Cao, Xiaoping Tang, Shaolong Shu, and Junsheng Zheng. Ultra short-term power load forecasting based on similar day clustering and ensemble empirical mode decomposition. *Energies*, 16(4):1989, February 2023.

[71] SM Bidoki, N Mahmoudi-Kohan, MH Sadreddini, M Zolghadri Jahromi, and MP Moghaddam. Evaluating different clustering techniques for electricity customer classification. In *IEEE PES T&D 2010*, pages 1–5. IEEE, 2010.

[72] Alexander Tureczek, Per Sieverts Nielsen, and Henrik Madsen. Electricity consumption clustering using smart meter data. *Energies*, 11(4):859, 2018.

[73] László Czétány, Viktória Vámos, Miklós Horváth, Zsuzsa Szalay, Adrián Mota-Babiloni, Zsófia Deme-Bélafi, and Tamás Csoknyai. Development of electricity consumption profiles of residential buildings based on smart meter data clustering. *Energy and Buildings*, 252:111376, 2021.

[74] Simone Eiraudo, Luca Barbierato, Roberta Giannantonio, Alessandro Porta, Andrea Lanzini, Romano Borchiellini, Enrico Macii, Edoardo Patti, and Lorenzo Bottaccioli. A machine learning based methodology for load profiles clustering and non-residential buildings benchmarking. *IEEE Transactions on Industry Applications*, 59(3):2963–2973, 2023.

[75] George J Tsekouras, Nikos D Hatziargyriou, and Emmanuel N Dialynas. Two-stage pattern recognition of load curves for classification of electricity customers. *IEEE Transactions on Power Systems*, 22(3):1120–1128, 2007.

[76] Qidi Wu, Xiaojun Qi, Edgar Fuller, and Cun-Quan Zhang. "follow the leader": A centrality guided clustering and its application to social network analysis. *The Scientific World Journal*, 2013:1–10, 2013.

[77] Gianfranco Chicco, Roberto Napoli, and Fabio Piglione. Comparisons among clustering techniques for electricity customer classification. *IEEE Transactions on Power Systems*, 21(2):933–940, 2006.

[78] Sergio García, Sergio L Toral, Federico Barrero, Luis Gallardo, and José Gómez. Two-level clustering methodology for smart metering data. *IEEE Transactions on Industrial Informatics*, 16(1):134–143, 2020.

[79] Fadi AlMahamid and Katarina Grolinger. Agglomerative hierarchical clustering with dynamic time warping for household load curve clustering. In *2022 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, October 2022.

[80] Min Xiang, Huayang Rao, Tong Tan, Zaiqian Wang, and Yue Ma. Abnormal behaviour analysis algorithm for electricity consumption based on density clustering. *The Journal of Engineering*, 2019(10):7250–7255, October 2019.

[81] Vasilis Michalakopoulos, Elissaios Sarmas, Ioannis Papias, Panagiotis Skaloumpakas, Vangelis Marinakis, and Haris Ch. Doukas. A machine learning-based framework for clustering residential electricity load profiles to enhance demand response programs. *Applied Energy*, 361:122943, May 2024.

[82] Claes Sandels, Joakim Widén, Andreas Molin, and Lars Nordström. Clustering residential customers with smart meter data using a data analytic approach. In *2019 IEEE Milan PowerTech*, pages 1–6. IEEE, 2019.

[83] Yue Yao, Xiaowei Zhang, and Dong Zhang. Residential electricity behavior classification model based on sparse denoising autoencoder and k-means. *Energy Reports*, 9:1536–1548, 2023.

[84] Gianfranco Chicco. Overview and performance assessment of the clustering methods for electrical load pattern grouping. *Energy*, 42(1):68–80, 2012.

[85] Teemu Räsänen and Mikko Kolehmainen. Feature-based clustering for electricity use time series data. In *International conference on adaptive and natural computing algorithms*, pages 401–412. Springer, 2009.

[86] Aleksandra Dedinec, Sonja Filiposka, Aleksandar Dedinec, and Ljupco Kocarev. Deep belief network based electricity load forecasting: An analysis of macedonian case. *Energy*, 115(P3):1688–1700, 2016.

[87] S. Zheng, Q. Zhong, L. Peng, and X. Chai. A simple method of residential electricity load forecasting by improved bayesian neural networks. *Mathematical Problems in Engineering*, 2018:1–10, 2018.

[88] P. Kádár and R. Lovassy. Spatial load forecast for electric vehicles. In *2012 4th IEEE International Symposium on Logistics and Industrial Informatics*, pages 163–168. IEEE, September 2012.

[89] J. Zhu, Z. Yang, M. Mourshed, Y. Guo, Y. Zhou, Y. Chang, and S. Feng. Electric vehicle charging load forecasting: A comparative study of deep learning approaches. *Energies*, 12(14):2692, 2019.

[90] J. S. Telle, N. Maitanova, T. Steens, B. Hanke, K. von Maydell, and M. Grottke. Combined pv power and load prediction for building-level energy management applications. In *2020 Fifteenth International Conference on Ecological Vehicles and Renewable Energies (EVER)*, pages 1–15. IEEE, September 2020.

[91] Naqash Ahmad, Yazeed Ghadi, Muhammad Adnan, and Mansoor Ali. Load forecasting techniques for power system: Research challenges and survey. *IEEE Access*, 10:71054–71090, 2022.

[92] Philip Hans Franses. A note on the mean absolute scaled error. *International Journal of Forecasting*, 32(1):20–22, 2016.

[93] Jack Kelly and William Knottenbelt. The uk-dale dataset, domestic appliance-level electricity demand and whole-house demand from five uk homes. *Scientific data*, 2(1):1–14, 2015.

[94] David Murray, Lina Stankovic, and Vladimir Stankovic. An electrical load measurements dataset of united kingdom households from a two-year longitudinal study. *Scientific Data*, 4:160122, 2017.

[95] Ben Anderson, David Eyers, Rebecca Ford, Diana Giraldo Ocampo, Rana Peniamina, Janet Stephenson, Kiti Suomalainen, Lara Wilcocks, and Michael Jack. New zealand green grid household electricity demand study 2014-2018. 2018.

[96] Pecan Street, Inc. Pecan street dataport. Dataset and data portal, 2020. Minute-interval residential energy use data spanning appliance-level consumption, EV charging, rooftop solar, water use, etc.

[97] P. Schober, C. Boer, and L. A. Schwarte. Correlation coefficients: appropriate use and interpretation. *Anesthesia & Analgesia*, 126(5):1763–1768, 2018.

[98] Z. Wang, J. Li, S. Zhu, J. Zhao, S. Deng, S. Zhong, and Z. Gan. A review of load forecasting of the distributed energy system. In *IOP Conference Series: Earth and Environmental Science*, volume 237, page 042019. IOP Publishing, 2019.

[99] Bishnu Nepal, Motoi Yamaha, Aya Yokoe, and Toshiya Yamaji. Electricity load forecasting using clustering and arima model for energy management in buildings. *Japan Architectural Review*, 3(1):62–76, 2020.

[100] Ane Blazquez-Garcia, Angel Conde, Aitor Milo, Roberto Sánchez, and Irantzu Barrio. Short-term office building elevator energy consumption forecast using sarima. *Journal of Building Performance Simulation*, 13(1):69–78, 2020.

[101] Phoong Seuk Yen et al. Seasonal autoregressive integrated moving average model for forecasting tourist arrivals in malaysia. *Review of International Geographical Education Online*, 11(4):790–797, 2021.

[102] Bin Zhong. Deep learning integration optimization of electric energy load forecasting and market price based on the ann–lstm–transformer method. *Frontiers in Energy Research*, 11:1292204, 2023.

[103] A. Rafati, M. Joorabian, and E. Mashhour. An efficient hour-ahead electrical load forecasting method based on innovative features. *Energy*, 201:117511, 2020.

[104] M. Kim. Characteristics and determinants by electricity consumption level of households in korea. *Energy Reports*, 4:70–76, 2018.

[105] B. Nepal, M. Yamaha, A. Yokoe, and T. Yamaji. Electricity load forecasting using clustering and arima model for energy management in buildings. *Japan Architectural Review*, 3(1):62–67, 2020.

[106] Y. Dai and P. Zhao. A hybrid load forecasting model based on support vector machine with intelligent methods for feature selection and parameter optimization. *Applied Energy*, 279:115332, 2020.

[107] A. Blázquez-García, A. Conde, A. Milo, R. Sánchez, and I. Barrio. Short-term office building elevator energy consumption forecast using sarima. *Journal of Building Performance Simulation*, 13(1):69–78, 2020.

[108] Z. Kang, M. Jin, and C. J. Spanos. Modeling of end-use energy profile: An appliance-data-driven stochastic approach. In *Proceedings of the IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society*, pages 5382–5388, Dallas, TX, USA, 2014.

[109] Gesche Huebner, Jack Cooper, Benjamin Jones, David Shipworth, Clare Elwell, Tadj Oreszczyn, and Sotiris Vardoulakis. Understanding electricity consumption: A comparative contribution of building factors, socio-demographics, appliances, behaviours and attitudes. *Applied Energy*, 177:692–702, 2016.

[110] Bo Li, Minyou Chen, Daniel M. Kammen, Wenfa Kang, Xiao Qian, and Leiqi Zhang. Electric vehicle's impacts on china's electricity load profiles based on driving patterns and demographics. *Energy Reports*, November 2021.

[111] Andrew S. Jin and Kelly T. Sanders. Characterizing residential sector load curves from smart meter datasets. *Applied Energy*, 366:123316, July 2024.

[112] Nicola Mihaylov, Boris Evstatiev, Seher Kadirova, Tzvetelin Gueorguiev, Tsvetelina Georgieva, and Aleksandar Evtimov. Load profile of typical residential buildings in bulgaria. In *IOP Conference Series: Earth and Environmental Science*, volume 172 of *4th International Scientific Conference SEA-CONF 2018*, page 012035, 2018.

[113] Juan A Dominguez-Jimenez, Javier E Campillo, Oscar Danilo Montoya, Enrique Delahoz, and Jesus C Hernández. Seasonality effect analysis and recognition of charging behaviors of electric vehicles: A data science approach. *Sustainability*, 12(18):7769, 2020.

[114] Jonathan Dowds, Sarah Howerter, Paul Hines, and Lisa Aultman-Hall. Integrated modeling of electric vehicle energy demand and regional electricity generation. 2024.

[115] Vikram Singh, Loveleen Kaur, and Jagdish Kumar. A review on electric vehicle charging and dc-dc converter topologies. In *2022 1st International Conference on Sustainable Technology for Power and Energy Systems (STPES)*, pages 1–6. IEEE, 2022.

[116] Mohamed El-Hendawi, Zhanle Wang, Raman Paranjape, Shea Pederson, Darcy Kozoriz, and James Fick. Electric vehicle charging model in the urban residential sector. *energies*, 15(13):4901, 2022.

[117] Weijie Jiang, Hamza Ameer, and Yujie Wang. Electric vehicle user profiling and spatiotemporal charging demand forecasting based on monte carlo method. In *2024 IEEE 25th China Conference on System Simulation Technology and its Application (CCSSTA)*. IEEE, 2024.

[118] Sheetal Deshmukh, Thamer Al-Abdullah, Mohsen P. Moghaddam, and Hemanshu R. Pota. Impact assessment of electric vehicles integration and optimal charging schemes under uncertainty: A case study of qatar. *IEEE Access*, 2024.

[119] As'ad Zakaria, Chengyan Duan, and Sasa Z. Djokic. Hosting capacity of distribution networks for controlled and uncontrolled residential ev charging with static and dynamic thermal ratings of network components. *IET Generation, Transmission & Distribution*, 18(6):1283–1301, 2024.

[120] Nattavit Piamvilai and Somporn Sirisumrannukul. Load profile simulations for smart charging of electric vehicles considering driving behavior and vehicle performance. In *2021 3rd International Conference on Smart Power & Internet Energy Systems (SPIES)*, pages 65–70. IEEE, 2021.

[121] W. Du, P. W. G. Bots, and J. G. Slootweg. Monte carlo simulation of load profiles for low-voltage electricity distribution grid asset planning. In *Proceedings of the 21st International Conference on Electricity Distribution (CIRED 2011)*, pages 1–4, Frankfurt, Germany, June 2011. CIRED. Paper No. 1016.

[122] Dinghao Liu, Yifan Li, Wei Zhang, Yudong Zhao, Bin Zhang, and Haibo Gao. Electric vehicle load forecast based on monte carlo algorithm. In *2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, volume 9, pages 530–534. IEEE, 2020.

[123] Åse Lekang Sørensen, Maria Claire Westad, Benjamín Manrique Delgado, and Karen Byskov Lindberg. Stochastic load profile generator for residential ev charging. In *E3S Web of Conferences*, volume 362, page 03005. EDP Sciences, 2022.

[124] David Fischer, Alexander Harbrecht, Arne Surmann, and Russell McKenna. Electric vehicles' impacts on residential electric local profiles–a stochastic modelling approach considering socio-economic, behavioural and spatial factors. *Applied energy*, 233:644–658, 2019.

[125] HJ Wang, B Wang, C Fang, W Li, and HW Huang. Charging load forecasting of electric vehicle based on charging frequency. In *IOP Conference Series: Earth and Environmental Science*, volume 237, page 062008. IOP Publishing, 2019.

[126] Xinwei Li and Alan Jenn. Energy, emissions, and cost impacts of charging price strategies for electric vehicles. *Environmental science & technology*, 56(9):5724–5733, 2022.

[127] Miadreza Shafie-Khah, Ehsan Heydarian-Forushani, Gerardo J Osório, Fábio AS Gil, Jamshid Aghaei, Mostafa Barani, and João PS Catalão. Optimal behavior of electric vehicle parking lots as demand response aggregation agents. *IEEE Transactions on Smart Grid*, 7(6):2654–2665, 2015.

[128] Morsy Nour, Sayed M Said, Abdelfatah Ali, and Csaba Farkas. Smart charging of electric vehicles according to electricity price. In *2019 international conference on innovative trends in computer engineering (ITCE)*, pages 432–437. IEEE, 2019.

[129] João Soares, Mohammad Ali Fotouhi Ghazvini, Nuno Borges, and Zita Vale. Dynamic electricity pricing for electric vehicles using stochastic programming. *Energy*, 122:111–127, 2017.

[130] Kai-Wen Cheng, Yuexin Bian, Yuanyuan Shi, and Yize Chen. Carbon-aware ev charging. In *2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, pages 186–192. IEEE, 2022.

[131] David B Richardson. Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews*, 19:247–254, 2013.

[132] Reza Fachrizal and Joakim Munkhammar. Improved photovoltaic self-consumption in residential buildings with distributed and centralized smart charging of electric vehicles. *Energies*, 13(5):1153, 2020.

[133] Stavros Sykiotis, Christoforos Menos-Aikateriniadis, Anastasios Doulamis, Nikolaos Doulamis, and Pavlos S Georgilakis. Solar power driven ev charging optimization with deep reinforcement learning. In *2022 2nd International Conference on Energy Transition in the Mediterranean Area (SyNERGY MED)*, pages 1–6. IEEE, 2022.

[134] Chengyin Li, Zheng Dong, Nathan Fisher, and Dongxiao Zhu. Coupling user preference with external rewards to enable driver-centered and resource-aware ev charging recommendation. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 3–19. Springer, 2022.

[135] Steffen Limmer. Dynamic pricing for electric vehicle charging—a literature review. *Energies*, 12(18):3574, 2019.

[136] Leloko J Lepolesa, Kayode E Adetunji, Khmaies Ouahada, Zhenqing Liu, and Ling Cheng. Optimal ev charging strategy for distribution networks load balancing in a smart grid using dynamic charging price. *IEEE access*, 12:47421–47432, 2024.

[137] Mari Halldis Tveit, Linn Bardal, Anne Gjerde, and Espen Stensrud. Behind-the-meter residential electric vehicle smart charging strategies: Danish cases. In *2022 International Conference on Renewable Energies and Smart Technologies (REST)*, volume 1, pages 1–6. IEEE, 2022.

[138] Arnob Ghosh and Vaneet Aggarwal. Menu-based pricing for charging of electric vehicles with vehicle-to-grid service. *IEEE Transactions on Vehicular Technology*, 67(11):10268–10280, 2018.

[139] Sergejus Martinenas, Peter Bach Andersen, Katarina Knezović, Mattia Marinelli, and Chresten Træholt. Electric vehicle smart charging using dynamic price signal. In *2014 IEEE International Electric Vehicle Conference (IEVC)*, pages 1–6. IEEE, 2014.

[140] Chenbei Lu, Lei Yu, Chao Wang, Qing-Chang Wang, Mohammad Shahidehpour, and Dionysios C. Aliprantis. Deadline differentiated dynamic ev charging price menu design. *IEEE Transactions on Smart Grid*, 14(1):502–516, 2022.

[141] Leloko J. Lepolesa, Isaac Mokube, Tinashe Maluleke, Tawanda Mugadza, Luka Kamjii, and Felix Tushabe. Optimal ev charging strategy for distribution networks load balancing in a smart grid using dynamic charging price. *IEEE Access*, 12:47421–47432, 2024.

[142] Jiayang Tu, Hao Zhang, Wei Li, Xiaohui Liu, and Yao Huang. A coordinated charging strategy for users in old residential communities considering price incentive. In *2024 14th International Conference on Power and Energy Systems (ICPES)*, pages 1–6. IEEE, 2024.

[143] Weilian Ji, Yu Chen, Mingzhu Liu, Xinyi Zheng, and Honghua Liu. Research on pricing strategy of ev charging load agent in residential areas considering peak-shifting and valley-filling. In *2019 IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2)*, pages 578–582. IEEE, 2019.