

**INTELLIGENT SCHEDULING FOR RESIDENTIAL
LOADS BASED ON DEMAND RESPONSE
CONSIDERING REAL-TIME PRICE FORECASTING**

BY

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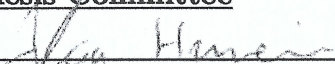
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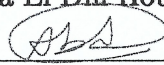
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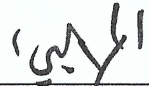
This thesis, written by **MOAYAD ISAMULDEEN OSMAN** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING**.

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This thesis is wholeheartedly dedicated to my beloved family. Without your unwavering encouragement, and support, none of my successes would be possible

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In the name of Allah, the Most Gracious, the Most Merciful. All praise is due to Allah, who has granted me the strength, guidance, and wisdom to complete this thesis.

Firstly, I am deeply grateful to my parents for their unwavering encouragement, endless support, and boundless love throughout this journey. This work is dedicated to my father, who sadly passed away before its completion. I hope this thesis stands as a reflection of the values he instilled in me. May Allah forgive him and grant him Jannah. To my beloved siblings, your presence has been a source of inspiration and motivation. I aspire to be a role model for you. I also extend my heartfelt appreciation to my advisor, Dr. Houssin, for his invaluable guidance, patience, and expertise. I am grateful for your unwavering support and encouragement. I would also like to express my gratitude to Dr. Abido and Dr. Kassas for their continued support and valuable feedback. Your insights and suggestions have enriched my work and contributed significantly to its refinement and development.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	vi
LIST OF TABLES	ix
LIST OF FIGURES	x
LIST OF SYMBOLS	xi
LIST OF ABBREVIATIONS	xii
ABSTRACT (ENGLISH)	xiii
ABSTRACT (ARABIC)	xv
CHAPTER 1 INTRODUCTION	1
CHAPTER 2 BACKGROUND AND RELATED WORK	4
2.1 Smart Grids and Demand Response	4
2.2 Artificial Intelligence in Price Forecasting	8
2.2.1 Early Applications of Artificial Intelligence in Electricity Price Forecasting	9
2.2.2 Deep Neural Networks in Electricity Price Forecasting	10
2.3 Artificial Intelligence in Load Scheduling	15
CHAPTER 3 ELECTRICITY PRICE FORECASTING	20
3.1 Real-Time Pricing Scheme	20
3.2 Price Forecasting Models	22

3.2.1	Feedforward Neural Network (FNN)	23
3.2.2	Long Short-Term Memory (LSTM)	24
3.2.3	Convolutional Neural Network (CNN)	27
3.3	Price Forecasting Results	29
3.3.1	Dataset	29
3.3.2	Evaluation Metrics	30
3.3.3	Simulation Result	30
3.3.4	Results Discussion	41
CHAPTER 4 OPTIMIZED LOAD SCHEDULING		43
4.1	Residential Load Model	44
4.2	Scheduling Optimization	45
4.2.1	Optimization Technique	46
4.2.2	Problem Formulation	49
4.2.3	Objective Function	50
4.3	Optimized Power Consumption	51
4.3.1	Power Consumption	54
4.3.2	Reduction in Electricity Costs and Peak to Average Ratio . . .	55
CHAPTER 5 CONCLUSION		57
REFERENCES		60
VITAE		69

LIST OF TABLES

2.1	A Summary of Reviewed Algorithms For Forecasting Electricity Prices	14
2.2	A Summary of Reviewed Algorithms for Load Scheduling	19
3.1	Training Options for All Electricity Price Forecasting Models	31
3.2	Parameters of the Feedforward Neural Networks (FNN) Model	33
3.3	Parameters of the Proposed Convolutional neural network (CNN)-FNN Model	38
3.4	Performance Comparison of All Tested Models	41
4.1	Typical Household Appliances Power Ratings and Operating Duration.	45
4.2	Genetic Algorithm Parameters	48

LIST OF FIGURES

2.1	Concept Illustration Showing Incorporation of Various Components and Technologies That Make Up a Smart grid (SG) [1]	5
2.2	Demand response (DR) Management and Load Optimization in a Smart Home Through Home Energy Management System [1]	7
3.1	Typical Real-Time Pricing (RTP) Tariff Model	22
3.2	Structure of a Feedforward Neural Network	23
3.3	Illustration of the Architecture of an LSTM Cell	25
3.4	The Components of a CNN	28
3.5	FNN Model Architecture	32
3.6	CNN-FNN Architecture for Price Prediction	37
3.7	Simulation Results for the Proposed Model Showing the Foretasted Prices in Comparison to Actual Prices	39
4.1	The Flowchart of the Genetic Algorithm (GA) Technique	48
4.2	RTP Tariff Model Used for Verification Test	52
4.3	The Average Household Electricity Consumption Profile	53
4.4	Power Consumption Profile Before and After Using the Intelligent Scheduler	54
4.5	Total Cost of Electricity for Scheduled and Unscheduled Cases	55
4.6	Peak to average ratio (PAR) for Scheduled and Unscheduled cases	56

LIST OF SYMBOLS

Δ	Change in value
γ	The weighing factor for the objective function

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional neural network
DNN	Deep Neural Networks
DR	Demand response
EA	Evolutionary Algorithm
EC	Electricity costs
FNN	Feedforward Neural Networks
GA	Genetic Algorithm
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
NN	Neural Networks
PAR	Peak to average ratio
RE	Renewable energy
RMSE	Root Mean Squared Error
RTP	Real-Time Pricing
SG	Smart grid

THESIS ABSTRACT

NAME: Moayad Isamuldeen Osman

TITLE OF STUDY: Intelligent Scheduling for Residential Loads Based on Demand Response Considering Real-Time Price Forecasting

MAJOR FIELD: Electrical Engineering

DATE OF DEGREE: September 2024

Residential energy demand is on the rise, compounded by the widespread adoption of renewable energy sources. This trend poses a challenge for power system operators, who find their ability to regulate electricity generation increasingly limited. Such limitations threaten the overall security of the system. To mitigate these risks, demand response techniques offer a promising solution by enabling control over the consumption side of the system. However, these methods often fall short when applied to residential consumers due to consumer response fatigue. To address this issue, an intelligent scheduler for residential loads is proposed in this study. Utilizing artificial intelligence, the scheduler aims to enhance the effectiveness of demand response programs targeted at residential consumers. The proposed model comprises several components, including a residential load model, a Real-Time Pricing forecasting model based on a Deep

Learning Neural Network (DNN), and a load scheduler employing Genetic Algorithms (GA). The DNN proposed in this model adopts a combined architecture, integrating Convolutional Neural Network (CNN) and Feedforward Neural Network (FFNN) components. Trained on historical datasets, the DNN is capable of forecasting electricity prices with a day-ahead manner. These predicted prices serve as input for the load scheduler, which then generates optimized schedules for residential loads by shifting them away from peak demand. Thus, minimizing electricity costs and reducing the peak to average ratio. Consequently, the intelligent scheduler facilitates demand response efforts from both the aggregator and consumer sides, fostering a more efficient and responsive energy ecosystem.

ملخص الرسالة

الاسم: مؤيد عصام الدين عثمان

عنوان الدراسة: الجدولة الذكية للأحمال السكنية بناءً على استجابة الطلب مع الأخذ في الاعتبار توقعات الأسعار في الوقت الفعلي

التخصص: الهندسة الكهربائية

تاريخ الدرجة العلمية: ربيع ثاني 1446

زيادة الطلب على الطاقة المنزلية، مع تفاقم الاعتماد على مصادر الطاقة المتجددة بشكل واسع. هذا الاتجاه يشكل تحدياً لمشغلي نظام الطاقة، الذين يجدون قدرتهم على تنظيم إنتاج الكهرباء محدوداً بشكل متزايد. مثل هذه القيود تهدد الأمان العام للنظام. للتخفيف من هذه المخاطر، تقدم تقنيات الاستجابة للطلب حلاً واعداً من خلال تمكين التحكم في الجانب الاستهلاكي من النظام. ومع ذلك، فإن هذه الطرق غالباً ما تكون غير كافية عند تطبيقها على المستهلكين المنزليين بسبب تعب الاستجابة للمستهلكين.

للتعامل مع هذه المشكلة، يُقترح في هذه الدراسة مجدول ذكي لأحمال المنازل. باستخدام الذكاء الاصطناعي، يهدف المجدول إلى تعزيز فعالية برامج الاستجابة للطلب المستهدفة للمستهلكين المنزليين. يتكون النموذج المقترح من عدة مكونات، بما في ذلك نموذج للحمل المنزلي، ونموذج لتوقع الأسعار الفعلية الزمنية استناداً إلى شبكة عصبونية عميقة التعلم، وجدول زمني يعتمد على خوارزميات وراثية.

النموذج المقترح للشبكة العصبونية العميقة يعتمد على بنية مشتركة، حيث يدمج مكونات الشبكة العصبونية الاصطناعية التكاملية وشبكة عصبية ذات تغذية أمامية. تُدرب الشبكة على مجموعات من البيانات التاريخية، وتكون قادرة على توقع أسعار الكهرباء بشكل مسبق باليوم. تكون هذه الأسعار المتوقعة مدخلاً لمجدول الاحمال، الذي يُولد بدوره جداول زمنية استثنائية لأحمال المنازل من خلال تحويلها بعيداً عن اوقات الذروة. وبالتالي، يُقلل من تكاليف الكهرباء ويُقلل من نسبة الذروة. وبالتالي، يُيسر المجدول الذكي جهود الاستجابة للطلب من كل من جانب مشغلي الطاقة وجانب المستهلك، مما يعزز نظام الطاقة بشكل أكثر كفاءة واستجابة.

CHAPTER 1

INTRODUCTION

Demand for electric energy is rapidly increasing worldwide. This increase is driven by many factors such as economic development and an exponential growth in population numbers [2].

As a result, electric utilities are expanding generation capacities in order to meet the increase in demand. However, environmental concerns limit the types and quantity of generators constructed. This has pushed utilities toward the growing trend of Renewable energy (RE) resources. While safe and practical in nature, RE resources present a threat to the security and reliability of power systems. This is due to their variable and intermittent nature which induces an imbalance between generation and demand that affects consistent and reliable operation of power systems [3]. Moreover, this imbalance introduces disruptions to the stability of the power systems' frequency. Variations in frequency present a notable risk to power grids, with potential repercussions spanning from compromised performance of household appliances to more severe implications for pharmaceutical and industrial operations.

Nevertheless, with advanced developments in information and communication in-

frastructure, SGs are projected to provide the flexibility required to integrate these modern systems. Furthermore, SGs are considerably more stable and efficient than conventional power grids [4]. In an SG, DR offers a wide range of potential benefits such as the opportunity for residential consumers to reduce their Electricity costs (EC). Consumers who participate in DR programs must either consent to turning off their appliances upon receiving a signal, or they are no longer eligible for the flat tariff. Furthermore, EC change based on their program participation. In return, consumers will receive economic incentives.[5].

While DR is widely used among large industrial consumers, and despite the expected value of DR as a valuable asset, its adoption among residential consumers remains significantly lower. This is primarily due to the need for continuous monitoring of ECs, as well as responding to utility signals in order to turn off certain loads. In addition, the constant need of devising an appropriate schedule in response to DR signals renders DR programs unappealing to the average user. Therefore, this causes response fatigue and inconvenience for residential consumers, steering them away from participating in DR.

In this work, an Artificial Intelligence (AI) scheduler is proposed. The scheduler will enable the application of DR for residential consumers by eliminating response fatigue. The system utilizes Neural Networks (NN) techniques to forecast RTP prices of electricity for the next 24 hours based on historical data. Based on the predicted EC, the system employs GA to optimally schedule residential home appliances on or off to minimize EC as well as the PAR. Thereby automating EC monitoring and home appliance scheduling, and thus, eliminating the primary barriers to the adoption of

DR programs for residential consumers.

The structure of this thesis is outlined as follows: Chapter 2 provides an introduction to SGs, DR and the application of AI in electricity price forecasting and load scheduling. Chapter 3 is dedicated to exploring the application of NN in electricity price forecasting. Chapter 4 focuses on examining optimized scheduling of residential loads using GA. The thesis concludes with Chapter 5, which summarizes the findings and results of this work and suggests areas of future work.

CHAPTER 2

BACKGROUND AND RELATED WORK

2.1 Smart Grids and Demand Response

SGs and smart meters are integral components of modern energy management systems, revolutionizing the traditional utility infrastructure to enhance efficiency, reliability, and sustainability. An SG is a digitally enabled electricity network that integrates advanced communication, sensing, and control technologies to optimize the generation, transmission, and distribution of power [6]. These grids employ real-time data analytics and automated systems to monitor and adjust electricity flow, enabling dynamic response to changing demand patterns and grid conditions.

Smart meters, as part of SG infrastructure, are sophisticated devices installed at residential and commercial premises to measure and monitor electricity consumption in real-time [7]. Unlike conventional analog meters, smart meters facilitate two-way communication between consumers and utility providers, allowing for remote meter

reading, billing, and control. By providing detailed insights into energy usage patterns, smart meters empower consumers to make informed decisions about their electricity consumption, promoting energy conservation and cost savings. Figure 2.1 illustrates the concept of the future electricity system involving SGs.



Figure 2.1: Concept Illustration Showing Incorporation of Various Components and Technologies That Make Up a SG [1]

Residential DR, enabled by SGs and smart meters, is a key strategy for managing electricity demand during peak periods and promoting grid stability [8]. DR programs aim to encourage residential consumers to adjust their electricity usage during peak periods, offering financial incentives or time-based rates. Despite potential benefits like cost reduction and grid reliability enhancement, residential adoption remains low. Lack of awareness, upfront costs, behavioral inertia, and inadequate incentives contribute to this.

Consequently, integrating AI schedulers with smart meters can revolutionize residential DR. AI algorithms can analyze consumption patterns, weather forecasts, and grid conditions to optimize energy usage. By communicating with smart meters, AI schedulers can automatically adjust appliances or devices to minimize consumption during peak times while ensuring user comfort and preferences [9]. This real-time optimization simplifies participation for consumers, reducing the need for manual intervention and increasing the attractiveness of DR programs.

Moreover, AI schedulers can personalize strategies based on individual household habits, further enhancing effectiveness. This level of customization addresses behavioral inertia by aligning DR actions with consumer preferences, thus increasing engagement. Additionally, AI-driven insights can educate consumers about their energy usage patterns, fostering awareness and empowering informed decision-making [10].

Therefore, through DR programs, utility companies incentivize consumers to adjust their electricity consumption in response to fluctuating prices or grid constraints. Smart meters play a crucial role in facilitating this process by enabling real-time communication between utilities and consumers, allowing for automated load-shifting or load-reduction strategies during peak demand hours. By participating in DR initiatives, residential customers contribute to overall grid reliability and efficiency while potentially benefiting from reduced electricity costs. Figure 2.2 shows a home energy management system that incorporates a smart meter, a scheduler, and smart residential appliances.



Figure 2.2: DR Management and Load Optimization in a Smart Home Through Home Energy Management System [1]

However, successful implementation relies on addressing barriers like initial costs. Subsidies or incentives for AI-enabled devices could alleviate financial burdens, particularly for low-income households. Furthermore, robust cybersecurity measures are essential to protect consumer data and ensure system reliability [11].

In addition, inaccurate electricity price forecasting presents a formidable obstacle to the realization of residential DR initiatives, as unreliable price predictions undermine its efficacy. As noted by [12], erroneous forecasts can lead to suboptimal decision-making among consumers, deterring their engagement in DR programs. When households cannot anticipate peak pricing periods accurately, they may fail to adjust their electricity usage accordingly, missing opportunities to reduce costs and alleviate strain on the grid. Consequently, the potential benefits of DR, such as load

balancing and carbon emissions reduction, remain underexploited. To overcome this barrier, improving the accuracy of electricity price forecasting through advanced algorithms and data analytics is imperative. Only with precise forecasts can residential consumers make informed choices about their energy consumption patterns, thereby unlocking the full potential of DR strategies.

In summary, integrating AI schedulers with smart meters offers a promising solution to enhance residential DR. By automating optimization and personalizing strategies, it addresses key barriers to adoption, such as the accuracy of electricity price forecasting, paving the way for a more efficient and sustainable energy future. Hence, leveraging advanced algorithms and data analytics can significantly improve the precision of price forecasts, enabling consumers to make informed decisions about their energy usage and participate more effectively in demand response programs. This integration of AI and smart meters empowers households to respond proactively to fluctuating electricity prices, maximizing cost savings and grid reliability while minimizing environmental impact

2.2 Artificial Intelligence in Price Forecasting

AI has revolutionized numerous industries by providing sophisticated tools for data analysis, pattern recognition, and decision-making. In the context of electricity price forecasting, AI encompasses a range of techniques, including machine learning and deep learning, which have been extensively researched and applied. The primary advantage of AI in this domain is its ability to handle vast amounts of data and

uncover hidden patterns that traditional methods might miss.

2.2.1 Early Applications of Artificial Intelligence in Electricity Price Forecasting

Initial AI applications in electricity price forecasting primarily relied on machine learning algorithms, such as support vector machines (SVM), decision trees, and ensemble methods like random forests. These approaches demonstrated improved performance over classical statistical models by effectively capturing non-linear relationships and interactions among variables. For example, studies by [13] and [14] showed that machine learning techniques could achieve higher accuracy in short-term electricity price predictions compared to traditional models like ARIMA and GARCH.

The study in [13] developed ARIMA (AutoRegressive Integrated Moving Average) models to predict next-day electricity prices in the Spanish market. The models demonstrated the ability to capture the main features of electricity price series, including seasonality and volatility. Also, the results showed that ARIMA models could provide reasonable forecasts for electricity prices. However, the study focused on the Spanish electricity market. Electricity markets can differ significantly across regions due to regulatory, structural, and demand differences. In addition, ARIMA models, while effective, might not capture all the complex dynamics of electricity prices, such as sudden price spikes due to unforeseen events.

On the other hand, the review in [14], provided a comprehensive overview of statistical techniques for modeling and forecasting electricity loads and prices, emphasizing

time series analysis. It reviewed various models, including ARIMA, GARCH, and regime-switching models, and discussed their applicability and limitations in the context of electricity markets. Nevertheless, while the study reviewed various models, a direct comparison of their performance on the same dataset was not extensively covered.

2.2.2 Deep Neural Networks in Electricity Price Forecasting

As computational power and data availability increased, the focus shifted towards more complex AI models, particularly deep learning. Deep learning, a subset of machine learning, involves neural networks with multiple layers that can model intricate data structures. The transition from traditional machine learning to deep learning marked a significant improvement in handling the high volatility and non-linear nature of electricity prices.

Deep Neural Networks (DNN) are a subset of machine learning algorithms that consist of multiple layers of interconnected neurons. Each layer in a DNN captures different levels of abstraction from the input data, allowing the network to learn intricate patterns and relationships. Popular architectures of DNN include FNN, CNN, and recurrent neural networks (RNNs), each with unique advantages for various types of data. In addition, electricity prices prediction is heavily researched both at the aggregator and consumer level. In literature, many machine learning price forecasting models are developed utilizing real statistical analysis of real-time pricing data. FNNs are among the simplest forms of DNNs and have been applied in electricity price forecasting with varying degrees of success. FNNs have been used to model the

non-linear relationships between historical price data and future prices. For instance, [15] demonstrated that FNNs could effectively predict short-term electricity prices by leveraging historical prices and other relevant features such as demand and weather data.

The authors in [16] successfully apply a multilayer NN model built using MATLAB NN toolbox with an 8-20-1 architecture to forecast electricity load and price. The model effectively captures complex relationships between input and output layers due to its multilayer structure. Historical load and price data, along with weather information, are identified as influential factors. Specific inputs such as previous hour, day, and week load/price data, along with day-specific variables (e.g., hour of the day, weekday, and whether it is a working day), are employed for accurate forecasting. The price forecasting results demonstrate the NN model's effectiveness. The Monthly Mean Absolute Percentage Error (MAPE) for price forecasting varies between 3.945% and 13.7635%, with a standard deviation of 2.758%. However, the paper lacks a comparative analysis with other advanced forecasting models, such as Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and hybrid models, since comparative studies could highlight the relative strengths and weaknesses of different approaches. Moreover, it was observed that the accuracy of the model falls to lower than 5% specifically during peak times.

In [17], researchers implement a wavelet neural network algorithm with a Decomposition-Prediction-Reconstruction frame is employed to forecast real-time prices based on historical data. The accuracy of the forecasting result is shown to be within 10%, and even lower than 5% during peak hours (8:00 am to 5:00 pm),

which is crucial for implementing the price-responsive DR strategy. Nevertheless, the study focuses on real-time price forecasting and optimization; however, real-time adaptation to dynamically changing conditions in the grid and market prices is not fully addressed.

Authors in [18] propose an RTP forecasting model that combines the least-square (LS) fitting function and the grey prediction technique (GPT). This model effectively captures both the deterministic and stochastic components of RTP, providing accurate day-ahead price predictions. The RTP data is categorized into a deterministic part and a stochastic part, then, the deterministic and stochastic prices are forecasting by utilizing the least square fitting function and grey prediction model, respectively. Simulation results show that the average forecasting error rate is approximately 4.4%, with errors lower than 5% during most of the day, particularly from 12:30 pm to 10:00 pm. This high accuracy demonstrates the model's reliability in predicting real-time electricity prices. The study primarily focuses on RTP forecasting and load scheduling for home appliances. Future research could explore integrating these methods with other smart grid technologies, such as demand response programs and energy storage systems, to enhance overall grid efficiency and stability.

In paper [19], authors propose an artificial NN based methodology to forecast electricity load and price. They introduce an enhanced Recurrent Neural Network (RNN) model specifically designed for short-term price and load forecasting in smart grids. The model aims to improve prediction accuracy by capturing temporal dependencies in the data. The model is a combination of long short term memory (LSTM) and FNN. The research emphasizes the critical role of feature selection and data prepro-

cessing in enhancing the performance of the forecasting models. By selecting relevant features and applying appropriate preprocessing techniques, the model can better understand and predict the complex patterns in the data. The proposed method showed a Mean Absolute Error (MAE) of 17.44%, which shows an improvement in comparison to a regular RNN or a FNN; nevertheless, it is quite high when compared to relevant literature.

Finally, authors in [20] present a Transformer-based deep learning network for locational marginal price (LMP) forecasting. This network is designed for multistep-ahead LMP prediction, leveraging the sequence-to-sequence (seq2seq) architecture commonly used in natural language processing. The Transformer-based model was evaluated against conventional deep learning models, such as LSTM, Bi-LSTM, GRU, Bi-GRU, and TCN. The results indicate that the proposed model achieves superior accuracy in various prediction scenarios. While the study compares the Transformer-based model with several deep learning models, future research should consider comparing it with hybrid approaches that combine machine learning models such as: LSTM-CNN or CNN-FNN. Such comparative studies could highlight the relative strengths and weaknesses of different forecasting techniques. The proposed method in the paper had a Root Mean Squared Error (RMSE) of 6.35% and a MAE of 4.49%. Table 2.1 shows a summary of the literature reviewed ([16]-[20]) in electricity price forecasting.

Table 2.1: A Summary of Reviewed Algorithms For Forecasting Electricity Prices

	ALGORITHMS	DESCRIPTION	LIMITATIONS
Early Applications of Artificial Intelligence	ARIMA	The results showed that ARIMA models could provide reasonable forecasts for electricity prices	ARIMA models, while effective, might not capture all the complex dynamics of electricity prices, such as sudden spikes due to unforeseen events
	ARIMA and GARCH	It reviewed various models, including ARIMA, GARCH, and regime-switching models, and discussed their applicability and limitations in the context of electricity markets	A direct comparison of their performance on the same dataset was not extensively covered
Deep Neural Networks	Multilayer NN model built using MATLAB NN toolbox	The price forecasting results vary between 3.945% and 13.7635%	The accuracy of the model falls to lower than 5% specifically during peak times
	A wavelet neural network algorithm with a Decomposition-Prediction- Reconstruction frame	The accuracy of the forecasting result is shown to be within 10%, and even lower than 5% during peak hours	Real-time adaptation to dynamically changing conditions in the grid and market prices is not fully addressed
	A combination of the least- square (LS) fitting function and the grey prediction technique (GPT)	Simulation results show that the average forecasting error rate is approximately 4.4%, with errors lower than 5% during most of the day	The study does not explore integrating these methods with other smart grid technologies
	An enhanced RNN that combines LSTM and FNN	The proposed method showed an MAE of 17.44%	Error is quiet high when compared to relevant literature
	Transformer-based deep learning network	The proposed method in the paper had an RMSE of 6.35%, and MAE of 4.49%	No comparison with hybrid approaches that combine DNN models

In this study, we focus exclusively on forecasting day-ahead electricity prices for residential consumers utilizing a RTP scheme. Our approach involves a comprehensive comparison of relevant DNN methods, including LSTM networks, CNNs, and various hybrid combinations of these models. The proposed deep learning network model demonstrates remarkably low error percentages, highlighting its potential for accurate and efficient price forecasting in SG environments.

2.3 Artificial Intelligence in Load Scheduling

Price-based DR in the residential sector is widely studied in recent research. Many intelligent schedulers have been developed using a multitude of algorithms and optimization techniques to minimize ECs.

The authors in [3] provide a comprehensive survey of many algorithms and techniques to apply DR using AI and NN. In addition, they conclude that different AI techniques are suitable for specific tasks. For instance, artificial NN are best suited for load and price forecasting, and Evolutionary Algorithms (EAs) are best suited for scheduling.

In paper [21], authors propose a home energy management system (HEMS) that utilizes heuristics to manage energy reallocation. The focus is on shifting energy consumption patterns away from peak periods and/or high electricity prices. The system differentiates residential loads into two categories: fixed power appliances and flexible power appliances. The problem is formulated as a constraint optimization problem and solved using two heuristics: the GA and the Harmony Search Algorithm (HSA).

Both GA and HSA demonstrate effectiveness in minimizing electricity expenses and PAR. Numerical results indicate that the GA can reduce electricity costs by 0.9% and PAR by 15%, while the HSA achieves cost reductions of 3.98% and PAR reductions of 5.8%. Furthermore, the current study does not integrate SG technologies or price forecasting into the HEMS. Incorporating smart grid technologies could enhance communication and coordination between the grid and residential consumers, while price forecasting could improve the system's ability to predict and respond to future price changes, optimizing energy usage and cost savings.

Authors in [22] evaluates the effectiveness of GA, Bat Algorithm (BA), and a hybrid Bat Genetic Algorithm (BGA) in optimizing home energy management. The primary objective is to minimize electricity costs, reduce the PAR, and improve user comfort (UC) by managing appliance operation times. Moreover, the study categorizes residential loads into three types: base load, shiftable interruptible load, and shiftable non-interruptible load. The optimization techniques are applied to schedule these loads under a Time of Use (TOU) pricing scheme. The proposed BGA, which combines the global search capabilities of GA with the local search strengths of BA, outperforms both GA and BA in cost reduction and PAR for both single and multiple home scenarios. Finally, the paper assumes a static TOU pricing scheme. However, energy markets can be highly variable. Future research could explore the robustness of these optimization algorithms under dynamic pricing conditions, such as RTP, where electricity prices fluctuate more frequently and unpredictably.

In [23], researchers introduce a novel energy management system for residential demand response (DR) utilizing Reinforcement Learning (RL) and Fuzzy Reason-

ing (FR). This integration aims to optimize the scheduling of household appliances by shifting their operation from peak to off-peak hours, considering user preferences and feedback. Furthermore, the system categorizes appliances into shiftable and non-shiftable types, applying different strategies for each. Shiftable appliances' operations can be rescheduled based on priority and user settings, while non-shiftable appliances are continuously powered. The proposed system was tested using a single agent to control 14 household appliances. The simulation results demonstrate that the approach can effectively smooth the power consumption profile and reduce electricity costs while respecting user preferences. The system achieved a reduction in electricity costs of 15% during morning peaks and 18.5% during evening peaks. Also, the research primarily focuses on the Q-learning algorithm integrated with fuzzy reasoning. A comprehensive comparison with other machine learning techniques and optimization algorithms, such as deep reinforcement learning, genetic algorithms, or swarm intelligence, would provide a broader perspective on the most efficient approaches for home energy management.

Researchers in [24] created a HEMS that leverages RTP to optimize household energy consumption. The proposed system consists of three phases: Real-Time Monitoring (RTM), Stochastic Scheduling (STS), and Real-Time Control (RTC). This integration aims to minimize the cost of energy consumption by adjusting the operation of household appliances based on real-time electricity prices. The STS phase utilizes stochastic dynamic programming (SDP) to create an optimal policy for appliance scheduling. This method takes into account the uncertainties in both RTP and power consumption patterns, thereby improving the decision-making process for

controlling household appliances. Moreover, the system categorizes appliances into three types: Cat1: Appliances that can be delayed, such as dishwashers and washing machines. Cat2: Appliances whose schedules depend on their charging characteristics, such as electric vehicles. Cat3: Thermostatically controlled appliances, such as water heaters and air conditioners. The proposed HEMS was tested with seven controllable appliances. The results show that the system can effectively reduce the cost of energy consumption by adjusting the operation of appliances based on RTP signals. The system achieved a reduction in daily electricity costs and demonstrated the ability to handle uncertainties in both RTP and power consumption patterns. However, user comfort is not taken into account.

In [25], the paper evaluates the performance of three heuristic algorithms—Wind Driven Optimization (WDO), GA, and Binary Particle Swarm Optimization (BPSO)—in managing energy consumption in a smart grid environment. These algorithms are used to schedule home appliances to reduce electricity costs, minimize the PAR, and create a balanced energy consumption pattern. The paper conducts simulations using MATLAB to compare the performance of the three algorithms based on daily electricity cost, energy consumption pattern, and PAR. It was concluded that GA demonstrates a balanced load shifting pattern, avoiding load peaks and extending the lifetime of household electrical circuitry. BPSO, on the other hand, tends to shift loads completely towards off-peak hours, resulting in high PAR and significant user delays. WDO manages to maintain a consistent energy consumption pattern with minimal peaks. In addition, the paper highlights that conventional optimization techniques like linear and nonlinear programming are slow and inefficient for man-

aging a large number of appliances. Heuristic algorithms such as PSO, Ant Colony Optimization (ACO), and GA offer faster convergence rates and better optimization capabilities for home energy management. 2.2 shows a summary of the literature reviewed ([21]-[25]) for load scheduling.

Table 2.2: A Summary of Reviewed Algorithms for Load Scheduling

ALGORITHMS	DESCRIPTION	LIMITATIONS
GA and HSA	GA reduced costs by 0.9% and PAR by 15% HSA reduced costs by 3.98% and PAR by 5.8%	No integration of GA technologies or price forecasting
BA, GA, and BGA	The proposed BGA combines BA and GA. It outperformed both BA and GA	The paper assumes a static TOU pricing scheme
RL and FR	The system achieved a reduction in costs by 15% during morning peaks and 18.5% during evening peaks	No comparison with other optimization algorithms
Real-Time Monitoring (RTM) Stochastic Scheduling (STS) Real-Time Control (RTC)	The system achieved a reduction in costs and demonstrated the ability to handle uncertainties in both RTP and power consumption patterns	User comfort is not taken into account
WDO, GA, and BPSO	GA has a balanced load shifting pattern, avoiding load peaks. BPSO tends to shift loads completely towards off-peak hours, resulting in high PAR WDO maintains a consistent energy consumption pattern with minimal peaks.	The paper assumes a static TOU pricing scheme

CHAPTER 3

ELECTRICITY PRICE FORECASTING

The main objective of this work is to develop an intelligent scheduler considering real-time pricing forecasting to enable DR for residential consumers. This section discusses the DNN electricity price forecasting models compared in this work and the results obtained for each model. The prices of electricity will be forecasted in an RTP day-ahead manner by utilizing artificial neural networks based on the CNN architecture and FNN.

3.1 Real-Time Pricing Scheme

RTP is a dynamic electricity pricing mechanism that adjusts EC based on real-time market conditions. Unlike traditional fixed-rate pricing, RTP reflects the varying costs of electricity production and distribution throughout the day, encouraging consumers to modify their usage patterns to take advantage of lower prices during off-peak peri-

ods. This system aims to balance supply and demand more efficiently, reduce overall EC, and promoting the integration of renewable energy sources [26].

Furthermore, RTP provides economic signals to consumers, prompting them to shift their electricity usage to times when prices are lower, which can lead to a more efficient utilization of the electricity grid and reduce the necessity for expensive peak-time energy production. Additionally, by aligning electricity prices with real-time market conditions, RTP can enhance grid stability and support demand response programs, which are crucial for integrating intermittent renewable energy sources [27].

Moreover, RTP empowers consumers to make more informed decisions about their energy consumption, fostering a more interactive and responsive energy market. However, the effectiveness of RTP depends on various factors, including the availability of advanced metering infrastructure, consumer awareness, and the ability to respond to price signals [28].

The RTP scheme is considered in this study. The notion of RTP has been around for a considerable time; however, its practical implementation has only become feasible relatively recently, thanks to significant advancements in advanced metering infrastructure technology. RTP offers advantages to retailers by reflecting the marginal cost of production and incentives customers to manage their electricity usage [24]. Figure 3.1 shows an example of real-time pricing model.

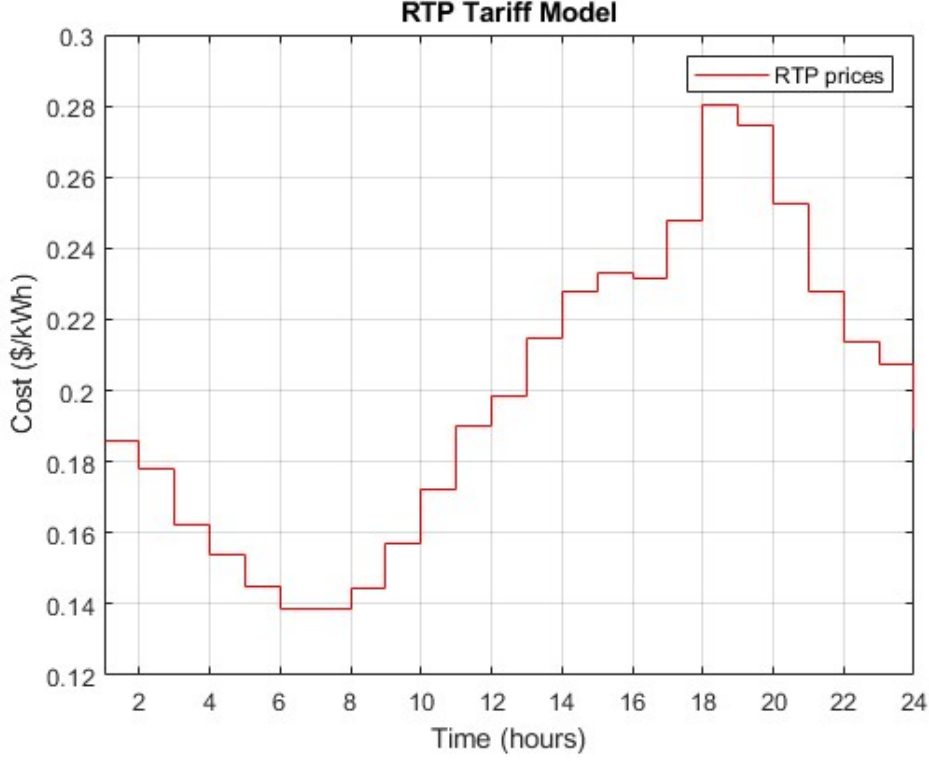


Figure 3.1: Typical RTP Tariff Model

In a RTP scheme, the hourly prices are based on day-head rates. This facilitates consumers in planning and making informed decisions to reduce their daily consumption. Nonetheless, this planning heavily depends on the accuracy of price prediction on both the utility company and consumer sides.

3.2 Price Forecasting Models

In this section, we discuss the various NN models employed for forecasting electricity prices. The models evaluated are the FNN, Long Short-Term Memory (LSTM), and Convolutional Neural Network CNN.

3.2.1 Feedforward Neural Network (FNN)

FNNs are a fundamental class of artificial neural networks that have gained significant attention in the field of machine learning and artificial intelligence. These networks are characterized by their simple structure, in which information flows unidirectionally from input to output layers through one or more hidden layers [29]. Unlike recurrent neural networks, FNNs do not have cycles or loops, making them particularly suitable for tasks where data does not inherently involve temporal or sequential relationships.

The following figure shows the typical structure of an FNN [30]:

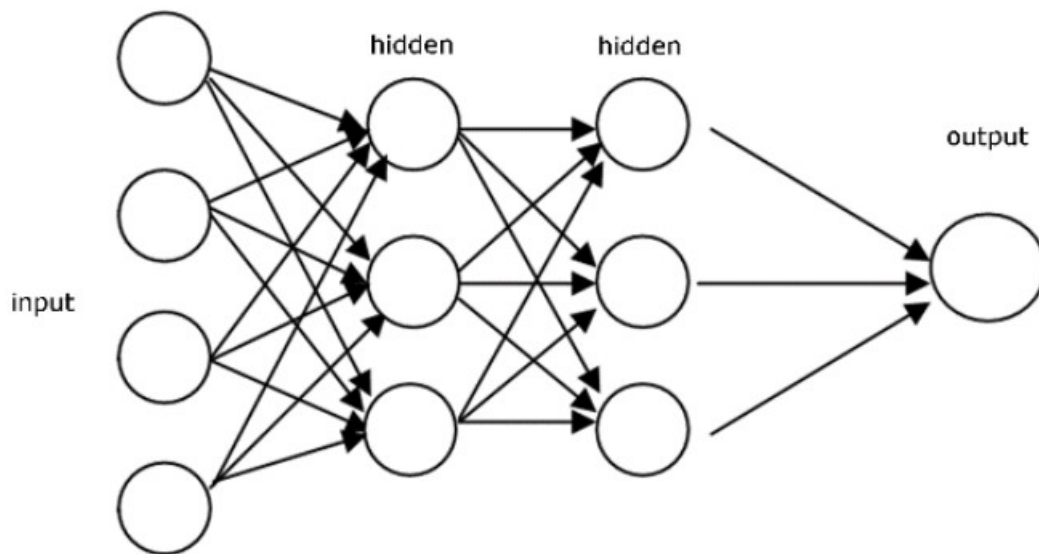


Figure 3.2: Structure of a Feedforward Neural Network

An FNN typically consists of three types of layers: the input layer, one or more hidden layers, and the output layer. Each layer is composed of nodes (also known as neurons) connected by weights. As described in [31], the mathematical operation

performed by each neuron can be described by the following equation:

$$y_j = f \left(\sum_{i=1}^n w_{ij} x_i + b_j \right) \quad (3.1)$$

where:

- y_j is the output of the neuron j ,
- x_i are the inputs to the neuron,
- w_{ij} are the weights of the connections,
- b_j is the bias term,
- f is the activation function.

The choice of activation function f can significantly impact the performance of the network. Common activation functions include the sigmoid function, the hyperbolic tangent function ($\tanh$), and the rectified linear unit (ReLU).

Moreover, training an FNN involves adjusting the weights and biases to minimize the difference between the actual output and the desired output. This process is typically carried out using backpropagation, an algorithm that calculates the gradient of the loss function with respect to each weight by the chain rule, iteratively updating the weights to reduce the error [32].

3.2.2 Long Short-Term Memory (LSTM)

LSTM networks are a special type of recurrent neural network (RNN) designed to effectively learn from sequential data [33], overcoming the limitations of traditional

RNNs such as vanishing and exploding gradients. LSTMs have proven to be highly effective in tasks involving time series prediction, natural language processing, and other sequential data problems [34]. A diagram of the LSTM cell structure is shown in the following figure [35].

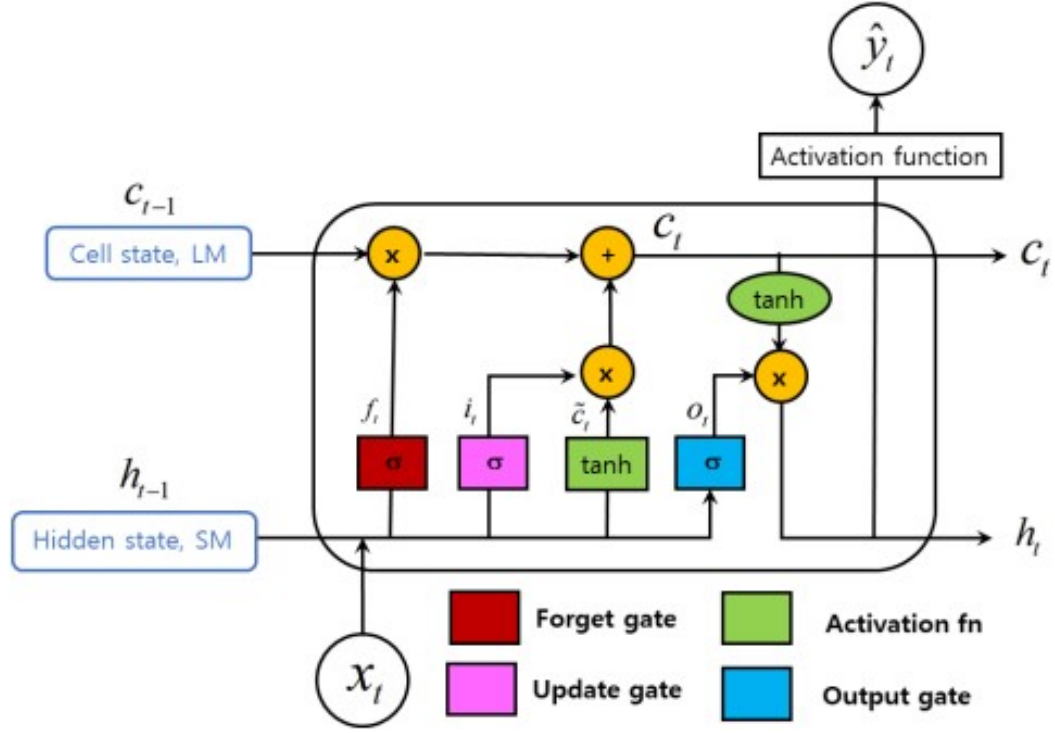


Figure 3.3: Illustration of the Architecture of an LSTM Cell

An LSTM network is composed of LSTM cells, each containing three gates: input gate, forget gate, and output gate. These gates regulate the flow of information and help the network maintain long-term dependencies. As reported in [36], the operations within an LSTM cell can be mathematically described by the following equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3.2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3.3)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3.4)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3.5)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (3.6)$$

$$h_t = o_t * \tanh(C_t) \quad (3.7)$$

where:

- f_t is the forget gate,
- i_t is the input gate,
- o_t is the output gate,
- $\tilde{C}_t$ is the candidate cell state,
- C_t is the cell state,
- h_t is the hidden state,
- σ is the sigmoid function,
- $\tanh$ is the hyperbolic tangent function.

Training LSTM networks involves optimizing the weights and biases through backpropagation through time (BPTT), a variant of backpropagation suited for sequence data. This process adjusts the parameters to minimize a predefined loss function, such

as cross-entropy loss for classification tasks or mean squared error for regression tasks [37].

3.2.3 Convolutional Neural Network (CNN)

CNNs are a class of deep learning algorithms designed for processing structured grid data, such as images. According to [38], CNNs are one of the most utilized deep learning networks, particularly effective for processing data with a grid-like topology such as images. They automatically detect significant features without human supervision by using layers of convolution and pooling operations, which mimic the hierarchical processing of visual data in the human visual cortex.

The architecture of a CNN consists of several key components [39]:

1. **Convolutional Layers:** These layers apply convolution operations to the input image using a set of learnable filters. The output, called feature maps, highlights various features of the image, such as edges or textures.
2. **Activation Functions:** After convolution, activation functions like ReLU (Rectified Linear Unit) introduce non-linearity to the model, enabling it to learn more complex patterns.
3. **Pooling Layers:** Pooling layers reduce the spatial dimensions of the feature maps, which helps to reduce the computational load and control overfitting. Common types of pooling include max pooling and average pooling.
4. **Fully Connected Layers:** These layers are similar to those in traditional

neural networks and are used at the end of the CNN to make predictions based on the learned features.

Figure 3.4 shows the different CNN layers [39].

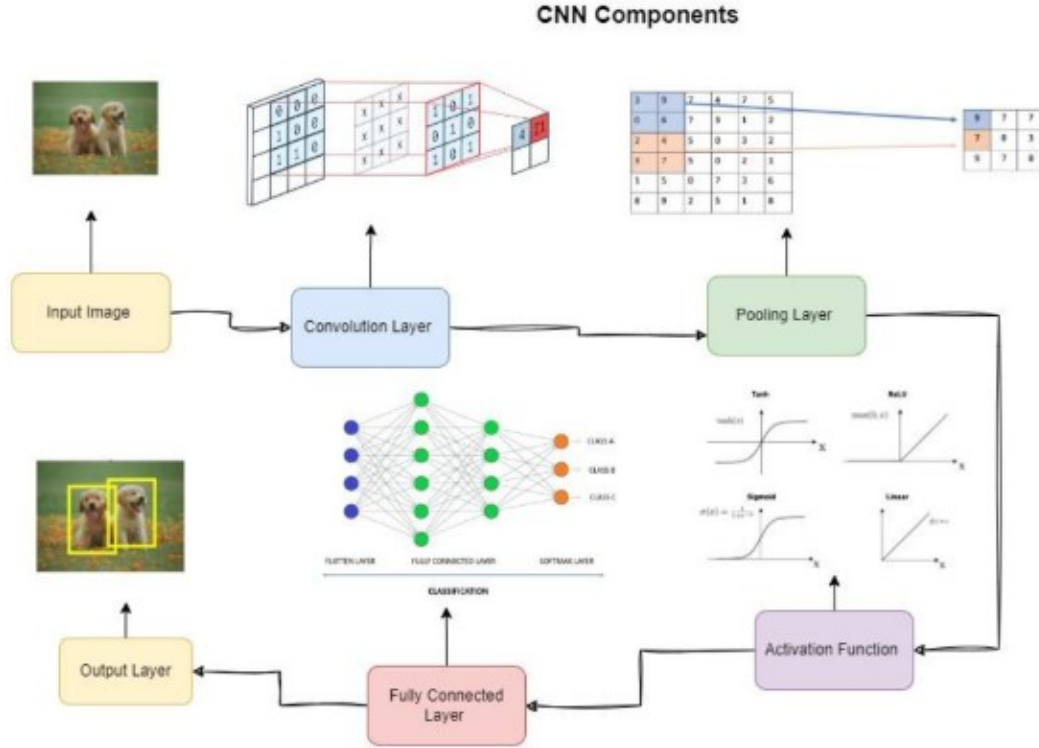


Figure 3.4: The Components of a CNN

According to [40], the operation of CNN can be mathematically described using the convolution operation:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t - \tau) d\tau \quad (3.8)$$

where f is the input image, g is the filter, and $*$ denotes the convolution operation.

3.3 Price Forecasting Results

This section delves into a comprehensive analysis of the electricity price forecasting models' performance. It is structured into several key subsections to provide a detailed overview of the dataset used in simulations, the training and testing options and parameters, the evaluation metrics employed, and the simulation results for each of the five models compared in this work: FNN, LSTM, BiLSTM, CNN, and CNN-FNN.

3.3.1 Dataset

Each designed architecture incorporates four input nodes that represent key features essential for accurately predicting electricity prices. These features are:

1. **Previous Day's Price Data:** This feature provides the RTP data from the same hour on the previous day, helping the model recognize daily price patterns.
2. **Previous Hour's Price Data:** By including the RTP data from the preceding hour, the model can capture short-term fluctuations and trends in electricity prices.
3. **Same Hour Previous Week Price Data:** This feature includes RTP data from the same hour in the previous week, allowing the model to account for weekly cyclical patterns in electricity demand and pricing.
4. **Weekday/Weekend Indicator:** A binary indicator that specifies whether the current day is a weekday or a weekend, which is crucial as electricity usage patterns often vary significantly between weekdays and weekends.

By integrating these selected features, the models are equipped to learn from historical trends and make accurate predictions of future electricity prices, thereby enhancing the efficiency and reliability of market operations.

Finally, to evaluate the performance of all forecasting models, the dataset entries from ID 4344 to 4368, representing the data from July 3, 2020, sourced from the Zn.F - Capital node, were used as the test set.

3.3.2 Evaluation Metrics

To verify the validity of the developed NN models, the following evaluation indicators are used: MAE, and MAPE. Equations (3.9-3.10) show how these indicators are defined:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (3.9)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|y_i - \hat{y}_i|}{y_i} \times 100 \quad (3.10)$$

3.3.3 Simulation Result

In the development of price forecasting models, the configuration of training options plays a crucial role in ensuring the effectiveness and efficiency of the training process. Properly set training options help in optimizing the model's performance and achieving accurate forecasting results. Table 3.1 details the training options used in our price forecasting models and their respective values.

Table 3.1: Training Options for All Electricity Price Forecasting Models

Option	Value
Max Epochs	200
Mini Batch Size	192
Initial Learn Rate	0.1
Gradient Threshold	1
Shuffle	Every Epoch
Verbose	1

Feedforward Neural Network

The FNN architecture consists of multiple layers, including an input layer, three hidden layers, and an output layer. The structure of the FNN is shown in the figure below:

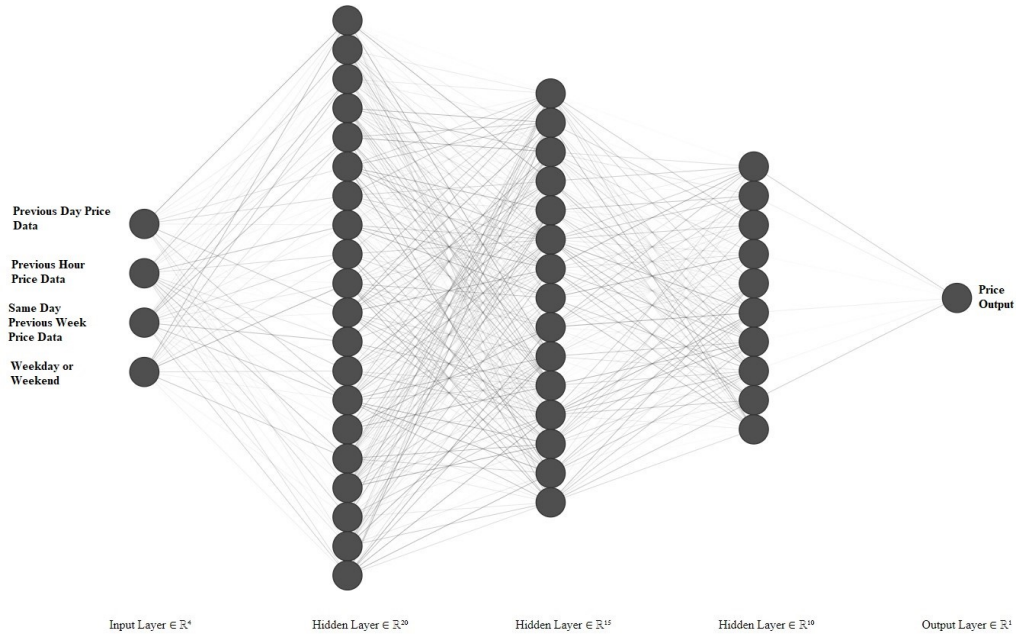


Figure 3.5: FNN Model Architecture

- **Hidden Layers:** The FNN model includes three hidden layers with the following configurations:
 - **Hidden Layer 1:** Contains 20 neurons, enabling the network to learn complex patterns from the input features.
 - **Hidden Layer 2:** Contains 15 neurons, refining the patterns learned in the first hidden layer.
 - **Hidden Layer 3:** Contains 10 neurons, further refining the learned patterns before passing them to the output layer.
- **Output Layer:** The output layer has a single neuron that predicts the future price.

Table 3.2: Parameters of the FNN Model

Option	Value
Hidden layer 1	20 neurons
Hidden layer 2	15 neurons
Hidden layer 3	10 neurons

The FNN model is trained using the Adam optimizer, which is known for its efficiency and adaptability in handling large datasets. The training options, as previously shown in 3.1, include parameters such as the maximum number of epochs, mini-batch size, learning rate, and more, all of which contribute to the model’s performance and accuracy.

The obtained results are as follows:

- **Mean Absolute Error (MAE):** The MAE for the model is 7.76%. This indicates that, on average, the absolute difference between the predicted prices and the actual prices is 7.76%.
- **Mean Absolute Percentage Error (MAPE):** The MAPE for the model is 14.91%. This metric provides a percentage-based error rate, showing that the model’s predictions deviate from the actual prices by an average of 14.91%.

These results demonstrate the effectiveness of the FNN model in forecasting prices. The relatively low MAE and MAPE values indicate that the model is capable of making accurate predictions, which is crucial for practical applications in price forecasting

Long Short-Term Memory

The architecture of the LSTM model includes an input layer, an LSTM layer, a dropout layer, a fully connected layer, and a regression layer, as described below.

- **Input Layer:** The input layer is a sequence input layer designed to accept multiple features as input. The number of features (*num_features*) depends on the dataset and the specific features used for forecasting.
- **LSTM Layer:** This layer consists of 200 hidden units. It processes the input sequences and retains long-term dependencies, which are essential for time series forecasting. The 'OutputMode' is set to 'sequence', indicating that the layer outputs the full sequence of predictions.
- **Dropout Layer:** A dropout rate of 20% is applied to prevent overfitting by randomly setting 20% of the input units to zero at each update during training.
- **Fully Connected Layer:** This layer has a single neuron, which aggregates the learned features from the previous layers and prepares the final output.
- **Regression Layer:** The regression layer outputs the final predicted value, which is suitable for continuous value prediction tasks.

The LSTM model is trained using the Adam optimizer, which is effective for training deep neural networks. The training process involves optimizing the model parameters to minimize the error between the predicted and actual prices.

The obtained results are as follows:

- **Mean Absolute Error (MAE):** The MAE for the LSTM model is 13.74%.

- **Mean Absolute Percentage Error (MAPE):** The MAPE for the LSTM model is 37.85%.

These results highlight the capabilities of the LSTM model in capturing temporal patterns in price data. However, the relatively higher MAPE indicates that there is room for improvement in the model's accuracy.

Bidirectional Long Short-Term Memory

The architecture of the BiLSTM model includes an input layer, two LSTM layers (one in each direction), a dropout layer, a fully connected layer, and a regression layer. Explanation of Layers:

- **Input Layer:** The input layer is a sequence input layer designed to accept multiple features as input. The number of features (*num_features*) depends on the dataset and the specific features used for forecasting.
- **LSTM Layer 1:** This layer consists of 200 hidden units, processing the input sequences and retaining long-term dependencies. The 'OutputMode' is set to 'sequence', indicating that the layer outputs the full sequence of predictions.
- **Dropout Layer:** A dropout rate of 20% is applied to prevent overfitting by randomly setting 20% of the input units to zero at each update during training.
- **LSTM Layer 2:** This second LSTM layer also consists of 200 hidden units and is configured similarly to the first LSTM layer, further processing the sequences.

- **Fully Connected Layer:** This layer has a single neuron, which aggregates the learned features from the previous layers and prepares the final output.
- **Regression Layer:** The regression layer outputs the final predicted value, which is suitable for continuous value prediction tasks.

The results are as follows:

- **Mean Absolute Error (MAE):** The MAE for the BiLSTM model is 13.26%.
- **Mean Absolute Percentage Error (MAPE):** The MAPE for the BiLSTM model is 24.7962%.

The lower MAPE, compared to the unidirectional LSTM model, indicates an improvement in prediction accuracy.

Proposed Model

In this work, the price prediction model is developed using a DNN based on the CNN architecture. According to [41], CNNs are widely utilized in pattern recognition due to their ability to convolve parameters, extract features from input patterns, and achieve efficient modular data representation. Furthermore, DNNs can effectively rival recurrent networks in addressing certain challenges related to processing data sequences. This model was simulated and compared to different DNN architectures. Figure 3.6 illustrates the architecture of the proposed model.

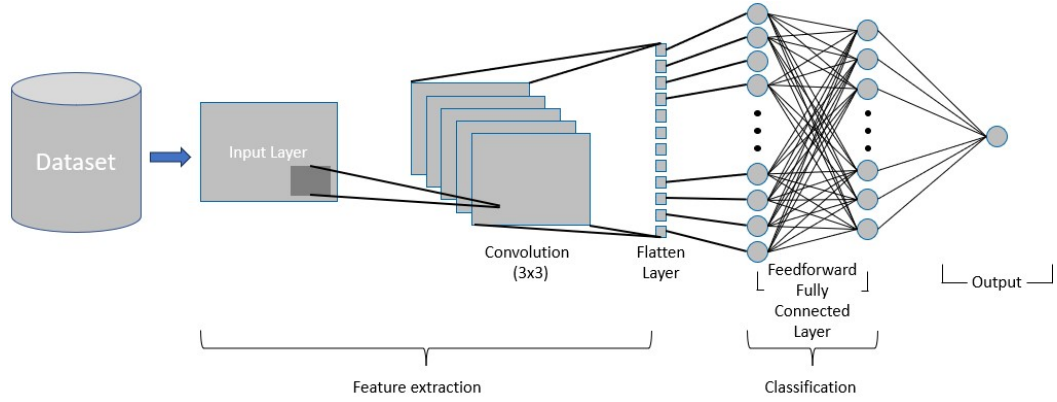


Figure 3.6: CNN-FNN Architecture for Price Prediction

Following the input layer, a CNN is employed to extract intricate patterns and spatial correlations from the input data. The CNN begins with an image input layer configured with dimensions $[1 \ 1 \ 4]$ to accommodate the four input features. Subsequently, a convolutional layer with 32 filters of size 3×3 is applied to capture local features and dependencies within the input. This is followed by max-pooling to down sample the feature maps and retain the most significant information.

After the CNN layers, the output from the convolutional layers is flattened through a flatten layer and passed through a fully connected FNN. The FNN consists of two hidden layers, the first with 32 neurons and the second with 16 neurons, followed by a single output neuron for predicting electricity prices. Each neuron in the hidden layers utilizes the Rectified Linear Unit (ReLU) layer activation function to introduce non-linearity and enable the network to learn complex relationships within the data.

Layer	Value
Input Layer	Dimensions [1 1 4]
Convolutional Layer	32 filters of size 3×3
Fully Connected Layer 1	32 neurons, ReLU activation
Fully Connected Layer 2	16 neurons, ReLU activation
Output Layer	1 neuron

Table 3.3: Parameters of the Proposed CNN-FNN Model

Combining a CNN followed by an FNN to predict electricity prices is highly effective due to the unique capabilities of each architecture. The CNN excels at automatically extracting relevant features from input data, such as temporal dependencies and spatial correlations in electricity demand and related factors. By leveraging convolutional and pooling layers, the CNN effectively captures intricate patterns in the input features. The output from the CNN is then passed to the FNN, which further refines the extracted features and maps them to the desired output, i.e., RTP. The FNN learns the higher-level representations of the features learned by the CNN and incorporates additional context to make accurate predictions. Through backpropagation and gradient descent, both the CNN and FNN optimize their parameters to minimize prediction errors and improve forecasting accuracy. The obtained results of the proposed model:

- **Mean Absolute Error (MAE):** The MAE for the combined model is 3.95%.
- **Mean Absolute Percentage Error (MAPE):** The MAPE for the combined

model is 7.60%.

Figure 3.7 shows the simulation results for the validation test.

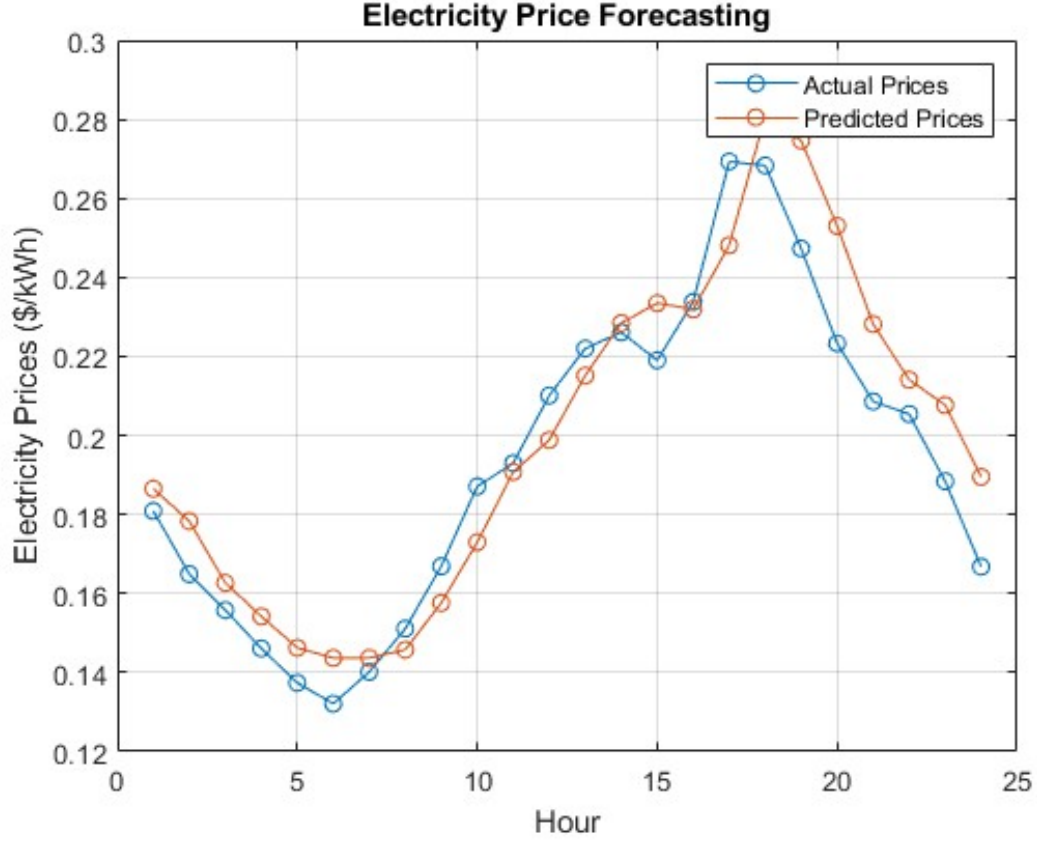


Figure 3.7: Simulation Results for the Proposed Model Showing the Foretasted Prices in Comparison to Actual Prices

It can be observed that the CNN-FNN model outperformed the previously discussed models, including the FNN, the LSTM, and the BiLSTM models, in terms of both MAE and MAPE. Moreover, the significant improvement in performance can be attributed to the unique capabilities of the CNN-FNN architecture:

- **Feature Extraction:** The CNN excels at extracting intricate patterns and spatial correlations from the input data, which includes temporal dependencies

in electricity demand. By using convolutional and pooling layers, the CNN effectively captures local dependencies and significant features that might be missed by a traditional FNN or BiLSTM model.

- **Dimensionality Reduction:** The max-pooling layers in the CNN help reduce the dimensionality of the data while preserving the most important features, thus simplifying the task for the subsequent fully connected layers.
- **Non-Linearity and Complexity:** The use of ReLU activation functions in the fully connected layers introduces non-linearity, enabling the network to learn complex relationships within the data that contribute to more accurate predictions.
- **Sequential and Hierarchical Learning:** By combining a CNN with an FNN, the model leverages the hierarchical feature learning of the CNN with the high-level abstraction capabilities of the FNN, leading to improved generalization and prediction accuracy.

To provide a clear comparison of the different models used for electricity price forecasting, the table below summarizes the results for each model:

Model	MAE (%)	MAPE (%)
FNN	7.76	14.91
LSTM	13.74	37.85
BiLSTM	13.26	24.7962
Proposed CNN-FNN model	3.9552	7.6039

Table 3.4: Performance Comparison of All Tested Models

3.3.4 Results Discussion

Table 3.4 above clearly demonstrates the superiority of the CNN-FNN model in terms of both MAE and MAPE. Here’s a detailed discussion of why the proposed model achieved the lowest error rates:

The FNN model served as a baseline. It was able to capture some of the underlying patterns in the data but lacked the capability to efficiently handle temporal dependencies and intricate feature extraction.

The BiLSTM model was designed to capture both past and future context in the data. However, its relatively higher error rates indicate potential over-fitting or the complexity of the model being unsuitable for the given dataset.

Nevertheless, the proposed CNN-FNN model achieved the lowest MAE (3.9552%) and MAPE (7.6039%). This can be attributed to its ability to perform feature extraction. The CNN component excels in extracting intricate patterns and spatial correlations from the input data, effectively capturing local dependencies. Furthermore, max-pooling layers in the CNN help reduce data dimensionality while preserving

essential features. Also, ReLU activation functions in the fully connected layers introduce non-linearity, enabling the network to learn complex relationships within the data. At the same time, the combination of CNN and FNN leverages hierarchical feature learning of the CNN and high-level abstraction capabilities of the FNN, resulting in better generalization and accuracy. These factors collectively contribute to the CNN-FNN model's ability to make more accurate predictions, as reflected in the lowest MAE and MAPE among the compared models.

CHAPTER 4

OPTIMIZED LOAD SCHEDULING

In this section, we explore the methodology for load scheduling technique for residential settings. We detail the residential load model, the optimization technique used, the problem formulation, and define the objective function of the load scheduler. The purpose of the scheduler is to reduce total electricity cost by optimally shifting appliances away from peak price hours to cheaper price hours while simultaneously maintaining a low PAR. This is done by developing a scheduling algorithm based on GA. Additionally, we analyze the obtained optimized power consumption schedule, demonstrating how such strategies can lead to significant reductions in electricity costs and enhance overall power efficiency (PAR).

4.1 Residential Load Model

The residential load model will be composed of different smart household appliances.

These appliances are then categorized into three categories:

- A- Shift-able and interruptible: Appliances that are expected to operate for a fixed period each day. Nevertheless, this fixed period is not continuous. Thus, the scheduler can interrupt and shift these appliances to cheaper price hours.
- B- Shift-able and non-interruptible: Appliances which are expected to operate for a continuous fixed period each day (e.g. washing machine). This type of appliance cannot be interrupted and shifted by the scheduler. However, the consumer has the ability to designate a starting time for the appliance to operate.
- C- Non-shift-able base: Appliances expected to operate throughout the day and not be shifted nor interrupted (e.g. refrigerator).

The following table (4.1) presents a list of residential appliances, including their power ratings (in kW) and the duration of their operation. The power ratings of these appliances were sourced from [42], [43], [44], and [45].

Appliance classification	Appliance	Power Rating (kW)	Operating Duration (Hours)
Shift-able and Interruptible	Washing Machine	0.50	2
	Dishwasher	1.50	1
	Electric Oven	2.0	2
	Clothes Dryer	1.50	1
Shift-able and Non Interruptible	Air Conditioner	2.0	6
	Water Heater	3	3
Base Appliances	Refrigerator	0.2	24

Table 4.1: Typical Household Appliances Power Ratings and Operating Duration.

4.2 Scheduling Optimization

This section discussed the scheduling optimization of a residential load scheduler.

We discuss the optimization technique utilizing GA in detail, articulate the problem formulation, and define the objective function.

4.2.1 Optimization Technique

Since the problem of finding the optimal schedule of home appliances is a combinatorial optimization problem, it cannot be solved using traditional optimization techniques [46]. In addition, since the search space of the problem is extremely large, exhaustive search is computationally infeasible. Usually, meta-heuristic techniques are used to solve appliances scheduling problems. These techniques converge to high fidelity solutions in acceptable time.

For example, Nature inspired algorithms such as GA and PSO are heavily used in load scheduling [22]. These algorithms mimic biological processes to reach to acceptable solutions.

In this work, GA is used to solve the optimization problem. GA is a search technique inspired by natural selection [47]. The algorithm involves three steps. First, a set of random solutions is generated. In GA terminology, each solution is called chromosome. Then selection and reproduction are iteratively applied until the algorithm converges to a solution. Each chromosome in the current population is evaluated using a fitness (objective) function. Then, the best performing solutions based on a selection criterion are used to reproduce a new population. Solutions of the lowest fitness are passed directly to the next generation, which are the elite solutions. In this work, tournament selection is used, in this technique, tournaments between n – size of the tournament - solutions are carried out. The winner in each tournament is added to the mating pool. The reproduction process is achieved by using two different operations, Crossover and Mutation. In Crossover, the chosen chromosome is cut into parts that

are interchanged with parts from other chromosomes, thus creating a new population 80% of the population, other than elite solutions, will undergo Crossover. Variation is introduced to this algorithm using Mutation process. In Mutation, parts of the chromosome are randomly changed, hence, reducing the possibility of converging to suboptimal solutions.

In this work, Mutation occurs according to a Gaussian distribution to each element of the parent chromosome. Mutation rate decreases after each iteration. Finally, since the decision variables of the problem at hand are restricted to be integers, additional truncation step is performed after Crossover and Mutation to ensure that the new population is all integers [46].

The algorithm will stop when a stopping criterion is satisfied, in our case, when the average change in the fitness value of the current population is less than 10^{-6} [46]. Figure 4.1 showcases the flowchart of the GA.

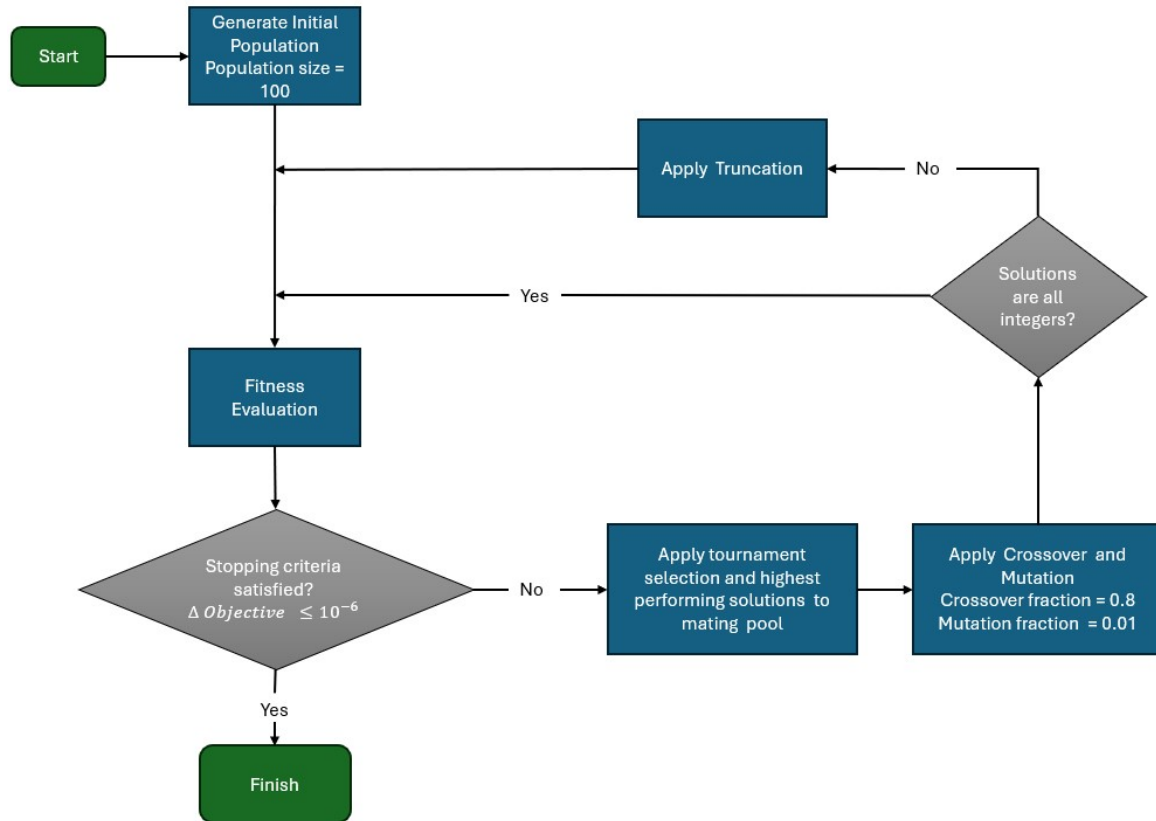


Figure 4.1: The Flowchart of the GA Technique

Table 4.2 shows the parameters of the employed GA.

Parameter	Value
Number of generation	100
Population size	100
Crossover fraction	0.8
Mutation fraction	0.01
Stopping criterion	$\Delta \text{Objective} \leq 10^6$

Table 4.2: Genetic Algorithm Parameters

4.2.2 Problem Formulation

The paper proposes an optimization model that aims to find the optimal schedule for the appliances in the residential load model. The objective is to both minimize electricity costs as well as PAR. Appliance scheduling is formulated as an optimization problem. The optimization function is defined as:

$$\text{minimize } \sum_{i=1}^{A_s} \sum_{j=x_i}^{Duration_i+x_i} (PR_i \times EP_j) \quad (4.1)$$

where: A_s is the total number of household appliances. PR_i represents power rating of appliance i in kW, $Duration_i$ denotes the operating time of appliance i , and EP_j is the cost of electricity at hour j in \$/kWh.

Furthermore, grid functionality can be significantly improved by lowering the PAR. To achieve this, total power must be calculated. P_T represents total energy consumed during a day and is determined by:

$$P_T = \sum_{h=1}^{24} \sum_{i=1}^{A_s} \sum_{j=1}^{Duration_i} PR_i \quad (4.2)$$

Then, the PAR is computed as follows:

$$\frac{P_{T_{Max}}}{P_{T_{Average}}} \quad (4.3)$$

where $P_{T_{Max}}$ represents maximum power within a time slot during the day. On the other hand. $P_{T_{Average}}$ represents the average of all power consumed throughout the day.

4.2.3 Objective Function

The main goal of the proposed system is minimizing total cost of electricity for residential consumers while simultaneously maintaining a reduced PAR. To achieve this objective, various factors are taken into account while formulating the objective function such as load types, ratings and electricity prices. The formulated objective function is weighted sum of the cost of electricity and the PAR incorporating equations (4.1-4.3) to reflect all these factors. Equation 4.4 showcases the objective function:

$$\text{Objective function} = (1 - \gamma) \times C_T + \gamma \times PAR \quad (4.4)$$

The constraints related to the objective function are:

$$h \in [1, 24] \quad (4.5)$$

where h is the number of hours during a day ranging from 1 to 24.

$$x \in [1, 24] \quad (4.6)$$

where x is the operational duration of an appliance.

$$Powerconsumption_{Sch} = Powerconsumption_{Unsch} \quad (4.7)$$

Equation 4.7 shows the requirement that power consumption without scheduling must equate to power consumption with scheduling. This condition is essential for ensuring consumer comfort, as it guarantees that each appliance operates for its des-

ignated duration without Without compromising its designated duration.

4.3 Optimized Power Consumption

The GA based optimizing scheduler receives the forecasted prices from the DNN model discussed in chapter 3. The parameters settings of the GA used in this paper are shown in Table 4.2. Multiple population sizes and number of generations have been tested, the values shown in Table 4.2 gave optimal results with the least computational power.

To verify the effectiveness of the proposed model, a case study is conducted to compare the unscheduled appliances' case and a case where the model was used to schedule appliances. Firstly, the input prices are the prices obtained from the DNN in the previous section. Figure 4.2 shows the RTP electricity prices taken from figure 3.7 being inputted to the GA scheduler.

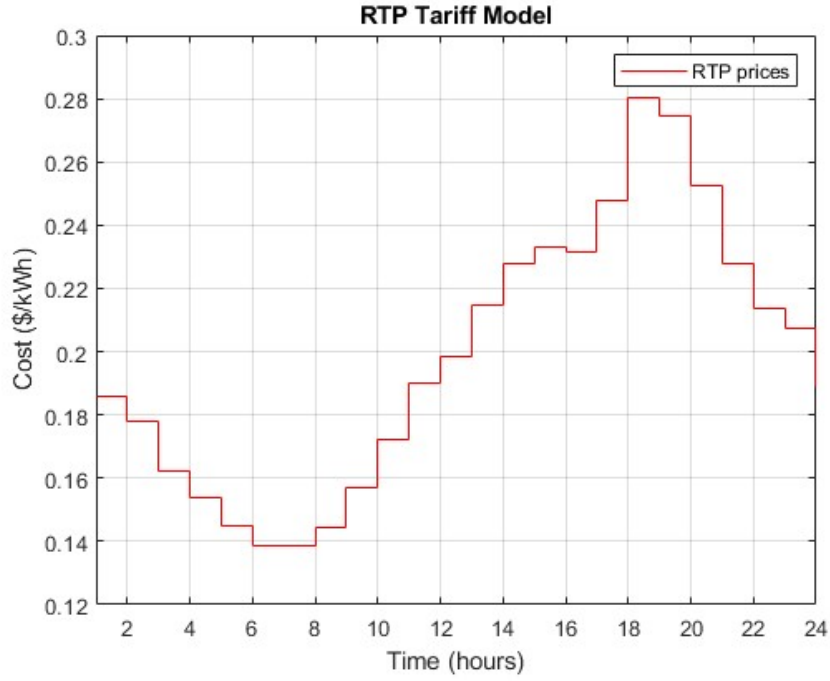


Figure 4.2: RTP Tariff Model Used for Verification Test

Furthermore, the unscheduled case used in the verification test is designed to reflect the average household electricity consumption profile (shown in figure 4.3 [48]). This model captures the typical patterns and loads found in residential settings, ensuring that the verification process is representative of real-world usage.

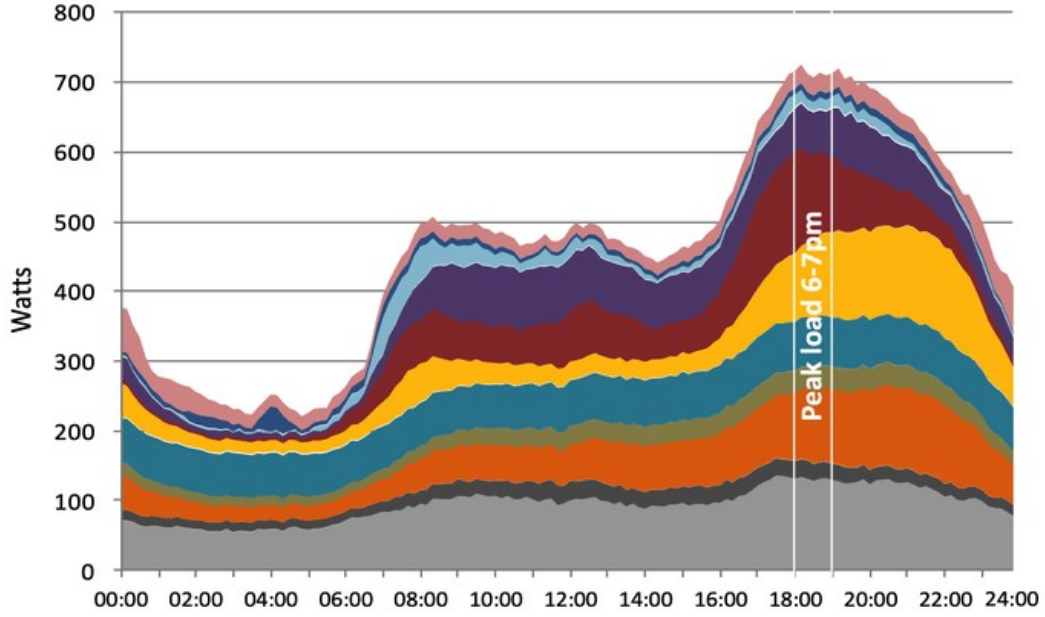


Figure 4.3: The Average Household Electricity Consumption Profile

Moreover, in terms of specific data, the average monthly electricity consumption for residential customers in New York is 861 kWh, which translates to approximately 28.7 kWh per day as reported in [49] and [50]. The total power rating of the appliances shown in the residential model is 33.8 kWh. This value is relatively close to the average daily consumption, accounting for variations in daily usage and peak times. This careful alignment ensures that the unscheduled case used in the verification test accurately represents a typical household's electricity consumption profile.

4.3.1 Power Consumption

The results of the verification test are shown in figure 4.4.

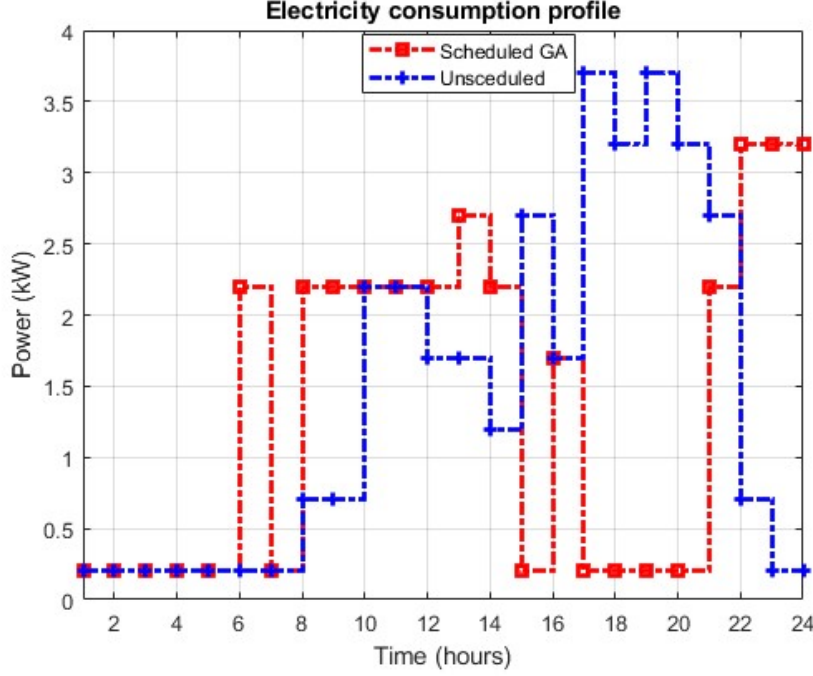


Figure 4.4: Power Consumption Profile Before and After Using the Intelligent Scheduler

It can be observed that the scheduler power consumption profile (shown in red) has been shifted away from peak hour prices (17:00 to 21:00) to cheaper hourly prices which ensures a cheaper electricity bill compared to the unscheduled case (shown in blue). Also, it can be noticed that the power consumption profile is smoother and contains no noticeable peaks that may disrupt the system during peak hours. Moreover, as discussed previously, user comfort is assured since all non-interruptible appliances will operate as intended.

4.3.2 Reduction in Electricity Costs and Peak to Average Ratio

The primary objective of implementing a smart scheduler is to reduce costs for residential users and alleviate the load during peak demand hours for operators. These performance metrics serve as benchmarks for evaluating the effectiveness of the GA optimizer. In Figures 4.5 and 4.6, the total electricity cost and PAR are depicted for both unscheduled and scheduled cases.

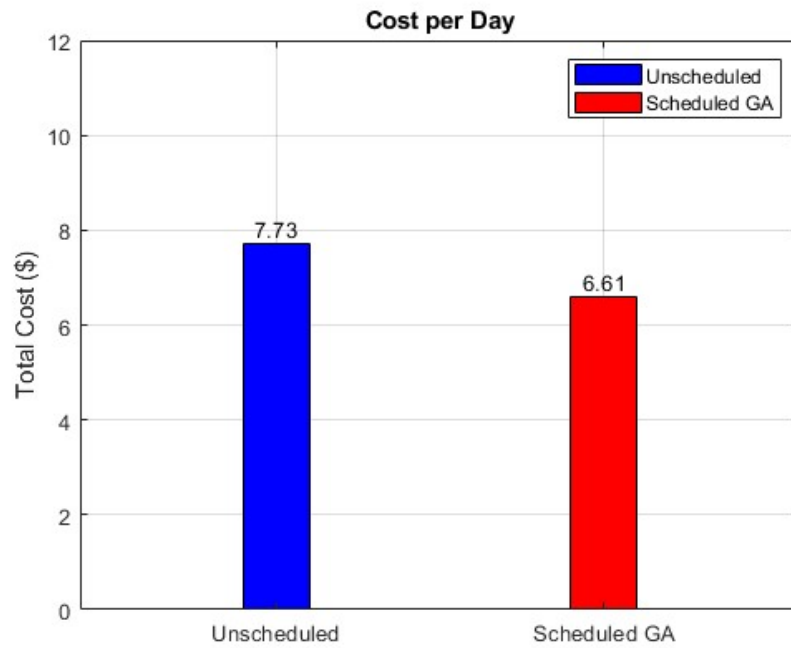


Figure 4.5: Total Cost of Electricity for Scheduled and Unscheduled Cases

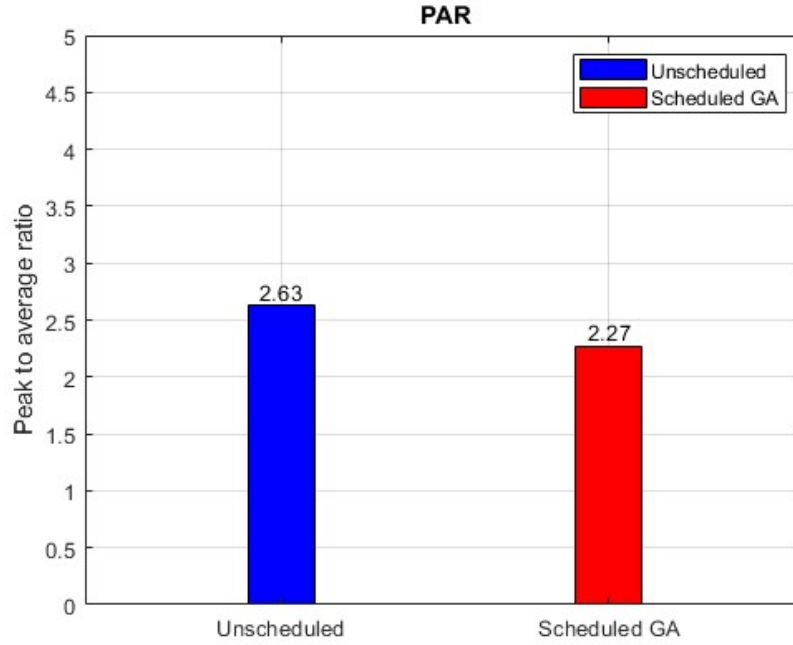


Figure 4.6: PAR for Scheduled and Unscheduled cases

Notably, the proposed scheduling solution in this case study minimizes total cost of electricity by approximately 14.49%. Furthermore, Figure 4.6 illustrates the PAR values before and after scheduling. The scheduled case reduces PAR by 13.69% compared to the unscheduled case, indicating a positive impact on user consumption behavior when utilizing GA for scheduling purposes.

CHAPTER 5

CONCLUSION

To conclude, in this work, an intelligent scheduler based on DNN and GA is proposed. Moreover, intelligent schedulers are presented as a solution to consumer response fatigue as it will be a valuable asset in enabling DR for residential consumers.

The proposed model combines a residential load model, a Real-Time Pricing forecasting model based on a DNN, and a load scheduler employing GAs. The DNN, adopting a combined architecture of CNN and FNN components, is trained on historical datasets to forecast electricity prices in advance. These forecasts serve as input for the load scheduler, which then generates optimized schedules for residential loads, thereby minimizing electricity costs and reducing the peak-to-average ratio. Several case studies were conducted to test the validity of the proposed models. The price forecaster showed an $MAE = 3.95\%$ and an $MAPE = 7.6\%$. Also, the optimization scheduler was tested and showed excellent results by reducing the EC by 14.49%, and the PAR by 13.69%.

All in all, the implementation of this intelligent scheduler holds promise for achieving a more efficient and responsive energy ecosystem. By facilitating demand response

efforts from both the aggregator and consumer sides, it paves the way for a sustainable and resilient energy infrastructure, aligned with the evolving demands of modern society.

This thesis has demonstrated the effectiveness of an intelligent scheduler that leverages DNNs and GA to optimize residential energy consumption. While the results are promising, investigating several aspects for future research can further enhance the capabilities and applications of the proposed models:

1. **Integration with Other Smart Grid Technologies:** Future work could explore integrating the intelligent scheduler with other emerging smart grid technologies, such as advanced metering infrastructure (AMI), distributed energy resources (DERs), and energy storage systems (ESS). Such integration could facilitate the development of a comprehensive minimum viable product (MVP) that offers a holistic approach to smart grid management, enabling more efficient and resilient energy ecosystems.
2. **Incorporation of Additional Factors in Price Forecasting:** The current model focuses primarily on historical electricity prices for forecasting. However, incorporating additional factors such as weather conditions, energy market trends, and grid demand-supply dynamics could improve the accuracy of price predictions. For instance, integrating weather forecasting data can help account for the impact of temperature and weather patterns on energy consumption and prices.
3. **User Behavior and Customer Patterns:** Another critical area for future re-

search is the incorporation of user behavior and customer consumption patterns into the optimization process. By understanding and predicting user behavior, the scheduler can tailor its optimization strategies to better match individual consumption habits, thus enhancing overall efficiency. Techniques such as machine learning and data analytics could be employed to analyze large datasets of user behavior, providing insights that can drive more personalized and effective demand response strategies.

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