Electricity Price Forecasting in the Ireland Day Ahead Market: A Machine Learning Approach

MSc Research Project
Data Analytics

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Student Name:	Chukwuwemeka Nwanze Okonji
Student ID:	22103970
Programme:	Msc. in Data Analytics
Year:	2023/24
Module:	Msc Research Project
Supervisor:	Dr.Catherine Mulwa
Submission Due Date:	14th December, 2023
Project Title:	Electricity Price Forecasting in the Ireland DayAhead Market: A Machine Learning Approach
Word Count:	
Page Count:	23

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Electricity Price Forecasting in the Ireland Day Ahead Market: A Machine Learning Approach

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Abstract

Electricity markets, evolving from state-owned monopolies to liberalized structures, necessitate accurate price forecasting due to the non-storability of electricity and the demand-supply equilibrium requirement. Focused on the Irish Day-Ahead market, this research employs machine learning, including LSTM, Stacked LSTM, CNN-LSTM, and MLP, to predict the market clearing price. Despite limited prior work on this market, the study evaluates four models, identifying the hybrid CNN-LSTM as the best performer with an RMSE of 0.025264, followed by 2-layer stacked LSTM and MLP. Although univariate in its approach, the research excels in capturing intricate market patterns. However, limitations include overlooking external factors like weather events, generation constraints, fossil and renewable fuels prices. Future work suggests expanding the model to consider fossil fuel and renewable energy prices, exploring the impact of trading volume, integrating weather data, evaluating across multiple markets, and optimizing model configurations for enhanced accuracy and robustness. This research contributes a benchmark for MCP forecasting in Ireland and offers insights for energy market stakeholders.

Keywords: **Day-ahead Electricity Market, Market Clearing Price (MCP), Long short-term memory (LSTM), Multi-Layer Perceptron. I-SEM**

1 Introduction

1.1 Background and Motivation

Electricity is an essential and special resource that cannot be held in vast quantities. Thus, a constant equilibrium between demand and supply is required. The electricity market like other public utility markets has traditionally been vertically integrated state-owned monopolies. Despite apprehensions about potential shortcomings, policymakers have pursued reforms in key energy industries, such as deregulation, aiming to enhance the efficient allocation of resources and the effectiveness of service supply. Electricity market liberalization began in the 1990s, with New Zealand and Sweden leading in 1994 and 1996, respectively. Other European countries followed suit with successful cases including the UK and Ireland, demonstrating high switching rates among household providers Shin and Managi (2017).

With the liberalization of the electricity market coupled with the non-storability of electricity, it has now become pertinent to be able to predict the load and prices of electricity. In this regard, load forecasting being a critical aspect of power systems management has garnered lots of traction as evident from the extensive research in this field. In contrast, research on price forecasting is relatively less abundant due the historical structure of electricity markets as monopolies limiting wholesale competition. However, with the evolving competitive electric markets, price forecasting has been gaining a lot of traction Panapakidis and Dagoumas (2016)

In the competitive electricity market, various stakeholders, including power generators, consumers, grid operators, and electricity aggregators, operate. This setup is a result of the deregulated power market, where consumers have the freedom to choose their suppliers based on their specific needs. In this market, electricity is viewed as a tradable commodity, rather than merely a service with a fixed value. To further promote competition and transparency in electric power trading, many countries have established a common platform known as a power exchange (PX) or electric power exchange (EPX)Shah and Chatterjee (2020)

In Ireland, the Integrated Single Electricity Market (I-SEM) is a unified wholesale electricity market that covers both Ireland and Northern Ireland. This integration with European electricity markets enables the seamless movement of energy across regions. The Day-Ahead Market conducts a daily auction at 11:00 a.m., allowing exchange members to trade electricity for 24 one-hour trading periods, with results available shortly after 11:45 a.m., ensuring efficient electricity trading. In the Day-Ahead Price market, participants submit bids for each hour of the following day. These bids are used by the Single Electricity Market Operator (SEMO) to determine the System Marginal Price, also known as the Market Clearing Price (MCP), for each trading hour. The MCP is the price at which the electricity market achieves balance without shortages or surpluses, representing the final outcome of the bidding process in a market free from supply and demand imbalancesYan and Chowdhury (2014)

That being said, Electricity prices are highly volatile. This volatility, characterized by fluctuations in prices across various timeframes, is a significant feature of electricity markets, akin to commodity markets. Unlike commodity markets with surplus storage capacity, electricity markets lack practical storage solutions, leading to pronounced short-term price volatility. This volatility is primarily driven by fundamental market factors and the inherent uncertainties in electricity generation and distribution, manifesting on hourly, daily, weekly, and seasonal scales. Factors like unexpected weather events, generator outages, emission constraints, and transmission line congestion contribute to these electrical imbalances, amplifying price volatility. This transformation in price dynamics, particularly following the liberalization of markets, heavily influences decision-making for market players, necessitating a thorough understanding of this parameter for effective risk management Benini et al. (2002)Tashpulatov (2013)

The aim of this project is to accurately predict the market clearing price of electricity in Ireland Day Ahead market using historical day ahead market prices using machine learning algorithms particularly the LSTM and MLP models.

1.2 Reserach Question and Objectives

Given the scarcity of research on predicting the market clearing price in the Irish Day-ahead market, the project proposes the following research question for investigation:

RQ: *"To what extent can we accurately predict the market clearing price in the Ireland Day Ahead Electricity Market Using Machine Learning techniques (i.e, LSTM, Stacked LSTM, CNN-LSTM and MLP) and which model demonstrates the highest predictive per-*

formance to support power generators, consumers, grid operators and electricity aggregators in Ireland"

In order to address the research question, the study intends to achieve the objectives specified in the table provided below:

Table 1: Research Objectives

ID	**Description**
1	Identify and critically review the literature concerning the electrical market evolution, factors affecting electrical prices and existing methods used in electrical prices forecasting
2	Extract lookback datasets from Semo website and combine the different lookback datasets to a single dataset
3	Data cleaning and Preprocessing; checking for missing values, identifying/removing outliers, removing noise/inconsistencies
4	Data Transformation and Feature Engineering of the cleaned data to prepare to be fed into the machine learning models
5	Implementation of various Regression Deep neural networks which includes Long short-term memory (LSTM) recurrent neural network, Stacked Long short-term memory (LSTM), CNN-LSTM Hybrid Model and Multi-Layer Perceptron (MLP) Model
6	Evaluation and comparing the performance of the implemented models with RMSE and MAE
7	Evaluation and comparing the performance of the Developed model with Existing Models with RMSE and MAE

The primary contribution of this project is the development of a predictive model for the Market Clearing Price (MCP) in the Irish Day-Ahead Market (DAM). This model aims to address the existing information gaps in MCP forecasting within the Irish market thereby enhancing the accuracy and reliability of MCP predictions in order to facilitate more informed decision-making in the Irish energy sector, contribute to the literature on energy market forecasting, and serve as a valuable tool for stakeholders in the Irish DAM.

The rest of this report is organised as follows: The second chapter gives a survey of existing literature on the subject, including examinations of existing approaches and a comparison of various relevant works. The methodology, as well as additional specifications such as the data pipeline, design architecture are presented in Chapter 3. Chapter 4 outlines the implementation, evaluation and result of the applied machine learning techniques while Chapter 5 gives the final conclusion as well as recommendation and future works.

2 Electricity Price Forecasting Literature Review

The purpose of this literature review is to delve into the evolution of the electricity market and to scrutinize the various methods and techniques currently employed in the prediction of electricity prices. Furthermore, we aim to conduct a comprehensive assessment of the performance of different approaches used to forecast market clearing prices. By examining recent peer-reviewed articles, this review aims to provide meaningful insights into this domain and underscore key findings from previous research endeavours. In essence, this literature review serves the purpose of shedding light on the study's aims, methodologies, and significant findings, offering a cohesive and coherent overview of the research conducted in the field of electricity price prediction. The scope of this literature review is the last 10 years with the exception of one benchmark paper which is before that period.

2.1 The Electricity Market

The production, transmission, and distribution of electrical energy require substantial financial investments, often leading to the establishment of natural monopolies that held control over these processes within specific geographic regions. Typically managed by single entities, these operations had the authority to set their own rates, subject to regulatory approval, ensuring a reasonable return on their considerable investments. However, to safeguard consumers from the consequences of monopolistic practices, regulatory measures became a global norm in the electricity industry. In regulated electricity markets, the core structure of a natural monopoly persists but operates under vigilant government oversight. Nevertheless, electricity prices in such markets tended to be high, and consumers' choices for services were often limited. In response to these limitations, the electricity market embarked on a journey toward deregulation. The traditional vertically integrated system underwent a transformation into three distinct businesses: generation, transmission, and distribution. This restructuring empowered consumers to select multiple providers according to their needs and preferences. Nonetheless, the transmission sector remained regulated to ensure equitable access to the network for all competitors Yan and Chowdhury (2010).

The move towards electricity market liberalization was initiated in the 1990s, with New Zealand leading the way in 1994, closely followed by Sweden in 1996. This momentum extended to several European nations, including the United Kingdom and Ireland Shin and Managi (2017).

To enhance competitiveness and transparency on a global scale, platforms such as power exchanges (PX) and electric power exchanges (EPX) have been established. These exchanges are designed to provide a transparent and reliable system for determining electricity transaction prices Shah and Chatterjee (2020).

One such power exchange platform is the Integrated Single Electricity Market (I-SEM) in Ireland, which amalgamates the Island of Ireland and European markets to facilitate the unrestricted flow of energy across borders. Originally initiated on November 1, 2007, as the single electricity market (SEM), it merged two distinct wholesale markets in Northern Ireland and Ireland. Operating as a centrally scheduled gross pool, it was established in response to the European Commission's 1996 directives, which advocated for the liberalization and regulation of electricity markets across EuropeDi Cosmo and Lynch (2016). SEM was managed by the Single Electricity Market Operator (SEMO), enabling generators and suppliers to submit bids specifying volume and price for specific time intervals. The market's pricing, known as the system marginal price (SMP), was determined through the Market Scheduling and Pricing algorithm, considering these bids and overall demand. Recognizing certain limitations in the former single electricity market (SEM) and to adapt to changing energy needs, the SEM underwent a transformation into the Integrated Single Electricity Market (I-SEM) on October 1, 2018 with the aim of addressing and improving upon these shortcomings. The new I-SEM introduced advanced markets, including day-ahead, intraday, and balancing markets, offering greater flexibility for participants across the island of Ireland Mohamed et al. (2022).

2.2 A Critical Review of Electricity Price Forecasting and Day ahead Market

Despite all the benefits brought about by the deregulation and restructuring of electricity markets, accurate price forecasting remains a paramount challenge. The underlying challenge in electricity price forecasting lies in the intricate interplay of diverse factors such as demand, fuel costs, generation plant orders, hydropower capacity, market strategies, and network congestion. Accurate price predictions are pivotal for effective power system operations, as they influence decisions related to power generation scheduling, fuel consumption, resource utilization, greenhouse gas emissions, power system simulation, and electricity demand modeling. This multidisciplinary field attracts the attention of various stakeholders, including utilities, grid operators, retailers, and aggregatorsPanapakidis and Dagoumas (2016). Furthermore, electricity markets are distinct from traditional financial markets in several respects, underpinned by their unique features. These markets are characterized by the non-storability of electricity, complex derivative contracts, and specific trading volumes. This non-storability makes electricity markets highly susceptible to external influences, such as seasonal variations in demand, regulatory uncertainties, production costs, and supply-demand imbalances, which contribute to price volatility Kalantzis and Milonas (2013)).

An additional layer of complexity arises from the need to balance electricity demand and supply effectively. The demand side exhibits high inelasticity during specific time intervals, necessitating precise demand-supply equilibrium to prevent blackouts or network overloads. On the supply side, the operation of inflexible and volatile electricity generation plants adds intricacy to energy distributionLehna et al. (2022). Within these electricity markets, most transactions occur in the day-ahead spot market, where electricity prices for the next day's delivery are established through auctions. For example, in the German spot market, day-ahead prices are determined via an auction at the European Power Exchange (EPEX SPOT) the day before at 12:00 pm, following the merit order principle. The market-clearing price is set based on the marginal cost of the last supplier securing an order, defining the spot price for the specific productLehna et al. (2022).

Another day-ahead market of note is the Irish Single Electricity Market (I-SEM) where System Marginal Price (SMP) is calculated using a cross-border hybrid electricity market integration algorithm called Euphemia. Orders in this market are made up of pairs indicating price and quantity, measured in £/MWh and MWh respectively. In the day-ahead market, each trading period spans an hour, with exchange members submitting the quantity in MWh for specific hours, accompanied by a specified price. Conversely, the intraday markets operate with half-hour trading periods, and members submit the quantity for these 30-minute intervals, along with corresponding prices. Electricity suppliers participate in the market by presenting their price-quantity pairs. Following the conclusion of the auction, Euphemia consolidates all orders per delivery hour in the I-SEM to determine the SMPRaouf Mohamed et al. (2021).

In summary, this section highlights the crucial nature of accurate electricity price forecasting, unique attributes of electricity markets, and the functioning of day-ahead markets. These insights empower energy market participants to make informed decisions and optimize their revenues.

2.3 A Critique of Machine Learning Models for Price Forecasting

Energy market traders prioritize market forecasting conditions to optimize trading revenues. This necessitates the use of forecasting models tailored to specific energy markets, given their location-dependent nature with unique auctions and procedures. Nonetheless, common techniques including machine learning models can be appliedMohamed et al. (2022).

As accurate day-ahead electricity price prediction holds paramount importance, several techniques have been deployed to forecast market clearing prices. Notably, Li and Becker (2021) conducted a study focusing on the influence of market coupling on electricity price forecasting. They explored hybrid Long Short-Term Memory (LSTM) deep neural networks and feature selection algorithms. The research outcomes underscore the significance of feature selection in achieving precise predictions and highlight the impact of integrated markets on the forecasting process. The study introduces three hybrid LSTM-based architectures for the European Power Market (EPF) and compares the predictive performance of two-step, autoencoder, and two-stage models. The findings emphasise the need for diverse features and greater interconnections for the efficient functioning of Europe-wide electricity markets.

In a related study, Peng et al. (2018) introduced a variation of LSTM-based algorithms by combining LSTM with the novel differential evolution (DE) algorithm, resulting in DELSTM. The model's evaluation using electricity prices from three regions revealed its superior forecasting accuracy compared to existing models. DE-LSTM displayed remarkable stability across various error metrics, suggesting its potential as an effective approach for electricity price forecasting and enhancing decision-making in power system operations.

Recognizing the increased integration of national electricity markets, Lago et al. (2018) presented methodologies aimed at integrating market dynamics into electricity price forecasting. Their goal was to enhance the accuracy and efficacy of predictive outcomes. The first approach involves a deep neural network that considers features derived from interconnected markets. Conversely, the second model leverages market integration to predict prices simultaneously in two distinct markets. The findings demonstrated significant improvements in forecasting accuracy, particularly between Belgium and France. This led to a reduction in the symmetric Mean Absolute Percentage Error (sMAPE) from 15.7% to 12.5%, highlighting the economic advantages of market integration regulations in other European Union regions.

Furthermore, traditional machine learning techniques have also been applied in electricity price forecasting. Yan and Chowdhury (2014) proposed a forecasting model for the mid-term electricity market clearing price (MCP), utilizing multiple Support Vector Machines (SVMs). This model enhances forecasting accuracy for both peak prices and the overall system performance when compared to a singular SVM. It is important to note that the effectiveness of these models depends on the careful selection of input data. The accuracy of the forecasting model significantly improves through the meticulous curation of training data and the precise prediction of sub-datasets.

In summary, this section offers a comprehensive review of various forecasting approaches. It covers deep learning techniques like LSTM and traditional machine learning methods such as SVM, providing valuable insights into the algorithms and techniques used in electricity price forecasting. These insights facilitate more informed decision-making and revenue optimization for participants in energy markets.

2.4 Comparison of Methods, Techniques and Results

This section compares the key points and findings of several research papers, aiming to elucidate the similarities and differences in their proposed methods and performance outcomes.

Focusing on Russia's wholesale electricity market, Patel and Thakur (2022) introduces an enhanced cascaded neural network for predicting the Market Clearing Price (MCP). The model achieves a minimum MAPE of 1.9%, outperforming other compared methods. In contrast, Jiang and Hu (2018) leverages a long-short-term memory (LSTM) recurrent neural network to forecast electricity prices. The model, incorporates additional variables like weather and oil prices, outperforms four alternative approaches in both the Australian and Singapore electricity markets, achieving a substantial 47.3% improvement in average daily MAPE.

Memarzadeh and Keynia (2021) proposes a hybrid forecast model that combines wavelet transform, feature selection, and a novel learning algorithm; this paper targets short-term power load and price prediction. Tested across various electrical markets, the model demonstrates strong performance, with MAPE values between 0.4% to 2.20%, effectively addressing the volatile nature of power load and pricing.

In summary, Patel and Thakur (2022) highlight an improved cascaded neural network, Jiang Hu (2018) leverage LSTM models with exogenous variables, and Memarzadeh and Keynia (2021) introduce a hybrid model utilising wavelet transform and feature selection. The studies exhibit varying degrees of forecasting accuracy, with Jiang and Hu (2018) reporting the most significant improvement (up to 47.3%). The research encompasses diverse electricity markets, including those in Russia, Australia, Singapore, Spain, the Pennsylvania-New Jersey-Maryland interconnection, and Iran, showcasing the versatility and efficacy of the proposed forecasting techniques.

The summarised comparisons are detailed comprehensively in the table 2 below:

Table 2: Table comparing related works on Electricity Price Prediction

Model Used	Evaluation Metric	Datasource	Results and Conclusion	Authors
Cascaded Feed Forward Network	MAPE,RMSE and MAE	Russian wholesale market	Outperforms others compared model with a MAPE of 1.9%.	Patel and Thakur (2022)
Developed LSTM-RNN	MAPE,RMSE	Dominion Energy Virginia USA	MAPE values ranging from 5% to 10%.	Haque and Rahman (2022)
LSTM, sequence model-based optimization technique (SMBO), Ensemble empirical mode decomposition (EEMD)	MAPE,RMSE	PJM Power Market Colombia	Reduction of MAPE by about 7% against the compared models.	Zhou et al. (2019)
LSTM	MAPE	Australian market at Victoria (VIC) region and the Singapore market	Improvement in the average daily MAPE reaches up to 47.3% against the compared models	Jiang and Hu (2018)
Wavelet transform (WT), Feature selection LSTM based algorithm	MAPE	Pennsylvania-New Jersey-Maryland (PJM) and Spain Electricity Markets	MAPE values ranging from 0.4% to 2.20%	Memarzadeh and Keynia (2021)

As seen in the previous sections, energy markets are undergoing significant transformations due to market liberalization and the evolution of energy sources. However, the diversity of conditions, such as political and climatic factors, leads to varying structures in energy markets across different countries. Consequently, research findings from one country may have limited applicability to others Ziel et al. (2015). Given the limited research on forecasting the Market Clearing Price (MCP) in the Irish Day-Ahead Market, this study is crucial to understand its unique market structure. The Long Short-Term Memory (LSTM) model, widely used in other markets, will be the benchmark for this project. Despite LSTM's proven performance, hybrid models often yield more accurate results Jiang and Hu (2018), prompting this research to also implement a hybrid LSTM model.

3 Methodology

3.1 Introduction

Research methodology is the approach or process employed in conducting research, encompassing the collection of tools and strategies for various research inquiries. Researchers must carefully select a robust approach to ensure optimal outcomes and accurate conclusions in their pursuit of extensive and precise research. This chapter describes the Scientist methodology that was followed in this project. The approach used for this project is a modified CRISP-DM pipeline.

3.2 Eletricity Forecasting Methodology Approach

The research methodology that was implemented in this paper to investigate the research question is a modified CRISP-DM pipeline that is a CRISP-DM model modified to fit the project requirements and objectives. The figure 1 below describes the modified CRISP-DM model for the market clearing price prediction.

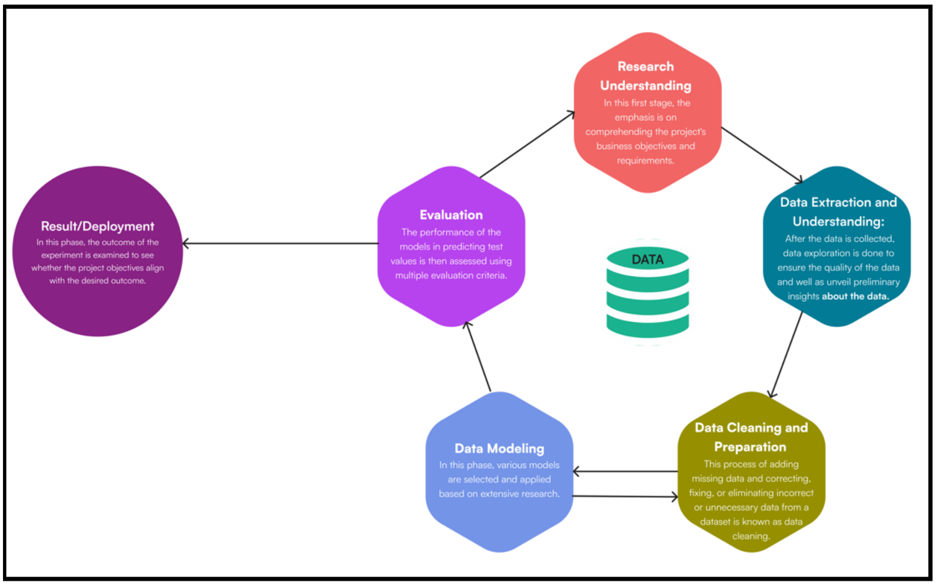

Figure 1: Eletricity Forecasting Methodology Approach

Research Understanding: In this first stage, the emphasis is on comprehending the project's business objectives and requirements. Subsequently, this understanding is transformed into a definition of the data mining problem and an initial plan aimed at achieving the stated objectives.

Data Extraction and Understanding: The data used in this project is obtained from the Semo PX website. After the data is collected, data exploration is done to ensure the quality of the data and well as unveil preliminary insights about the data.

Data Cleaning and Preparation: This process of adding missing data and correcting, fixing, or eliminating incorrect or unnecessary data from a dataset is known as data cleaning. It is the most crucial stage in preprocessing because it ensures that your data is ready to train models. This may include any of the following:handling missing values, identification/removal of outliers, removing noise and inconsistencies. After the data is cleaned, it is now ready for the machine learning techniques to be applied.

Data Modeling: In this phase, various models are selected and applied based on extensive research. Prior studies have showcased diverse strategies, and for this investigation, we will utilize Long Short-Term Memory (LSTM) networks, Multiple Layer Perceptron (MLP), and ARIMA time series models. The chosen models are initially executed and fine-tuned on a training set, constituting the model building process, to anticipate the output—forecasting future values, specifically the market clearing price.

Evaluation: The performance of the models in predicting test values is then assessed using multiple evaluation criteria.

Result/Deployment: In this phase, the outcome of the experiment is examined to see whether the project objectives align with the desired outcome.

3.3 Eletricity Forecasting Design Processflow

This section outlines the integration of the scientific methodology in the design process flow diagram. Initially, data is selected and compiled by merging two look-back datasets, spanning from November 2018 to October 2023, into a unified dataset. Python programming language is employed for analysis and experimentation, executed within the Google Colab IDE. Upon gathering the final dataset, it is imported into the Google Colab environment for data cleaning, including the identification and handling of missing data or outliers. Subsequently, the feature extraction phase focuses on isolating relevant data features. The dataset is then split into training and test datasets, with the initial four years designated for training and the last one and a half years for testing. Machine learning algorithms are applied to the training data, and the models are evaluated using the test data. The concluding phase involves the analysis of model performance, drawing insights and conclusions from the results. The design process flow overview is depicted in the figure 2 below.

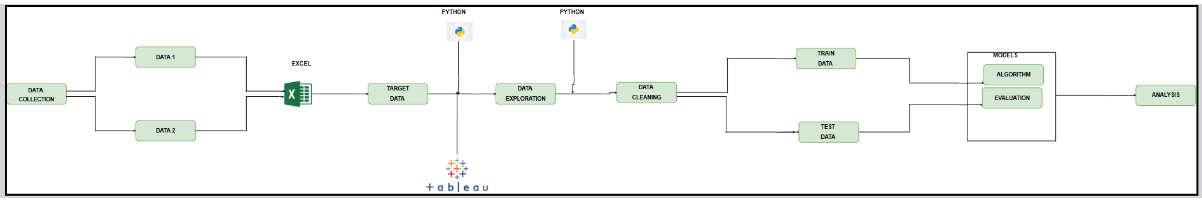

Figure 2: Eletricity Forecasting Design Process flow

3.4 Resources and Softwares Used

The following tools and technologies will be utilized to conduct this project, each chosen for its specific capabilities and contribution to the research workflow:

Python Programming language: this is an open-source language that one of the most widely used. For this project, we would be using the following python library to carry out various tasks; numpy, pandas, sci-kit learn, tensor flow, matplotlib, etc.

Microsoft Excel: Excel is a spreadsheet application widely used for data cleaning, manipulation, and initial exploration due to its user-friendly interface.

Google Colab: This cloud-based platform offers a collaborative environment for Python scripting, with the added benefits of free access to GPUs and ease of sharing, which enhances the computational capabilities and teamwork.

Tableau: Specialized in data visualization, Tableau provides intuitive and interactive dashboards that enable researchers to explore and present data in a visually compelling manner, thereby uncovering patterns and insights that might otherwise remain hidden.

These resources collectively form the technological foundation of our research, ensuring a comprehensive approach to data analysis and interpretation.

4 Implementation, Evaluation and Results of the Prediction of the Market Clearing Price of the Irish Day-ahead Market

4.1 Introduction

The chapter focuses on the implementation and evaluation of models used for predicting the day-ahead market's clearing price. It details the evaluation metrics for the models, the extraction, combination, and preprocessing of data, and the time series analysis conducted. Finally, a comparative analysis is presented. The performance of the implemented models is evaluated against each other, as well as against existing models in the field. This comparison highlights the strengths and limitations of each model, providing insights into their practical applicability.

4.2 Dataset

The dataset employed in this project was procured from the Semopx official website, within the document library section. It encompasses Historical Hourly Market Data, which details both price and volume information for two distinct periods:

- From the Go Live date (30th September 2018) to December 2020.
- From January 2021 to October 2023.

These periods yield two separate datasets. The historical data includes information from both the Day-Ahead Market (DAM) and the Intra-Day Market (IDM) auctions. However, the primary focus of this project is on the data pertaining to the Day-Ahead Market auction. The dataset features several columns, including: auction, timestamp, prices in euro and pounds, volumes information, Delivery Date, hour, interval as well as date information. For the purpose of this project, the timestamp and price columns are of particular interest, as the aim is to conduct a univariate time series prediction. The subsequent section will discuss the data cleaning, preprocessing, and initial data exploration and visualization processes in detail.

4.3 Data Preprocessing and Time series Analysis

4.3.1 Data Preprocessing

In this section, a multi-tool approach was employed for data integration, exploration, and processing. Excel, Tableau, and the Python language were used in transforming and analyzing the dataset. The initial preprocessing steps were conducted using Excel. The process began with merging two distinct datasets into a unified dataset. Subsequently, the Intraday Market data was filtered out, specifically focusing on the Day Ahead Market auction data. The refined dataset was then converted to CSV format for further analysis. Tableau was then utilized to conduct preliminary exploration and visualization, offering initial insights into the data trends. The line graph in figure 3 depicts the average price for each year, providing a clear representation of price trends over time.

Figure 3: Average Price per year

Figure 4 displays the plot of yearly average price against average volume, offering insights into potential relationships between price and volume dynamics as seen below:

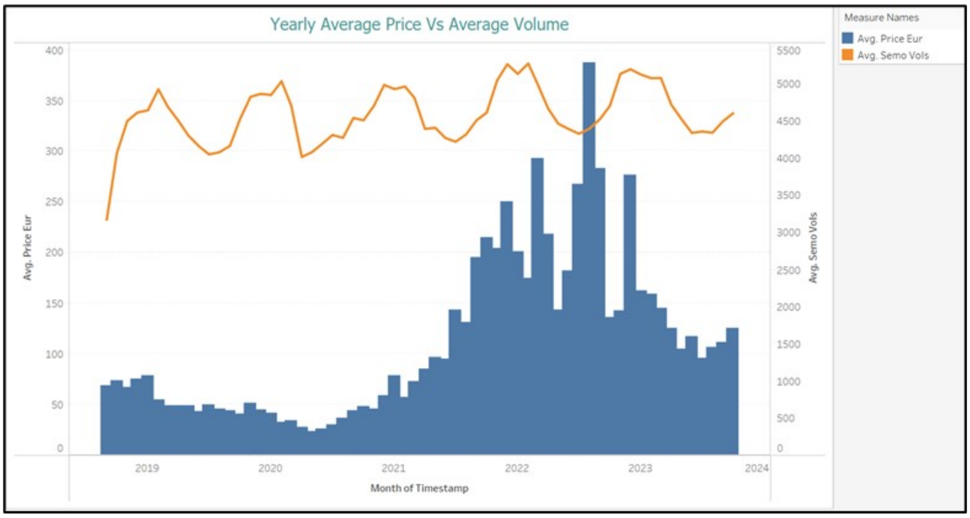

Figure 4: Yearly Average Price Vs Average Volume

Following the initial visual exploration, more data preprocessing steps were performed using Python programming language within the Google Colab IDE. The dataset comprises hourly prices and volumes of the Day-ahead market from September 30, 2018, to October 31, 2023, with dimensions of 44,569 rows by 18 columns. To align the dataset's start date with the beginning of October, the first two rows were removed. Following this, extraneous columns were discarded, retaining only the timestamp, price_euro, and sem_vol columns for analysis. A concise summary and descriptive statistics of the dataframe were generated, providing a comprehensive overview of the data. The dataset showed no missing values, eliminating the need for further data cleaning steps in this regard. The timestamp column was converted to a datetime format and temporal components such as month, year, date, time, week, and day were extracted. Finally, the timestamp column was designated as the index of the DataFrame.

Given the time series nature of the dataset, additional time series analysis was conducted to uncover temporal patterns and trends.

4.3.2 Time Series Analysis

Price Trends Analysis: The analysis begins with a line graph as seen in figure 5 and it illustrates how the price varies over the years. This visualization is crucial for identifying any long-term trends in the data.

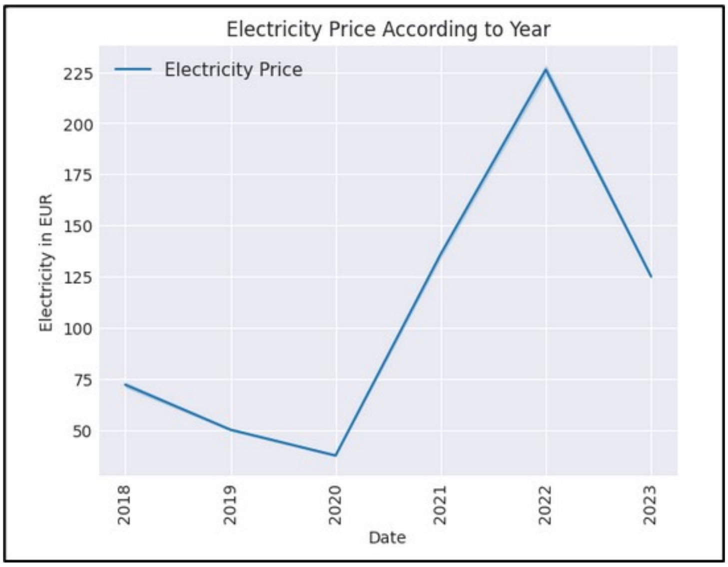

Figure 5: Price Trend Analysis

Price Distribution Analysis: An examination of the price distribution was also conducted. This analysis helps in understanding the spread and concentration of price points within the data set. See figure 6 below:

Figure 6: Price Distribution

Seasonal Decomposition: The seasonal decomposition of the time series data was performed to separate the trend and seasonal components. The trend plot isolates the underlying trend by removing the seasonal pattern, revealing the intrinsic price changes over time. Conversely, the seasonality is highlighted by subtracting the trend from the original data, showcasing the periodic fluctuations. The figure 7 show the addictive seasonal decomposition of our data.

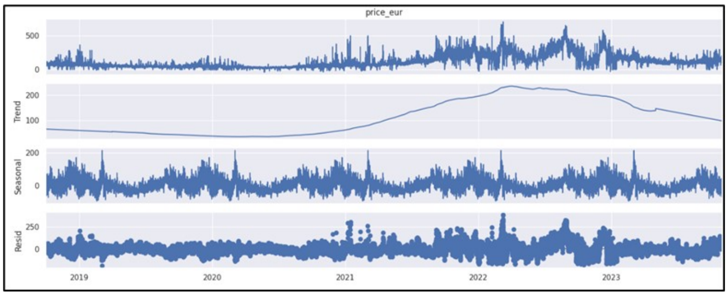

Figure 7: Seasonal Decompositon

Lag Plot Analysis: To assess autocorrelation, a lag plot is generated. The lag plot indicates a positive correlation at the hourly level. However, the correlation diminishes significantly as the lag increases from one day to one week, and further to one month. See figure 8.

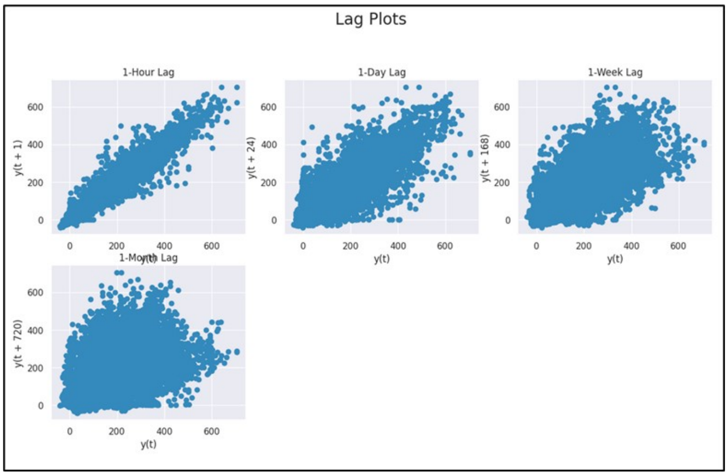

Figure 8: Lag Plots

Stationarity Test: Finally, the Augmented Dickey-Fuller (ADF) test was applied to determine the stationarity of the data. The results, depicted in the figure 9, confirms that the data is stationary.

```
ADF Statistic: -5.36793000559398
p-value: 3.9541404854253225e-06
Critical Values: {'1%': -3.4304969227193354, '5%': -2.861604936648082, '10%': -2.566804563660847б}
Reject the null hypothesis; the data is stationary.
```

Figure 9: Augmented Dickey-Fuller Test

With these analyses complete, the data is deemed ready for time series forecasting. The next section will detail the preparation of the data for the predictive models.

4.3.3 Feature Engineering and Data Transformation

The final stage of data preparation involves several key steps to ensure the data is suitable for feeding into machine learning models, particularly for time series forecasting using LSTM (Long Short-Term Memory) networks. This involved a series of essential steps to ensure the data was appropriately split, normalized, and formatted for training and testing.

Data Splitting: The dataset was divided into training and testing sets, with 80% allocated for training and 20% for testing. This corresponds to the first four years of data being used for training purposes, while the last year's data is reserved for testing. Figure 10 illustrates the train/test split, providing a visual representation of the data allocation.

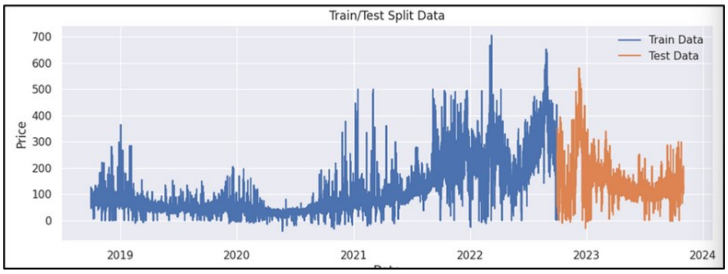

Figure 10: Train/Test Split Data Plot

Data Normalization: To facilitate more efficient training of the models, the data underwent a normalization process. This step is crucial for adjusting the scale of the data without distorting differences in the ranges of values.

Data Generation for the Neural networks: With the scaled data in hand, a crucial step involved framing it in a manner suitable for training a deep learning model, specifically an LSTM. This required defining a "lookback" period, specifying the number of previous timesteps utilized to predict subsequent ones. In this case, a lookback of 24 was chosen. The input data was then reshaped into a 3D tensor, adhering to the format [batch_size, timesteps, features], as per the LSTM model's requirements.

4.4 Implementation, Evaluation and Result for the Forecasting of the Market Clearing Price of the Irish Day-ahead Market

In this section, we apply supervised machine learning methods to address the research question. These methods are assessed using the Python programming language. Objectives 4 to 7 of the research project are achieved in this section. A variety of machine learning algorithms were evaluated to obtain the anticipated outcomes. The selection of algorithms for the solution was influenced by prior studies, as detailed in Chapter 2. Specifically, four algorithms were employed: LSTM, Stacked LSTM, MLP, and a hybrid CNN-LSTM model. The performance of the algorithms is rigorously evaluated using three key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics are selected for their effectiveness in assessing regression models, as demonstrated in the study by Abdellatif et al. (2023).

A brief description of these metrics are given below:

Root Mean Squared Error (RMSE): This metric evaluates a predictive model's precision by calculating the square root of the mean squared differences between the model's predictions and the actual observed values. A smaller RMSE signifies a more precise model, with a value of zero denoting an ideal model that perfectly predicts the observed values.

Mean Absolute Error (MAE): MAE quantifies the average magnitude of absolute errors between the predicted values and the actual data points in a dataset. A model with a lower MAE is considered more accurate. Unlike RMSE, MAE is less sensitive to outliers, which makes it a more robust metric for datasets with anomalous data points.

Mean Absolute Percentage Error (MAPE): MAPE computes the average percentage variance between actual and predicted values. It's expressed as a percentage, derived by averaging the absolute differences between predicted and actual values, normalized by the actual values, and then converted into a percentage. A lower MAPE indicates a model with better predictive accuracy.

4.4.1 Implementation, Evaluation and Results of LSTM model

The Long Short-Term Memory (LSTM) network is an advanced type of recurrent neural network (RNN), originally developed by Hochreiter and Schmidhuber. It has been further refined over time by various researchers to enhance its performance. The key feature of an LSTM network is its ability to capture and retain long-term dependencies within data sequences. This is made possible by its unique structure, which includes mechanisms that regulate the retention and discarding of information over extended periods. These mechanisms allow LSTMs to overcome the limitations of traditional RNNs, particularly in tasks that require the understanding of long-range temporal relationshipsLi and Becker (2021)

Implementation: In this research, the TensorFlow Keras library facilitated the creation of two simple LSTM models. The first model is a straightforward single-layer network, while the second includes an additional dense layer with 8 neurons and ReLU activation to better learn temporal patterns. The Adam optimizer with a learning rate of 0.0001 and Mean Squared Error as the loss function was compiled. Training spanned 20 epochs with a batch size of 32, incorporating ModelCheckpoint and EarlyStopping callbacks to optimize performance and mitigate overfitting. ModelCheckpoint preserves the optimal model based on validation loss, and EarlyStopping interrupts training if no improvement in validation loss is observed after 10 epochs.

Evaluation and Result:The evaluation of two LSTM-based models reveals that both exhibit similar loss and RMSE values, with the LSTM with Dense layer model showing marginally better performance in these aspects. The addition of a dense layer in the second model slightly impacted the results, introducing a marginal increase in MAE and MAPE.

4.4.2 Implementation, Evaluation and Results of Stacked LSTM model

Stacked LSTM involves increasing the number of hidden LSTM layers in the neural network. Stacking hidden layers in LSTM networks deepens the model, enhancing its deep learning capabilities. This depth is key to neural networks' success across various complex prediction tasks. For LSTMs, which process sequential data, additional layers mean abstracting data over time, effectively segmenting observations into different temporal scales for a more nuanced understanding.

Implementation: Utilizing the TensorFlow Keras library, this research implemented four neural network models with varying layers (1 to 3 additional layers) and units (32 to 128) to assess their impact on performance. The return sequence is set to true so as to return the full sequence as is necessary when stacking multiple layers apart from the last layer. All models were compiled with the Adam optimizer, a learning rate of 0.0001, and Mean Squared Error as the loss function. Training spanned 20 epochs with a batch size of 32, incorporating ModelCheckpoint to save the best-performing model and EarlyStopping to prevent overfitting by terminating training after 10 epochs without validation loss improvement.

Evaluation and Result: The analysis of Stacked LSTM models indicates that additional layers do not significantly boost performance, as reflected by consistent Loss and RMSE metrics and a slight increase in MAE. Initially, model accuracy improves but then plateaus, highlighting that the two-layer model performs as effectively as more complex structures. This suggests that simpler architectures may be adequate for certain datasets and tasks, and extra layers might not provide substantial benefits. Figures 11 and 12 provide a visual representation of the models' performance and comprehensive summary and , respectively.

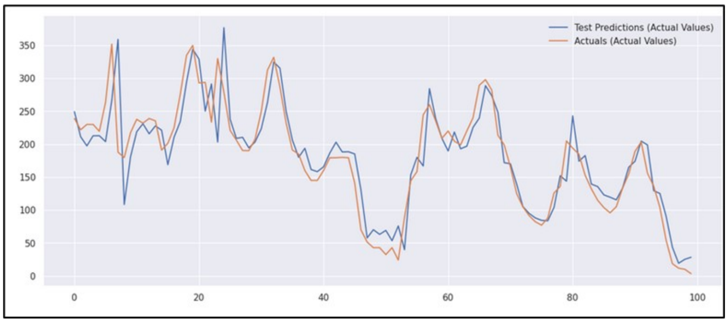

Figure 11: Actual vs Predicted for Stacked LSTM - 2 Layers Model

	Model	Loss	Root Mean Squared Error	Mean Absolute Error
0	LSTM	0.000720	0.026838	0.016901
1	LSTM with Dense layer	0.000719	0.026808	0.017070
2	Stacked LSTM - 2 layers	0.000713	0.026694	0.016591
3	Stacked LSTM - 2 layers with Dense Layer	0.000713	0.026699	0.016992
4	Stacked LSTM - 3 layers	0.000720	0.026838	0.016901
5	Stacked LSTM - 4 layers	0.000735	0.027114	0.017527

Figure 12: Evaluation Result for LSTM Models

4.4.3 Implementation, Evaluation and Results of CNN-LSTM

This is a type of encoder-decoder model. It is an encoder-decoder model that combines CNN and LSTM networks, the CNN serves as the encoder, filtering the input data. Originally developed for image recognition tasks, CNNs effectively process visual data for identifying patterns and features. They are also utilized in natural language processing to analyze sequential data. Following the convolutional layers, a pooling layer typically comes next, summarizing the convolved features into a more compact form. Subsequently, these pooled values are transformed into a lengthy, flat vector that serves as an intermediate representation before decodingLi and Becker (2021)

Implementation: This implementation also Utilizes TensorFlow's Keras library, the model features a Conv1D layer with specified filters and kernel size, activated by ReLU, followed by an LSTM layer with defined units and ReLU activation, with return sequences=True for full sequence output. This model was compiled with Adam optimizer (learning rate: 0.0001) and Mean Squared Error loss fuction, it trains over 20 epochs with a batch size of 32, using ModelCheckpoint to save the best model by validation loss, and EarlyStopping after 10 epochs without improvement. Four distinct models are evaluated to identify the best performer.

Evaluation and Result: The comparative analysis of four CNN LSTM models indicates that Model 4 outshines the rest, achieving the lowest loss (0.000638), RMSE

(0.025264), and MAE (0.015429). This model's efficacy stems from its design, which incorporates a Conv1D layer with 128 filters and a kernel size of 7, alongside dual LSTM layers with 256 units each, adeptly extracting spatial features and capturing temporal patterns. Notably, all models shared a four-layer structure, with variations in parameter values driving the performance differences. The sequential enhancement from Model 1 to Model 4 reflects targeted improvements in architecture and training, culminating in Model 4's superior predictive accuracy. The accompanying figures 13 and 14 shows the Actual vs Prediction plot and a summary of the implemented models' results.

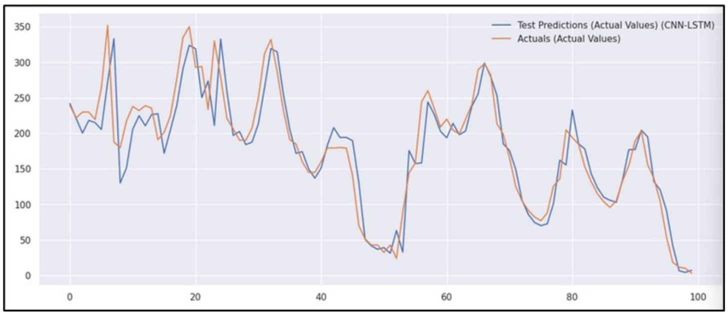

Figure 13: Actual vs Predicted for CNN-LSTM Model 4

	CNN LSTM Model	Loss	Root Mean Squared Error	Mean Absolute Error
0	CNN LSTM Model 1	0.000694	0.026350	0.016843
1	CNN LSTM Model 2	0.000664	0.025766	0.015957
2	CNN LSTM Model 3	0.000649	0.025475	0.015652
3	CNN LSTM Model 4	0.000638	0.025264	0.015429

Figure 14: Evaluation Result for CNN-LSTM Models

4.4.4 Implementation, Evaluation and Results of MLP

Multi-Layer Perceptron (MLP) Neural Networks is an advanced version of the perceptron model. Neurons within MLP, acting as computational units, process weighted inputs through activation functions, forming multi-layered structures. These networks consist of input, hidden, and output layers, with hidden layers capturing features at various scales. MLP training involves data normalization and employs stochastic gradient descent for weight adjustments through error back-propagation over multiple epochs. Weight updates can follow online learning for quick adjustments or batch learning for stability. Essential factors like learning rate, momentum, and learning rate decay influence these adjustments. MLP's strength lies in its ability to learn complex mappings and approximate various functions, making it versatile for predictive tasks in different domainsChinnathambi et al. (2018).

Implementation: In this research, the TensorFlow Keras library was utilized to construct a series of five MLP models, each with varying complexity due to different numbers of layers. The most intricate model, Model 5, consisted of a sequential arrangement of dense layers with neuron counts ranging from 256 to 16 and included dropout regularization to prevent overfitting. Each model was compiled with the Adam optimizer, a learning rate of 0.0001, and Mean Squared Error as the loss function. Training was conducted over 20 epochs with a batch size of 32, utilizing ModelCheckpoint to save the best model based on validation loss and EarlyStopping to halt training if no improvement was observed after 10 epochs. This systematic approach allowed the models to effectively learn temporal patterns and generalize well to new data.

Evaluation and Result: For this implementation, it was found that MLP Model 1 outperformed the others, registering the lowest loss of 0.000802, RMSE of 0.028315, and MAE of 0.018096. This model's architecture, which included a simple sequence of dense layers with 64 and 32 neurons and dropout for regularization, proved to be the most effective. In contrast, the more complex models, despite having additional layers and dropout regularization, did not yield better results, with higher loss and error metrics. These findings suggest that a less complex model architecture was adequate for the task at hand, and that increasing model complexity does not necessarily correlate with improved performance, especially when it may lead to overfitting. The figures 15 and 16 show the actual vs prediction plot and a summary of the MLP models

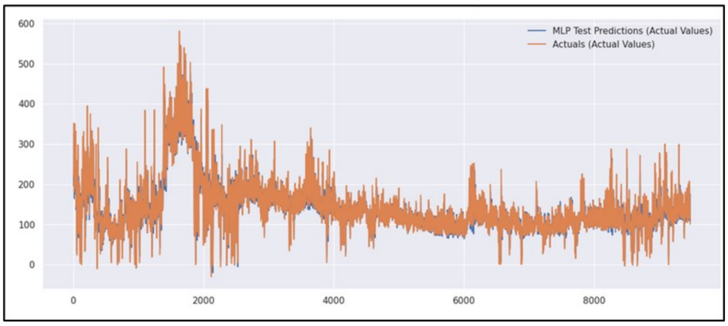

Figure 15: Actual vs Predicted for MLP Model 1

	MLP Model	Loss	Root Mean Squared Error	Mean Absolute Error
0	MLP Model 1	0.000802	0.028315	0.018096
1	MLP Model 2	0.001573	0.039658	0.028427
2	MLP Model 3	0.002190	0.046794	0.033505
3	MLP Model 4	0.007341	0.085681	0.069009
4	MLP Model 5	0.003578	0.059816	0.038139

Figure 16: Evaluation Result for MLP Models

4.5 Comparision of Developed Models

The evaluation of the developed models reveals distinctive performance characteristics. The CNN-LSTM model, specifically CNN LSTM Model 4, outshines others with the lowest Root Mean Squared Error (RMSE) of 0.025264, Mean Absolute Error (MAE) of 0.015429. This indicates superior predictive accuracy. On the other hand, the MLP Model 1 exhibits slightly higher errors with an RMSE of 0.028315, MAE of 0.018096.

The Stacked LSTM model with 2 layers also performs well but falls between the CNN-LSTM and MLP models in terms of accuracy, with an RMSE of 0.026694 and MAE of 0.016591. The CNN-LSTM Model 4 stands out as the most effective model for the given task, demonstrating its prowess in capturing intricate patterns within the data. Further optimization and exploration of hyperparameters could potentially enhance the performance of these models, addressing the nuances of the specific dataset and refining predictions. The figure 17 summarise the best performing models of the implementations.

Summary of Best Models based on RMSE:

	Model Type	Best Model	RMSE	MAE
0	CNN-LSTM	CNN LSTM Model 4	0.025264	0.015429
1	MLP	MLP Model 1	0.028315	0.018096
2	LSTM	Stacked LSTM - 2 layers	0.026694	0.016591

Figure 17: Comparison of Developed Models

5 Conclusion and Future Work

This research project has conducted a forecast of the market clearing price in the Irish Day-ahead market using several deep learning neural networks. The focus of this research is to evaluate the performance of four deep learning models and determine the best performing model. To the best of the candidate's knowledge, this research helps bridge the gap in the lack of related works focusing on the Irish Day-ahead market. Among the four models implemented, the hybrid CNN-LSTM model performs the best with the lowest RMSE of 0.025264. This is closely followed by the 2-layer stacked LSTM model, and lastly, the Multilayer Perceptron (MLP) model. This result aligns with previous research that highlights the superior performance of hybrid LSTM models over regular LSTM models. While this research has favorable evaluations and results in terms of the evaluation metric, it's important to acknowledge some of the project's limitations. Notably, the research exclusively tackles the MCP forecast problem from a univariate perspective, overlooking the impact of fossil fuel prices and the integration of renewable energy sources. Additionally, the research falls short in addressing external factors like unexpected weather events and generation imbalances that contribute to price volatility Nevertheless, this research serves as a benchmark for the forecasting of MCP, especially in Ireland where there is limited work in this regard. The model evaluation, as indicated by the RMSE and MAE values, shows that the developed model excels in capturing the intricate patterns within the market data.

Future Work: This research can be expanded by developing the forecasting model to consider additional factors influencing energy generation, such as the price of fossil fuels and the impact of renewable energy sources. Another aspect worth investigating is how the volume being traded affects the forecasted prices. Additionally, augmenting the dataset by integrating weather-related information with energy data can provide a more comprehensive understanding of the market's behavior. Evaluating the forecasting model across multiple electricity markets can also be explored. Lastly, there is always scope for further optimization and testing of other models or configurations to improve the accuracy and robustness of the forecasting model. This multi-faceted approach could provide a more comprehensive understanding of the market dynamics and improve the accuracy of future forecasts.

Acknowledgment

I would like to express my appreciation for and acknowledge the valuable guidance provided by Dr. Catherine Mulwa while going ahead with this research. Additionally, I also acknowledge the support of my parents.

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