THE REPUBLIC OF TURKEY

İSTANBUL KÜLTÜR UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

MODELLING ELECTRICITY GENERATION BASED ON COAL IN TÜRKİYE

Master of Science Thesis

by YASIR HASSAN MOHAMED

Department: Industrial Engineering

Program: Engineering Management

Supervisor: Assist. Prof. Duygun Fatih Demirel

MAY 2024

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MAY 2024 **Yasir Hassan Mohamed**

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Üniversite	**: İstanbul Kültür Üniversitesi**
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ÖZET

MODELLING ELECTRICITY GENERATION BASED ON COAL IN TÜRKİYE

Yasir Hassan MOHAMED

Bu tez, kömür yakıtlı elektrik santrallerine odaklanarak Türkiye'de elektrik üretim modellemesini araştırmaktadır. Türkiye'nin hızla yükselen ekonomisi enerji tüketiminde büyük bir artışa neden oldu ve kömür enerji karışımında kritik bir rol oynamaktadır. Çalışma, teknik, ekonomik ve çevresel faktörleri dikkate alarak kömür bazlı enerji üretiminin çeşitli yönlerini analiz etmek için kapsamlı bir yaklaşım benimsiyor. Tez, enerji talebindeki değişiklikler, teknolojik gelişmeler ve düzenleyici ortamların değişmesi gibi çeşitli durumları dikkate alarak kömürle çalışan elektrik üretiminde gelecekteki eğilimleri tahmin etmek için modelleme yöntemleri ve simülasyonları kullanır. Bulgular, Türkiye'nin enerji sektörünün uzun vadeli büyümesiyle ilgilenen politika yapıcılar, endüstri oyuncuları ve akademisyenler için yararlı bilgiler sağlamayı amaçlamaktadır. Son olarak, bu tez, teknik, ekonomik ve çevresel faktörleri içeren kapsamlı bir bakış sağlayarak Türkiye'de kömürle çalışan elektrik üretimini çevreleyen karmaşık dinamiklerin daha iyi anlaşılmasına katkıda bulunur. Türkiye'nin gelişen enerji ortamı bağlamında, bulgular karar vericilere rehberlik etmeyi ve kömür bazlı elektriğin geleceği için planları şekillendirmeyi amaçlamaktadır.

Anahtar Kelimeler: Elektrik, Talep Tahmini, Zaman Serisi Analizi, Doğrusal Regresyon.

Science Code: 90602

University	**: İstanbul Kültür University**
Instittute	**: Institute of Graduate Studies**
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ABSTRACT

MODELLING ELECTRICITY GENERATION BASED ON COAL IN TÜRKİYE

Yasir Hassan MOHAMED

This thesis investigates electricity generation modeling in Turkey with a focus on coal-fired power plants. Turkey's rapidly rising economy has led to a huge increase in energy consumption, and coal plays a critical role in the energy mix. The study takes a comprehensive approach to analyze various aspects of coal-based energy production, taking into account technical, economic and environmental factors. The thesis uses modeling methods and simulations to predict future trends in coal-fired electricity generation, taking into account various situations such as changes in energy demand, technological advances, and changing regulatory environments. The findings are intended to provide useful insights for policymakers, industry players and academics interested in the long-term growth of Turkey's energy sector. Finally, this thesis provides a comprehensive overview involving technical, economic and environmental factors, contributing to a better understanding of the complex dynamics surrounding coal-fired electricity generation in Turkey. In the context of Turkey's evolving energy environment, the findings aim to guide decision makers and shape plans for the future of coal-based electricity.

Keywords: Electricity, Demand Forecasting, Time Series Analysis, Linear Regression.

Science Code: 90602

1. INTRODUCTION

This chapter includes, Background Information, Aim of the Research, Thesis Question/hyphotesis and Research Significance/Contribution.

1.1.Background Information

Alparslan (2023) states that Turkey has traditionally generated a large amount of its electricity from coal. Gaining knowledge of historical patterns and trends in the production of electricity from coal offers insights into the variables affecting generation levels.

A variety of power generating sources are part of Turkey's energy infrastructure. Hard and lignite coal-fired power stations make up a significant portion of installed capacity. Turkey has large domestic coal deposits, mostly in the form of lignite. Nevertheless, the nation also depends on imported coal to meet its energy requirements. Coal availability and price can have an effect on forecasts.

Coal-fired electricity generation forecasting necessitates evaluating the total energy demand, which is strongly correlated with economic growth. Turkey's expanding industrial sector and economy are the main factors influencing the country's electricity usage.

With the exception of 2020 and 2021, coal generation in Turkey has averaged 113 TWh over the previous five years. 2020 saw a decline in the production of coal as five lignite plants were forced to shut down for six months as a result of their failure to comply with air pollution regulations. The soaring cost of hard coal caused a 1.7 TWh decline in coal generation in 2021.

Coal power generation increased by 10% annually in 2022 to 113.6 TWh. Additionally, this is somewhat more than 2018's peak yearly coal power generation of 113.2 TWh. Imported coal contributed to the coal power industry's comeback, in part because the market price ceiling was loosened in 2022. Market prices grew to the point where imported coal power plants could make a profit as power market prices increased. Due to its reliance on imported coal, the recently operational 1.3 GW coal-powered Hunutlu power station has increased import dependency.

Coal generation might be about to increase again, even if it seems to have plateaued during the past five years. The two units of Hunutlu only went online in October and June of last year, respectively, therefore its generation will probably be more noticeable in 2023. The long-term National Energy Plan, which was released at the end of 2022, also projects an increase in coal capacity of about 2.5 GW by 2035, from the current 21.8 GW. Despite widespread misconception, domestic coal does not dominate Turkey's coal generation. Import-dependent coal-burning power plants produced 25% more electricity in 2022 than did domestic coal-burning plants. Of the 10.2 TWh overall increase in coal power generation between 2021 and 2022, 8.3 TWh is attributed to imported coal.

Ever since 2010, the trend of increasing coal generation has also been fueled by imported coal. By 2022, the percentage of imported coal generation in overall power generation will have increased from 7% in 2010 to 20%. The amount of coal generated by imports as of 2022 is more than four times as much as it was in 2010 (14.5 TWh), at 63.2 TWh (Alparslan, 2023).

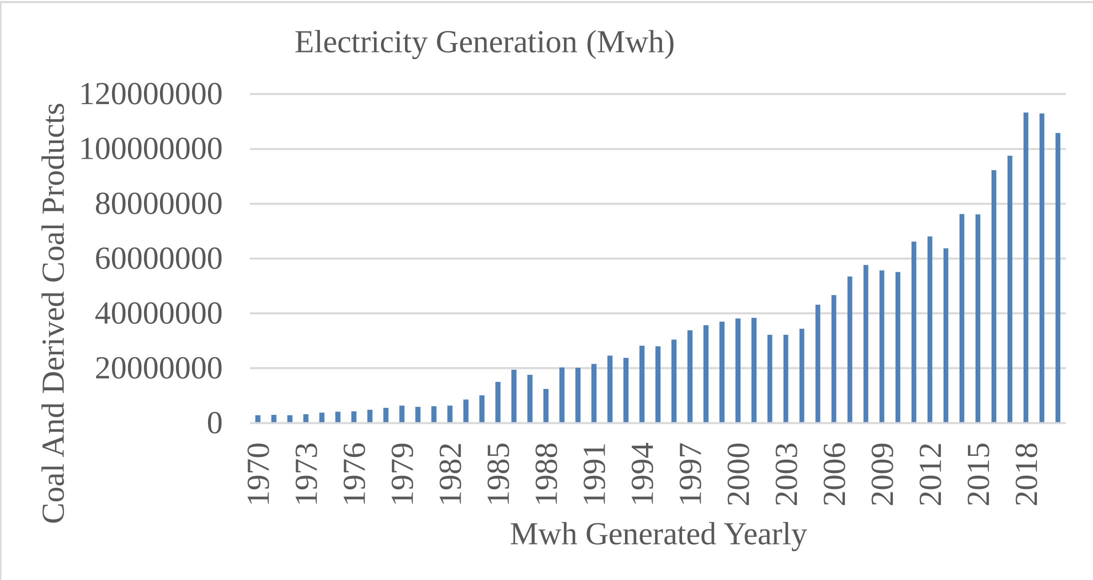

Figure 1.1: Electricity Generation

Figure 1.1 shows the generated Mwh from 1970 to 2018 it also reveals the trajectory of electricity generation from coal in Turkey. Over this period, the figures exhibit a notable increase, with the generation values represented in millions. In 1970, coal-based electricity generation stood at 2.82 million units, and by 2020, this had risen significantly to 105.81 million units.

Observing the data in five-year intervals, it can be identified important growth points. In 1975, the figure had already surpassed the 4 million mark, and by 1980, it had reached 5.96 million. The 1980s and early 1990s saw a steady increase, but it was in the mid-1990s that a more substantial upward trend began. In 1995, the generation exceeded 28 million, and by 2000, it had surpassed 38 million.

The mid-2000s witnessed a considerable surge, with the 2020 figure of 105.81 million representing a more than threefold increase from 2005. This surge could be indicative of increased industrialization and urbanization during this period, potentially leading to a higher demand for electricity.

It's important to note that while the data illustrates a general upward trajectory, there are some fluctuations. For instance, a dip in the late 1990s is followed by a resurgence in the early 2000s. Understanding the factors influencing these fluctuations would require a more in-depth analysis.

the data portrays a substantial growth in coal-based electricity generation in Turkey over the past five decades. This upward trend reflects the country's reliance on coal as a significant source of electricity, with the peak of 105.81 million units in 2020 highlighting the role of coal in meeting the increasing demand for electricity in the nation.

Table 1.1: Electricity Generation

Years	Electricity Generated (Mwh)	Years	Electricity Generated (Mwh)	Years	Electricity Generated (Mwh)
1970	2824500	1987	17653500	2004	34447600
1971	2980200	1988	12486600	2005	43192500
1972	2920800	1989	20269500	2006	46649500
1973	3243600	1990	20181300	2007	53430900
1974	3871300	1991	21561500	2008	57715600
1975	4113300	1992	24570800	2009	55685100
1976	4327300	1993	23759900	2010	55046400
1977	4892000	1994	28234700	2011	66217900
1978	5569200	1995	28046900	2012	68013100
1979	6438000	1996	30413600	2013	63786076
1980	5960300	1997	33860000	2014	76262682
1981	6136400	1998	35687500	2015	76165606.5
1982	6441200	1999	37030900	2016	92273097.7
1983	8577000	2000	38186300	2017	97476295
1984	10118300	2001	38417500	2018	113248625.2
1985	15027800	2002	32149100	2019	112894124
1986	19437300	2003	32252900	2020	105812004.1

The provided dataset represents historical electricity generation in megawatt-hours (MWh) over the years from 1970 to 2020. The corresponding values reflect the annual electricity output in Turkey during this period. This dataset serves as the foundation for a time series forecasting endeavor, where the goal is to predict future electricity generation from coal trends based on the established historical patterns.

1.2.Aim of the Research

The goal of the study is to create a prediction model that is dependable and accurate in order to project the amount of power that will be generated from coal in Turkey in the future. Enhancing knowledge of the variables affecting coal-based electricity generation is the aim, and stakeholders, policymakers, and energy planners will find the tool useful. Informed decision-making, effective resource management, and the alignment of power generation techniques with technological, environmental, and economic factors are the main goals of the research.

In order to accomplish this goal, the following research objectives must be met:

1. Collect historical data on the production of power from coal.
2. Select a modeling strategy that best fits the data and task, by Considering time-series models or machine learning algorithms.
3. Clear and precise data

1.3.Thesis Questions/Hypotesis

The following questions are answered in this research:

1. Given the various variables affecting power output, how can precise and trustworthy prdictive models be created to estimate Turkey's coal-based energy generation?
2. In the Turkish context, which modeling techniques such as time-series models and machine learning algorithms are best suited for forecasting coal-based energy generation, and why?
3. How reliable is Turkey's historical data on coal-based energy generation, and what can be done to make it more reliable for predictive modeling using data preprocessing techniques?

- The first question clarifies to forecast Turkey's coal-based energy generation, accurate and reliable predictive models must be created using a comprehensive approach that takes into account the various aspects influencing power output. Creating models that accurately predict the energy system while simultaneously capturing its complexity is a difficult task.

- While the second question gives a viewpoint of Choosing between time-series models and machine learning algorithms, or a combination of both, depends on the specific requirements of the forecasting task. It is often beneficial to experiment with different models and select the one that provides the most accurate and interpretable results for the given context of forecasting coal-based energy generation in Turkey.
- And the third question assesses that the reliability of historical data on coal-based energy generation in Turkey is crucial for building accurate predictive models

2. LITERATURE REVIEW

In the previous several decades, Turkey's electricity generation landscape has experienced considerable changes, with a growing emphasis on diversifying energy sources to meet rising demand and address environmental concerns. Historically a major component of Turkey's energy mix, coal has come under fire for its effects on the environment and the need to switch to greener energy sources. Because of this, estimating Turkey's coal-based electricity output level has emerged as a crucial component of energy planning and policy development.

The goal of this review of the literature is to present a thorough summary of the work that has been done on coal-based electricity generation forecasts in Turkey. The review looks at the approaches, models, and important factors used in earlier research to find patterns, gaps, and areas that could use more investigation. In order to effectively negotiate the issues connected with energy security, sustainability, and environmental conservation, policymakers, energy planners, and researchers must have a thorough understanding of the dynamics of coal-based electricity generation predictions.

The research will examine the development of laws, regulations, and technological breakthroughs that have formed Turkey's coal-based energy generation landscape, providing historical context. It will also examine the variables affecting the nation's supply and demand for power, taking into account population demographics, economic growth, and international energy trends.

The literature research will also examine the different forecasting methods used to estimate the amounts of power generated by coal. By comprehending the advantages and disadvantages of various methodologies, forecasting models that are more precise and dependable and that are customized to the particularities of Turkey's energy system may be developed. These methodologies range from conventional time series models to sophisticated machine learning algorithms.

Future research initiatives and policy recommendations will be informed by the insights gathered from the evaluation of the literature as the country struggles to balance energy security and sustainability.

Through cultivating an enhanced comprehension of the intricacies associated with the prediction of coal-based power generation in Turkey, interested parties can make knowledgeable choices that correspond with the nation's energy objectives and bolster a more sustainable and robust energy future.

2.1. Demand Forecasting

El filali (2022) states that demand forecasting has recently become increasingly crucial because of the severe financial and health problems brought on via COVID 19. The business climate is now unclear, and client demand has undergone significant change as a result of this phenomena. As a result, it is crucial for businesses to employ a system that can generate precise projections in order to take the required steps to prevent stockouts, resource waste, and to boost competitiveness. Due to its capacity to model enormous data sets and tackle complex issues, An abstraction technique called deep learning (DL) has shown promise over traditional methods such as machine learning (ML), neural networks (ANN), and statistical time series forecasting. Its use is confined to the manufacturing sector, though. The researchers introduce the Gated Recurrent Unit (GRU) deep learning technique in the study. Using actual information from a Moroccan manufacturer of electrical goods, they compare the suggested strategy with straightforward Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) examples. To be capable of automatically choose the best hyperparameters for each model, They utilize Gridsearch to configure every model used in the study.They utilize Gridsearch to configure every model used in the study. Then, they analyze the outcomes using the root mean square error (RMSE) and the symmetric mean absolute percentage error (SMAPE) methods. Comparing the findings indicates that the GRU technique generates forecasts that are more accurate than those produced by the other LD models.

Chen (2023) investigated that demand forecasting (DF), which predicts the products that customers are anticipated to buy in the near future, is crucial to supply chain management. Although machine learning methods are frequently employed to create DF models, in addition, are more vulnerable to data tainting assaults. The research investigates the possibility of deliberate poisoning assaults against DF models While using linear regression, the aggressor manipulates the actions of prediction models centered on a certain goal collection without affecting The accuracy of the prediction as a whole. In addition to developing A modification of regression values technique to conduct targeted poisoning attacks in black-box situations, additionally, the researchers developed a paradigm of gradient refinement for focused regression poisoning in white-box environments. they also talk about some potential defenses against their attacks. Two real-world datasets are used in extensive experiments using four models of linear regression. The outcomes demonstrated that their assaults were quite successful and can control less than 1% of the training samples while still achieving a significant prediction deviation.

Bagnasco (2015) indicates that some of the largest users of electric energy are large buildings. Building energy demand is thought to account for roughly 32% of global energy use. 36% of CO2 emissions in Europe are caused by buildings. Interest in Building Management Systems (BMS) has grown as a result of the necessity to meet Europe's 2020 energy targets, which call for a 20% increase in EU energy efficiency and a 20% decrease in greenhouse gas emissions from the EU since 1990. Additionally, this expansion has also been facilitated by the requirement to guarantee operational goals with the lowest possible energy costs and environmental effect.. These technologies have the potential to reduce energy use and associated costs. Load forecasting is a common issue and a crucial component of electrical distribution systems, and it can be a helpful feature of a general-purpose BMS. A number of research on short-term load forecasting have been developed, frequently utilizing fuzzy systems, artificial neural networks (ANN), evolutionary programming, statistical models, regression techniques, state-space techniques, and fuzzy systems. Of these algorithms, ANN has drawn the most interest due to its well-defined model, simplicity in implementation, and high efficacy. When low- and medium-voltage energy distribution networks are taken into consideration, load forecasting is able to offer crucial data for efficiency and energy assessment conducted by a single utility. System economics can also benefit from load predictions. As a matter of fact, it can offer useful data for anticipating opportunities and hazards. Up to system-scale forecasts from individual end users and improved load management strategies are required by the emerging the smart grid concept and the energy market. It's getting more and more crucial to match the unpredictable renewable generation with the real need. Load forecasting with lead times ranging from a few minutes to several days is an essential tool for efficiently managing buildings and infrastructure. Since an accurate prediction will result in control imbalance on the network, the new paradigm of smart grid management depends on the exchange of data between the site and the main grid forecast.. In micro-grid configurations which are mainly anticipated in future power systems this might be quite significant.

Nguyen's article (2022) presented Unexpected occurrences like epidemic breakouts, natural disasters, or significant scandals frequently come with a disrupted supply chain and extremely variable demand. In addition, academics have recently discussed the need for fresh AI uses to enhance decision-making in emergency situations. Natural language processing, in example, makes it possible to analyze unstructured information in spoken languages, like internet news articles, that may be a useful resource for knowledge during upheaval occurrences. The study gives rise to this line of research since it uses sentiment analysis to forecast the volatility of the demand for medicinal items during emergency conditions. Thus, a strategy that combines effective methods of artificial intelligence with current Models for predicting were suggested. to improve Demand prediction during disruptive periods, a structure enabling the combination of A sentiment analysis approach based on deep learning was developed to extract and organize data from pharmaceuticals., and the demand for medicines was formed using the recovered combining organized and unstructured data information relevant news. A COVID-19 epidemic and pharmaceutical scandal are two instances of upsetting things that occurred in the French to which the framework was also applied. Results showed that applying sentiment analysis improved the accuracy of demand forecasts.

Venkitasubramony (2023) assumes one of the most difficult categories for demand forecasting is fashion. the paper offers a thorough examination of the different forecasting techniques applied in the fashion sector. To forecast consumer demand for fashion products, special attention is paid to developments in artificial intelligence and machine learning techniques. Based on the forecasting approach used by researchers, carefully acquired literature is reviewed and the papers are separated into qualitative, statistical, artificial intelligence (AI), and hybrid methodologies. the analysis highlights the difficulties in anticipating demand, and it concludes with recommendations for further research.

Tanizaki's (2018) research suggests employing machine learning for restaurant business demand forecasting. While many studies have utilized point-of-sale (POS) data for forecasting, it's essential to create a customized demand forecasting model that considers specific factors such as location, weather, and events for each individual restaurant. To address this need, we've developed a machine learning-based demand forecasting model that effectively incorporates these various input factors. In the paper, they delve into the details of the machine learning model for demand forecasting and present the results of its validation using real restaurant data.

Ensaf et al (2022) described that Accurate sales forecasting is essential to any successful retail firm in the cutthroat business environment of today, where sales are of utmost importance to businesses. By preventing overproduction and minimizing overstock, it can aid in inventory management" (Islam & Amin, 2020 et al). "Additionally, by predicting costs, it can be a fantastic tool for boosting a business profitability" (Huang, & Soopramanien, 2019; Islam, 2021; Nazarpour, 2021; Verstraete, 2020 et al). "Future sales are impacted by a number of significant factors. These elements can be found by looking at the patterns in sales for a retail store's overall sales or the sales of a particular product. "It's crucial to remember that the level of predicting difficulty differs based on the product. Some goods, like milk, have steady yearly consumption, making it simple to forecast their sales" (Chopra & Meindl, 2016; Padilla, & Molina, 2021). Other products, like clothing and furniture, have the long-term patterns and seasonal variations in their sales patterns, which complicate the forecasting process .

2.2. Areas of Demand Forecasting

Posch (2022) describes that one of the most important components of effectively running restaurants and staff canteens is accurate demand forecasting. Specifically, accurate forecasting of future menu item sales enables accurate food supply ordering. This ensures a minimal quantity of food waste before consumption from an environmental perspective, and from a managerial one, it is essential to the restaurant's profitability. Therefore, forecasting potential values of the daily sales amounts of specific things on the menu is of importance to us. Several significant seasonalities, trend shifts, gaps in the data, and outliers are evident in the accompanying temporal sequence. they suggest a forecasting method that can be easily understood by humans and is only based on data that has been extracted from point-of-sale systems. Consequently, in order to forecast future sales, they provide two generalized additive models. they examine two data sets that comprise several time series gathered over a 20-month period at a sizable staff canteen and a casual dining establishment. they demonstrate that the attributes of the examined restaurant data are fit by the suggested models. Additionally, they contrast their method's predictive performance with that of other recognized forecasting techniques.

Kavya (2023) assumes that for life to live and flourish, water is a crucial resource. Water resources are under increasing stress due to rising population and economic expansion, which necessitates monitoring water use. At the same time, water supply is steadily declining. Over the past several years, there have been numerous focus on implementing operational and monitoring automation for the system, A longside the management of the water supply using an effective system for managing water. A water supply system may be controlled most effectively with the assistance of a temporary water demand forecast, and correct predicting lowers running expenses and conserves vitality. Even so substantial inquiry, India has unable to put demand forecasting into practice for effective water management. As a result, the model for artificial intelligence-based Predicting water demand in the near future is the main emphasis of the study. Nine models employing both machine learning and deep learning techniques have been compared Utilizing data related to water usage for the city of Hubli in the Karnataka state between 2020 and 2021. The most appropriate predictive model was evaluated utilizing The flow meter with measurements taken at 10-minute intervals and both single- and multiple-variate time series predicting models. . In the case of a multivariate model, meteorological factors and calendar inputs (such as the time of day, holidays, etc.) were taken into account in addition to the amount of water used data. In one-way time series prediction, The water usage alone was utilized to anticipate the water use. According to the results, Deep learning models demonstrated superior performance compared to machine learning models.. Specifically, the Long-Short Term Memory (LSTM) model shows the most accurate predictive execution in both situations, achieving a mean absolute error of 0.11 m3 per hour, In the case of the univariate model, it achieved a mean absolute error of 2.96 m3, for the multivariate model. To maintain sustainable water resource management, the immediate water need for every location can be predicted using the best predictive model.

"Dong et al., 2023[a]" suggests that due to the fact that human behavior is continually evolving, studying the temporal-spatial characteristics of tourism demand might be difficult. To ensure that preserve the integrity of the traits that drive tourism demand, The research provides a spatial-temporal characteristic augmentation model. To learn spatial-temporal properties, the tourist model is specifically represented as an arbitrary graph using the technique of steady-state analysis. The researchers used convolutional filters to transform Transforming the feature series into a series of images, meanwhile... maintaining the partnership between the spatial and temporal characteristics in order to improve the feature acquisition capability regarding thin features. The digital traces of visitors from the metropolitan region of Zhuhai are used to illustrate the efficiency of the strategy. The suggested approach beats cutting-edge tourism demand forecasting techniques, according to numerical trials.

"Dong et al., 2023[b]" suggested for effective tourism management, a reliable estimate of tourist demand is essential.

The development of tourism demand estimation is significantly hampered by the seasonal and non-stationary aspects. To solve this issue, they needed a forecasting model for tourism demand that works well. The unique model for predicting tourism demand put forward in the paper is created mechanism-guided attention as the foundation. The instance is divided into three divisions: the first determines the demand time series degree of stationarity; the second creates a directed focus method to enhance neural networks' ability to recognize features, and the third produces forecasts of tourism demand while utilizing the recurrent neural network with complete connectivity that was created to recognize intricate details of the demand time series. The suggested model aids in recognizing the characteristics of Cyclic patterns and deviations from a straight-line or linear trend in data on tourism demand with the right training procedure, the model retains good forecasting accuracy. Case studies demonstrate that, when compared to other conventional forecasting techniques, the suggested method can accurately predict the daily tourism demand of Macau, China.

Babai (2022) reveals that the majority of supply chain management choices are based on demand estimates. These judgments level of detail resulted in various forecasting needs. For instance, forecasts made over longer periods of time and at greater altitudes, are needed for supply chain strategy choices, but forecasts at lower levels, over shorter durations, are necessary for inventory replenishment decisions. The 'normal' amount of aggregation of data does not always yield the most precise estimates. In some circumstances, combining data or predictions At lower levels, this involves breaking down information or projections from greater magnitudes, or merging forecasts at different degrees of accumulation may enhance forecast accuracy. In the academic literature, the practices of cross-sectional and temporal aggregation techniques are well established. It has been stated more recently that these two strategies do not fully utilize the data that is accessible at different supply chain hierarchical levels. Consequently, taking into account In the field of forecasting, discussions regarding forecasting hierarchies across various dimensions, including time, and the integration of forecasts at different hierarchical levels have been advised. Based on a thorough search, the study offers a thorough evaluation of the literature on Aggregating data and applying hierarchical forecasting techniques in the context of supply chains. The review allows with the aim of identifying important investigation gaps and the presenting of a study schedule.

Ulrich (2023) discovered that Model-based approaches are still a viable choice for predicting consumer demand. While this method enables the use of a model based on theoretical justifications to analyze demand, each model option is linked to particular presumptions that must be met in order for the model to be legitimate. In the retail industry, customer demand is frequently modeled as a method similar to poison, particularly when a distribution with a negative binomial is used. An increasing interval between arrivals, which characterizes the likelihood distribution between consecutive happenings, is connected to Poisson-type processes. As the broad a Poisson-process assumption is plausible, the analysis of the data using a publicly available dataset from a significant supermarket reveals that the purchase behavior is highly dependent on the type of product. A weekly shopping excursion is also strongly preferred by clients at this store.

Qin (2023) suggests for gas utilities and decision-makers to develop dependable gas availability schemes, manage supply agreements, and run effective operations to satisfy the rising gas demand, accurate mid-term projections of gas consumption is essential. The infrequent monthly info collection and the diverse consumption patterns of different usage categories present challenges for mid-range gas consumption forecasts. By combining clustering, deep contrastive learning, and federated learning techniques, this work offers An innovative Federated Contrastive pretraining scheme - Local Clustered Finetuning paradigm (FedCon-LCF). The suggested approach can make use of Pooling data from multiple gas companies to tackle data scarcity challenges while protecting privacy, and using the diverse patterns for local clustered regression can accomplish high-performance forecasting. The Forecasting-Oriented Contrastive Learning model (FOCL), that is capable of efficiently extracting data and provide detailed representations of time series data to enable precise predicting, is created with the integration of a multi-scale regression loss and an improved hierarchical contrastive loss. The suggested technique is assessed using a dataset gathered from eleven gas firms spread over eleven Chinese cities, totaling 17648 clients across 10 use categories. With an average improvement of 16.52% in MAE and 25.30% in MSE for gas demand forecasting three, six, nine, and twelve months ahead, the proposed strategy beats the benchmark LSTM model.

Lasek (2013) states that one of the key components of an effective Demand forecasting is a part of the restaurant yield revenue management system. Sales forecasting is crucial for restaurants, both standalone establishments and chains.. Restaurant chains collect sales transaction data, which can be studied both at the corporate and store levels. Investigating the vast amounts of transaction data at the individual store level enables each restaurant to enhance its product and operations management (e.g., scheduling product preparation, inventory replenishment), which in turn lowers running expenses and improves food quality. On the other hand, gathering pertinent data from all of the restaurants can help a lot with company strategic planning. Management is able to measure brand loyalty, evaluate business trends, analyze pricing elasticity, and evaluate the effects Effect marketing initiatives on revenue and brand awareness. For the restaurant industry, there isn't a study of forecasting techniques. The paper's goal is to evaluate and categorize restaurant sales forecasting approaches that have been published in the previous 20 years. Historically, restaurant revenue forecasting revenues has largely judgment based. Most in the restaurant sector still employ this method frequently. A managerial expert's intuitive forecast is the foundation of judgmental approaches. However, predicting restaurant sales is a difficult process because it depends on a lot of variables, including time, the weather, economic conditions, and sporadic events, among others. Because of this, judgmental approaches are unreliable. Many different models with different levels of sophistication have been put out to increase the accuracy of restaurant forecasting.

Borucka (2023) imply that demand prediction is a crucial element of planning, management, and sustainable expansion of the supply chain, however it's a difficult process since demand is influenced by a variety of seasonal elements that are many, frequently unknown, or both. Limited information availability is another issue. Particularly, businesses without cutting-edge IT infrastructure are forced to rely solely on information gleaned from past sales data. In order to estimate short-term demand for goods with development trends and notable seasonal fluctuations in sales this research applies and compares a variety of mathematical models. The purpose of the study is to show that, even with sparse empirical data and unknown demand-influencing variables, it is still possible to use specific mathematical techniques to find a time series that accurately captures the sales of a good with noteworthy seasonal fluctuations and a pattern. The seasonal ARIMA (Autoregressive integrated moving average) model, the TBATS (Trigonometric exponential smoothing state space model with box-cox transformation, ARMA errors, trend, and seasonal component), and the ETS (exponential smoothing) model using Fourier terms are all considered in the work. The examples are marketed as another option to well-known models based on machine learning techniques. since they are frequently equally effective while being more difficult to interpret. A case study was used to present the chosen techniques. The best option was determined by comparing the data and highlighting how each of the employed strategies could enhance supply chain demand forecasting.

Doganis (2005) indicates that owing to the intense rivalry in the modern world, the majority of production companies are constantly working to boost their revenues and decrease their expenses. Since precise revenue projections results in better customer support, less Missed income, merchandise returns, and additional factors effective scheduling of production, it is unquestionably a cheap way to achieve the aforementioned aims. Due to the limited durability of numerous food items and because product quality is crucial for consumer health, effective sales forecasting tools may be highly beneficial. for the food industry. they provide a comprehensive arrangement for creating Predictive models designed for forecasting sales data with nonlinear time series patterns, in the study. The technique combines the neural network architecture based on the radial basis function (RBF) and a custom-designed genetic algorithm (GA), two artificial intelligence technologies. The approach is successfully used using fresh milk sales data that is supplied by a significant dairy product manufacturer.

Panda (2023) stated that the majority of businesses demand forecasting is becoming more important in today's industry for effective supply chain and demand management. due to the varied wants of consumers and rising levels of corporate competition. Demand projections are outside the purview of any planning choices because they have a direct impact on a business profitability. Inaccurate demand estimation can result in either surplus of inventory, which finally leads to a increased likelihood of waste and expensive expenses to cover, or insufficient stock, which causes stockouts and, in the end drives customers to the firm's rivals. Demand forecasting is one of the most popular methods for just these reasons.

“Sajid Ali” served as the assistant editor who oversaw the assessment of this submission and gave his approval for publication. essential elements of a company's logistics administration and strategic planning Its significance is made clear by the fact that numerous business divisions rely on its results: the monetary division employs it to calculate expenses, income margins, and the amount of capital needed; The marketing division utilizes it to strategize and evaluate the result of different techniques for marketing on sales volume. Meanwhile, the acquisition division can rely on it to formulate investment plans spanning short and long-term horizons. Lastly, the operations department can effectively manage their operational plans with this information well-in advance procurement of the required raw materials, machinery, and personnel. The procurement division can design their financial strategies, both short- and long-term. Forecasts are therefore quite helpful, and they might benefit financially from their great accuracy, Enhance the management of the demand-supply chain, and decrease waste.

2.2.1. Forecasting Models

Andreas (2020) explains in an energy utility, predicting electricity prices is a crucial activity that is required for proprietary trading, production in power plants schedule optimization, as well as other technical matters. Recalculating the order book using projections of market principles such as demand or sustainable input is a promising method for electricity price forecasting. Nevertheless, this method necessitates a thorough statistical examination of market data. the research investigates if machine learning may be used to reduce this statistical effort.

Sevgi (2022) describes that energy becomes more and more crucial in that population, living conditions, and industry all rise. Consequently, it is crucial for nations to model and forecast their energy use. The studies conducted to estimate use of energy were reviewed, and the indicators found in the books were were categorized based on the social, economic, and environmental aspects the three primary facets of sustainability. Turkey's energy usage was estimated using four models based on sustainability. GDP, power sales prices, imports, population, and temperature are examples of input variables, and gross energy consumption is an example of an output variable. Artificial Neural Networks were used to test and compare the models (ANN). The Social-Economic-Environmental model that performs the best has the highest R2 value (0.99912) and the lowest MSE value (0.0001114). This model was employed to project Turkey's energy consumption from 2021 to 2025.

Altun (2010) presented an approach for estimating Turkey's long-term need for power. for this, two artificial neural network structures (a recurrent neural network and a three-layered backpropagation neural network) were created and evaluated. Forecasts were completed for the years 2008 through 2014. The study focuses on economic data since economic issues are the primary determinants of long-term forecasting. Lower percent mistakes are produced by the suggested method, particularly in the recurrent neural network. The outcomes of the artificial neural network forecasts were also contrasted with the official projections.

Amber (2015) shows that in the UK, 26% of the yearly electricity usage of a typical Campus of Higher Education is consumed in the administration buildings. Energy managers benefit greatly from a precise electricity consumption estimate in a number of ways, including the creation of targets for energy consumption and future energy budgets. they created two models—a genetic programming (GP) model and a multiple regression (MR) model—to predict the amount of power used per day of an administration building at the London South Bank University's Southwark campus in London. The five significant separate factors —wind speed, weekday index, relative humidity, ambient temperature, and sun radiation—are incorporated into both models. These variables daily values were gathered from 2007 to 2013. The models are trained on data sets from 2007 to 2012, and tested on data sets from 2013 onwards. Analysis and comparison are done between the estimated test findings for each model and the actual electricity use. Finally, some inferences regarding the two models' respective performances with respect to their forecasting skills are made. The findings show that the GP model outperforms the MR model, with a Total Absolute Error (TAE) of 6% as opposed to 7% for the MR model.

Kaytez (2015) shows that Predicting electricity usage with accuracy is crucial for developing countrie’s energy planning. In order to accurately project future power consumption needs, a number of novel methodologies have been developed over the past ten years for electricity consumption planning. Two novel methods being used for energy consumption forecasting are support vector machines (SVMs) and least squares support vector machines (LS-SVMs). The LS-SVM is used in this work to forecast Turkey's energy usage for electricity. Apart from the conventional regression analysis, the use of artificial neural networks (ANNs) is taken into consideration. Using historical information from 1970 to 2009., the models use installed capacity, population, total subscribership, and gross electricity generation as independent variables. In the study, forecasting outcomes are compared with one another using a variety of performance criteria. An investigation of the receiver operating characteristics (ROC) is used to ascertain the sensitivity and specificity of the empirical findings. The outcomes show that the suggested LS-SVM model is a rapid and precise forecast technique.

Rostum (2020) explains that by analyzing historical data, the process of electric load forecasting is crucial in predicting future electric load demand and peak load. It has been demonstrated by numerous investigations that load forecasting errors raise operating expenses. So, Power system security and dependability depend on an accurate electric load forecast. It also increases a power system's dependability, energy efficiency, and electrical firms' earnings. There has been a notable increase in the use of forecasting methods in recent years. Readers can use this survey to summarize and contrast the most recent, widely accepted research on electric load forecasting. Additionally, it summarizes the most pertinent studies on load forecasting conducted during the previous ten years, talks about the various approaches to load prediction, and projects future developments in this area.

Li (2023) describes that multivariate time series (MTS) forecasting using deep neural networks (DNNs) has received much research in various fields. The strategy additionally been used to forecast sales of products, which is crucial for the tactical growth of businesses.

To effectively merge these relevant aspects into a single framework, nevertheless, requires taking into account their long- and short-term relationships. Due to the complicated and constantly dynamic surroundings of sales time series, This is especially difficult for sales in real time projections with numerous key elements. Additionally, DNN-based approaches failed to accurately identify steady linear associations among time series data for sales involving multiple variables.

A brand-new multi-stage long short-term memory model that leverages prior information and envisions a future-oriented prespective (SLSTPKNet) is suggested as a solution to these problems. The two-layer convolutional neural network (TLCNN) and the two-stage LSTM (TSLSTM) are combined into a single system to simulate interdependent relations between product sales and upcoming influential elements. The system builds beneath the model based on the kinds of various influential elements. The fundamental part of long-short-term modeling is TLCNN and TSLSTM, and it is a useful method for identifying dynamic designs made by combining the results from many phases and strata. Robust (the ability of a model) associations between time series are difficult for DNN to capture, hence An active co-integration mechanism (DCI) is used. Domain prior knowledge (PK) (development of a model) is incorporated as supervisory data to further improve the model's performance to grasp long-term short-term patterns from complicated environments. On the Galanz and Cainiao sales datasets, extensive tests are run. SLST-PKNet significantly outperforms 11 cutting-edge baselines in terms of performance. To further confirm its generalizability, the suggested model is additionally tested on the traffic and exchange rate two fresh datasets.

Gustriansyah (2022) stated that inaccurate sales forecasting (SF) results in stocking up or running out of goods, which can raise inventory costs and lower earnings and return on investment. Stock-outs can also reduce sales or competitive advantage by reducing customer loyalty and opportunity to win new clients. The Recency-Frequency-Monetary (RFM) model is combined with the decision-making (Best-Worst Method/BWM) and data mining methods (k-Means) the study's suggested retail SF model, known as the SalesKBR. The BWM was used to extract factors that significantly affect retail square feet (SF). The RFM model was utilized for evaluation, and the product clustering findings were improved with the use of the k-Means approach and six validity indices.

The BWM extraction results that correspond with the retail company datasets revealed that the three major factors that considerably influence SF are quantity, regularity and financial. The outcomes also demonstrated the decent accuracy of SalesKBR as a retail SF model. As a result, it might be used to predict future retail sales and perhaps serve as a different approach to coming up with wise and effective management choices.

Díaz (2023) describes that water scarcity and energy demand in pressured irrigation networks are currently posing significant problems for management of irrigation districts (IDs). Furthermore, the majority of the most recent water distribution systems in IDs were created to run as needed, which complicates ID administrators' Making decisions every day. Knowing Several days ahead of schedule, the water demand would make system oversight easier and contribute to the reduction of both water use and energy expenses. Longer term forecasting models are required for the optimal administration and enhancement of the IDs' water-energy nexus. In the study, a fresh hybrid design (dubbed LSTMHybrid) A method for predicting irrigation water demand for one week at a specific ID size has been established. It combines fuzzy logic (FL), genetic algorithms (GA), LSTM encoder-decoder, and dense or fully neural networks with connections (DNN). Python was used to create LSTMHybrid and apply it on an actual ID. The ID's irrigation water requirement (m3) from one to seven days, solar radiation (MJ m 2), mean temperature (C), and reference evapotranspiration (mm) are all given before the initial day of forecast were the best input variables for LSTMHydrid.

The best LSTMHybrid model was chosen, and it contained Fifty LSTM units for The section of the model dedicated to encoding information, consisting of 409 LSTM cells for The part of the model focused on decoding, in addition to the DNN submodel, which incorporates three hidden layers, each having 31, 96, and 128 neurons. With a collective sum of 1.5 million parameters, LSTMHybrid was able to achieve a representativeness of about 94% and an accuracy of over 20%.

Ali (2020) discovered that over the past ten years, supply chain management has grown in importance among researchers. The capacity to give firms a strategic competitive advantage is the reason for its increasing significance. Demand management is one of a number of supply chain functions. It focuses on the company's capacity to satisfy client needs by keeping the necessary inventory. Organizations must foresee demand considering sales projections making use of sales trends to effectively satisfy client requests if they are to successfully meet those wants. Numerous forecasting issues have been solved using fuzzy temporal sequence. The purpose of the research is to develop and put into practice a fresh fuzzy time series framework to forecast sales for effective supply chain demand management. the strategy, which they have developed, was previously used to estimate the enrollment of university students and performed more accurately than other approaches. This essay will first define sales forecasting, demand management, then go over the fundamentals of fuzzy time series. The suggested structure will next be presented and used to forecast sales using a dataset containing monthly milk production figures over time carton sales in an extreme shopping. To wrap up the research study, future research areas will be identified.

Singha (2022) describes demand as the inclination or readiness of consumers to pay a particular price for a desired good or service. Businesses employ a variety of forecasting methods to foresee client demand in order to make critical strategic decisions regarding a variety of supply chain-related issues, for instance, in areas such as customer service levels, inventory management, manufacturing planning and control, and more. However, forecasting model errors introduce uncertainty and pose a substantial challenge to decision-makers. Businesses need to reduce those forecasting errors more and more as a result of the constantly shifting market dynamics. the study, examined how sophisticated machine learning algorithms, such as multi-layered perceptron models (MLP), convolution neural networks (CNN), long-short term memory (LSTM) connections, and more., were applied to the process of predicting future data points in a time-ordered sequence. they then conducted a analyzing in comparison to determine which algorithm produced the best results. they used the Kaggle dataset titled "Store Item Demand Forecasting" to do the analysis.

Guinoubi (2021) explains that the globalization, economic change, and technical advancement that have recently emerged in the modern industrial world force businesses and industries to be more receptive, to satisfy and meet all of the market's needs, and to adapt to the evolution of their clients. Demand forecasting is vital for corporate performance because of this. The study has described various forecasting techniques and their applications based on the literature. Next, a case study was started in an agri-food company that produces ice with the goal of reducing costs over the long term and determining the best forecast for this kind of product while taking into account past sales.

Sukree (2023) indicates that there are many small and medium-sized retail businesses today that utilize both in-person and virtual distribution channels. Subsequently, each channel is separated into a number of sub-channels in order to influence the inventory control system of the retailer. Customer's needs may not be fully satisfied by all product categories or available quantities, or some products may surpass demand. These increase labor, shipping, and storage costs, but most crucially they put the store at risk of losing sales and earnings. The research presents a way for managing Product stock for retail establishments with many channels by projecting client demand using machine learning. The method will assist such retailing stores in managing their inventory successfully. they make reference to the product sales data obtained from a Thai retail firm. These are the daily sales statistics that were collected from each shop location for every product from 2017 to 2021. The 178,548 entries in the dataset are utilized to build The demand forecasting models for both the 7-day and 30-day time horizons. The research primarily concentrates on using the CatBoost algorithm to develop a model for demand forecasting. The effectiveness is evaluated in comparison to models produced by the linear regression algorithm and the XGBoost algorithm. The 30-day demand forecasting model's Symmetric Mean Absolute Percentage Error

(SMAPE) is 24.47%, while the 7-day demand forecasting model's SMAPE is 24.13%, according to the efficiency evaluation.

Wang (2023) indicates that planning the coal departure path depends on accurately estimating China's primary coal-consuming sectors' need for coal. The study's research objects are the steel, thermal power, chemical, and building materials sectors. To create composite forecasting models for coal demand within each industry, this paper blends data-driven characteristics and decomposition-ensemble concepts. Ultimately, it empirically investigates the factors influencing coal demand in these industries and tracks their evolutionary trends. First, the models built in the study based on data features have much more stability and accuracy in predictions compared to other traditional combination models and single models. Second, industrial policies, economic fluctuations, and the thermal power industry's increasing reliance on energy-saving and emission-reduction measures all have an impact on the demand for coal across all four industries. Third, from 2021 to 2025, four industries' combined coal demand will decrease and then increase, reaching 2.88 billion tons by 2025; the trends in coal consumption will be significantly diversified among industries, with the thermal power industry's coal demand decreasing and then increasing, the building materials industry's coal demand remaining stable, and the Demand for coal in the chemical and steel sectors exhibiting a varying downhill trajectory and drop rate.

Gustriansyah (2019) indicated that multiple products are being predicted to sell in order to manage the amount of stock on hand and reduce any shortages or excesses. When sales can be predicted with accuracy, consumer demand can be met quickly, and suppliers' cooperation can be appropriately maintained so that the business does not lose out on clients and sales. In order to increase the effectiveness of the inventory system, the study uses Single Exponential Smoothing (SES) to estimate sales of various products (6,877 products). The most crucial factor in measuring the accuracy of the prediction is the measurement accuracy of the forecast, which is done utilizing a standard measurement in this investigation called Mean Absolute Percentage Error (MAPE). Results indicated that the SES method's multiproduct prediction accuracy percentage is high, as evidenced by the Mean Absolute Percentage Error (MAPE) value of 1.06% obtained using the smoothing value = 0.9.

Shayea, (2022) explains the rapid expansion of mobile broadband (MBB) services has resulted in a substantial increase in mobile data traffic. This upsurge in data usage can be attributed to various factors, including a significant growth in the number of subscribers and the proliferation of mobile applications, necessitating a higher bandwidth capacity. Mobile service providers are continuously enhancing the efficiency of their networks through upgrades and investments in newer generations of mobile networks. However, these improvements alone may not be sufficient to meet the future demands for spectrum. To address this challenge, the paper introduces a time series forecasting model aimed at predicting future spectrum requirements, which is based on the growth of spectrum efficiency in MBB networks. This model relies on two crucial sets of input data: the average spectrum efficiency per site and the number of sites per technology, spanning from 2015 to 2025, the model is used to forecast how efficiently the spectrum will be used in Turkey, Malaysia, and Oman. Standard statistical models including the Moving Average (MA), AutoRegression (AR), Autoregressive-Moving-Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) are compared to the suggested model. The anticipated outcomes show that, compared to 2015, The typical spectral efficiency and its expansion will persist to increase by a few times by 2025. The information Based on these predictions model can be utilized as input information to predict the necessary spectrum allocation for a specific country in the future. Planning the network infrastructure for fifth generation (5G) and sixth generation (6G) technology is furthered by the study.

2.3. Energy Transition

Pouris (2015) explains with coal accounting for 90% of the country's electrical production, South Africa is largely dependent on non-renewable energy sources. Even though South Africa is now diversifying its methods for generating power, coal is still predicted to play a major role in the near future due to the country's abundance of the resource. The nation's fresh water resources are under more stress due to the usage of these resources for industrial purposes, especially the generation of electricity. This combined with the semi-arid climate means that managing and catching water requires a multidisciplinary approach. The research's objective is to present a 20-year estimate of water usage patterns in the industry that generates power using coal. As there aren't many reliable water forecasts available on a national and worldwide scale, this study's findings offer a fresh perspective to help developing nations make decisions about water management and policy.

Un News, et al (2023) provided that the need for energy has increased along with the expansion of industrial activity, which has increased carbon emissions and contributed to global warming. Globally, there is now consensus on the need to reduce pollution levels and develop low-carbon economies. Numerous issues need to be addressed, such as growing pollution levels and higher energy consumption as a result of increased industry automation (Prasad, 2016). Between 2000 and 2021, the amount of energy derived from renewable sources increased significantly, making it the second most popular energy source behind coal. Optimizing energy productivity, environmental friendliness, and sustainability requires accurate energy forecasting, particularly in the case of renewable energy. Over $10 trillion was spent on energy supply worldwide in 2021, making up almost 12% of the world's gross domestic product (GDP). Asia accounted for the majority of the world's energy consumption, followed by Europe and North America (IEA, 2022). China's electricity is mostly produced by coal-fired power stations, which produced 65% of the nation's total energy output in 2019. In order to avert the eventual collapse of the ecosystem, which provides the majority of the energy and resources required for human survival and is currently experiencing serious challenges as a result of emissions caused by humans, the United Nations has called on people to participate in the "urgent war against nature"(UN News, 2021a). According to recent reports, limiting global warming to 1.5°C this century will require reducing emissions over the next eight years while simultaneously increasing the use of renewable energy sources. This target is unlikely to be met without significant action from major polluting nations(UNEP, 2021; UN News, 2021b). One of the main sources of emissions created by humans is energy use and production, which accounts for around 78% of greenhouse gas emissions worldwide (GC, 2020). The type of economic activity and associated emissions are determined by a country's industrial structure, which includes energy production and consumption (Sun et al., 2020). The main cause of emissions is overconsumption of energy.

2.4. Time Series Demand Forecasting

Guo (2018) stated that an essential component of the growth of the national economy is electricity. One of the features of producing electric power is that it cannot be stored in vast quantities, instead, power generation and consumption must always be in balance. The voltage quality will suffer greatly if it is not met. In addition to increasing power consumption, the excessive voltage fluctuation has an impact on the electrical equipment's longevity and safety. The prediction of electric net generation is crucial for the country's economy to achieve the balance between power generation and energy consumption. It is crucial for a nation's power department to distribute resources for power generating in a reasonable manner and to choose the best course of action for power planning. Multiplying net power by running hours yields the amount of electric net power generated. The total power supply load, also known as net power, is the product of the integrated electrical load and network loss.

Numerous scholars have put up various techniques to forecast the quantity of electricity required for their activity. In order to achieve short-term forecasting of electric energy from photovoltaic conversion, A. Bugała proposed “a conventional statistical technique based neural modeling that was carried out with the use of Statistica software” (Bugała et al., 2018). Zhong, Yang, Cao, and Yan (2017) used an integrated particle swarm optimization method and a gray theory model to increase the prediction accuracy from a substantial quantity of real data from two different power plants in China.

A daily prediction model for solar power generation based on weather forecast data was proposed by (Kim et al) and is integrated into a solar photovoltaic (PV) monitoring system that is used commercially in Korea. “Research has shown that this model outperforms previous prediction models” (Kim, Kim, Yoo, & Lee, 2017). In order to effectively forecast monthly trend and volatility in electric energy, Lio Guo quoted

“E. Gonzalez” that he introduced the autoregressive integrated moving average model (ARIMA) (GonzalezRomera, Jaramillo-Moran, & Carmona-Fernandez, 2006). Some studies (Eseye, Zhang, & Zheng, 2018; Leone, Pietrini, & Giovannelli, 2015; Mohandes, 2002; Niu, Wang, & Wu, 2010; Xia, Zhang, & Cao, 2017; Zeng & Qiao, 2013; Zhirui & Runing, 2013) used alternative techniques to forecast power generation. In order to forecast daily peak load values in April 2010, Türkay employed temperature, electricity price, and real electrical load values as economic factors from 2006 to 2009 (Türkay & Demren, 2012). Even though there are numerous approaches for predicting electricity generation, the prediction factor that is included varies depending on the circumstances, therefore it is not suitable for widespread use.

Hess (2021) shows that cities all across the world are shaped by meal delivery services like Uber Eats. The study deals with short-term demand forecasting on a grid, enabling, for instance, predictive routing applications. they provide a strategy that combines traditional forecasting and machine learning techniques, and they adjust model selection and evaluation to normal demand, which is intermittent with a double-seasonal pattern. An empirical investigation demonstrates that, assuming at least two months of data are available, an exponential smoothing-based technique trained on previous demand data alone delivers best accuracy. It has been shown that machine learning yields more accurate prediction results compared to conventional techniques having more constrained demand timeline.

Babaveisi (2022) shows that spare components used in equipment maintenance and repair require effective resource management techniques. Planning requires accurate forecasting, especially when there is uncertainty about demand. The planning and forecasting models are not thoroughly studied in the existing studies on spare parts with intermittent demand, which concentrate on the forecasting model alone. In order to maximize planning and forecasting judgments and minimize sub-optimality, the researchers look at how two models interact. In this work, two mathematical models were presented, one of which is a planning model that calculates the stock level, the allocation of spare part orders to suppliers, the allocation of equipment repairs, and the number of intervals across the planning horizon. The second model is a Support Vector Machine (SVM) forecasting model. In the planning model used for forecasting, demand estimate is carried out via piecewise linearization while taking uncertainty into account. Model optimization is accomplished by an interactive process. they make use of an empirical study from an oil firm that provides data on the supply chain for replacement parts. The findings demonstrate that piecewise demand estimation and decision integration optimize costs, increase forecasting precision, and enhance planning effectiveness. Additionally, the provide practitioners with a number of insights that clarify choices made in spare part planning and forecasting.

Holt (2004) discovered an exponentially weighted moving average is a technique for reducing sporadic variations with the following advantageous characteristics: it requires little data and gives older data less weight. Simply computing the weighted average of two variables, the mean value from the previous time interval and the present value of the variable, yields a new value for the average. These advantageous characteristics are used in this study to both smooth recent random fluctuations and continually update seasonal and trend adjustments. These could then be forecasted by extrapolating them into the future. The method's adaptability, along with its computational efficiency and minimal data needs, make it particularly ideal for industrial settings where a high number of forecasts are required for sales of individual items.

Yuta (2019) explains that the bullwhip effect is a well-known example of the propagation of variation under stochastic demand from downstream to upstream. Studies in the literature assume deterministic lead times, but production disruptions could make them stochastic. In this study, the researchers examined the weighted moving average forecast's bullwhip effect under stochastic lead time. they theoretically express a performance metric on the bullwhip effect under a broad context. What influences the bullwhip effect is forecasting factors and the lead time distribution according to numerical data.

Abdel-Aal (2022) shows that demand forecasting is a crucial role for maintaining industrial stability. high variability and thus the presence of the unfavorable bullwhip effect in the supply chain are the results of a severe lack of demand forecasting. As a result, there is excess inventory or poor service, which leads to fewer profits and worse supply chain efficiency. An innovative forecasting technique is created in this study for reasonably short-term demand forecasting. The novel method combines curve fitting using gregory newton interpolation with the basic moving average. The created approach comprises two stages: the first is data preparation (smoothing), where the data are cleaned of any potential noise, and the second is forecasting, where a forecast for a new period is formed. For the first phase, the simple moving average is employed twice, and for the second phase, Gregory-Newton forward interpolation is used. The suggested approach takes into account trend- and seasonally-affected datasets independently. In order to assess how well of the technique, numerical examples are used. There are comparisons with other accepted approaches from the literature. Results indicated a high potential for applying the novel strategy to practical problems.

3. METHODOLOGY

Predicting future trends in coal-fired electricity generation is a critical undertaking that requires a methodical, data-driven approach. This methodology use a blend of statistical and machine acquiring methods to create an organized framework for estimating Turkey's coal-based energy generation. Stakeholders in the energy industry can maximize resource allocation, make well-informed decisions, and improve the production and distribution efficiency of power by following this thorough technique.

To forecast coal-fired electricity generation time-series forecasting models are considered as a quantitative forecasting methods:

Time series models, which comprise the following techniques, and causal models(linear regression) are the two major models

- Smoothing methods (simple moving average, weighted moving average, and exponential smoothing)
- Linear Regression method.

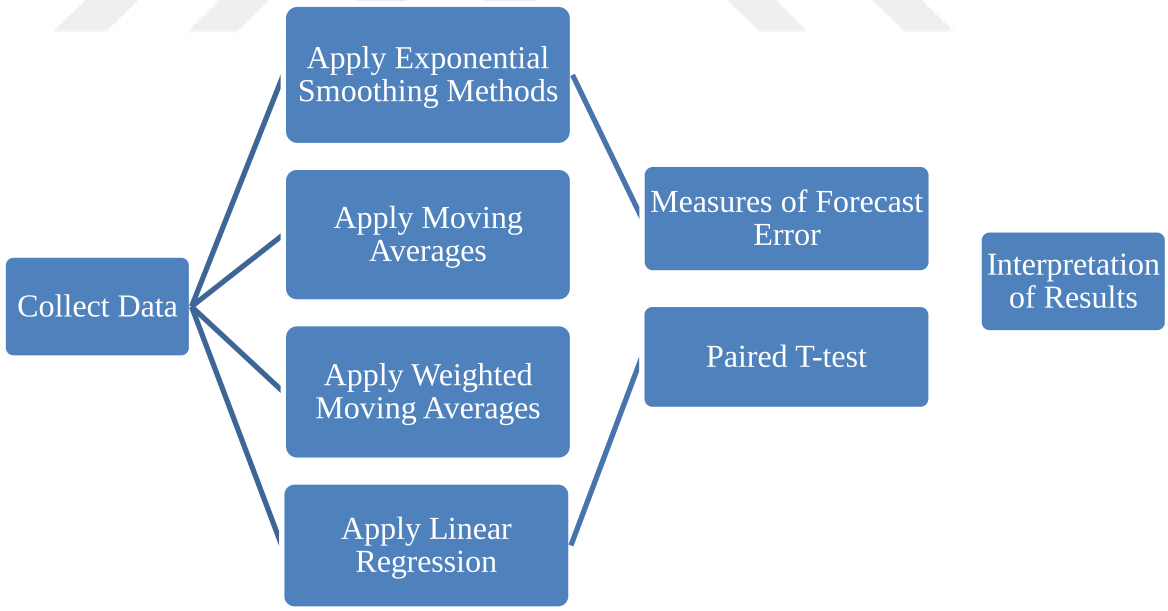

Figure 3.1: Flow Chart of the Methodology

Figure 3.1 shows the flow chart of the methodology and it illustrates that the research has followed the explaind series respectively, first, data has been collected to forecast a future electricity generation from coal, second, to make forecast, diffrent methods have been applied such as exponential smoothing, moving averages, weighted moving averages, and linear regression, third, to select the least values for the forecasted data measures of forecast error have been applied, fourth, paired t-test is analysed to compare the results of the different methods, and lastly, results has been interpreted.

3.1. Time Series Models

A time series is a design created through a series of observations of the demand for a good or service in the chronological order in which they happened.

A time series' fundamental patterns are:

Horizontal (fluctuation in demand relative to a fixed mean).

- Trend: gradual rise or fall in the time series' mean over an extended duration of time.
- Seasonal: a cyclical pattern of rising and falling demand that changes according to the day of the week, month, or season.
- Cyclical: Periodic rises and declines of the time series across extended time periods (around trend) (years or decades).
- Random: erratic and unpredictable changes in demand.

These models project future values using historical (previous) values from the time series.

- Smoothing methods: when a time series is essentially stable (i.e., there are no notable trends, seasonalities, or cyclical components), are employed to average out irregular or random components.
- Simple moving average or moving average method: The prediction for a time series' next period is the average of its *n* most recent data values.

$$\frac{\sum \boldsymbol{Most\ recent\ n\ data\ values}}{\boldsymbol{n}} \quad 3.1$$

- Weighted moving average method: The prediction for a time series' subsequent period is the average of the series' most recent *n* data values, but the *n* data values are weighted so that the sum of the weights equals 1.

$$\sum \textbf{weight} \times \textbf{Value} \qquad 3.2$$

where the sum of all weights = 1

- Exponential smoothing method: A time series' forecast for the following period is calculated as the current period's forecast plus a proportion (α) of the forecast error in the current period.

$$\boldsymbol{F_t = \alpha * A_{t-1} + (1-\alpha)F_{t-1}} \qquad 3.3$$

where Ft = forecast for time period t, At–1 = actual demand or value for the previous period, Ft–1 = forecast where α is the smoothing constant for the preceding period, where $0 < \alpha < 1$

3.2. Linear Regression

Forecasts for future periods (more than one) in a time series can be made using a trend line (projection) created using the least-squares approach when the time series has a linear trend that rises or decreases with time.

The Linear Regression equation is y = a + bt.

$$\boldsymbol{y = \mathbf{a} + \mathbf{bt}} \qquad 3.4$$

$$\mathrm{b}=\frac{(\sum \boldsymbol{ty}-\frac{\sum \boldsymbol{t}\sum \boldsymbol{y}}{\boldsymbol{n}})}{(\sum \boldsymbol{t^2}-\frac{(\sum \boldsymbol{t})^2}{\boldsymbol{n}})} \qquad 3.5$$

$$\mathrm{a}=\frac{\sum \boldsymbol{y}-}{\boldsymbol{n}}-\boldsymbol{b}\frac{\sum \boldsymbol{t}}{\boldsymbol{n}} \qquad 3.6$$

where a = y-intercept, b = slope of the line, and n = number of data points

The least-squares method, establishes the specific trend line forecast that minimizes the MSE between the time series' actual observed values and the trend line forecasts, which is also employed in regression analysis. The time period serves as the independent variable, while the time series' actual observed value serves as the dependent variable.

3.3. Measures of Forecast Error

Any prediction must include accuracy as a key component.

Forecast error (Et)

$$\boldsymbol{ET = AT - FT} \qquad 3.7$$

where At is the predicted value or demand for time period t, while Ft is the actual value or demand.

Tools to measure forecast errors are:

- Mean squared error (MSE): The prediction model with the lowest mean squared error is subsequently chosen for anticipating demand. The average of the squared prediction errors for the historical data is derived.

$$\boldsymbol{MSE = \frac{\left[\sum(At - Ft)^{2}\right]}{n}} \qquad 3.8$$

- Mean absolute deviation (MAD): The forecasting model that minimizes this parameter is chosen to estimate demand. The mean of the absolute values of all forecast error is determined.

$$\boldsymbol{MAD = \frac{[\sum|(At - Ft)|]}{n}} \qquad 3.9$$

- Mean absolute percentage error (MAPE): The forecasting model that minimizes this metric is chosen to estimate demand. The mean of the absolute percentage values of all forecast mistakes is derived as a percentage.

$$\boldsymbol{MAPE = \frac{[(\sum|(At - Ft)|x(100)]}{n}} \qquad 3.10$$

Before analysis, the error measure is often chosen depending on other factors, such as sensitivity (e.g., MAD is less sensitive to individual large forecast errors than MSE).

3.4. Paired T-Test

A statistical technique is a paired t-test for comparing the means of two groups that are related. The term "paired" denotes that the observations in the two groups have a one-to-one connection. Each observation in one group is matched or paired with a specific observation in the other. A paired t-test is most commonly used when measurements are collected on the same people or things under various conditions or at different times.

The following are the key steps in doing a paired t-test:

Create Hypotheses: The null hypothesis (H0) states that the means of the two related groups are the same.

The means of the two related groups are not comparable, according to the alternative hypothesis (H1).

Gather Information: Collect paired data, where each pair comprises measurements taken on the same persons or items under various situations or at different times.

Differences should be calculated as follows: Calculate the difference between the two measurements for each pair.

Calculate the difference's mean and standard deviation: Calculate the difference's mean and standard deviation.

Determine the T-Statistic: Use the t-statistic formula, which is the mean difference divided by the difference's standard deviation multiplied by the square root of the number of pairings.

Establish Degrees of Freedom: The quantity of freedom degrees is equal to the number of pairs minus one.

Choose the Critical Region and Make a Decision: Compare the estimated t-statistic to the t-distribution's critical value based on the degree of significance(e.g., 0.05).

Make a decision: Dismiss the null hypothesis. if the estimated t-statistic falls inside the crucial range. Otherwise, the null hypothesis is not rejected.

The paired t-test is widely employed when researchers want to compare the means of two conditions but are concerned about subject variability. The test decreases the impact of individual variations by pairing observations, making it a powerful tool in experimental and longitudinal studies.

4. IMPLEMENTATION AND RESULTS

4.1.About Data

This study's main goal is to use several forecasting techniques to predict future changes in Turkey's coal-fired power output. Our goal in examining the historical dataset is to find trends, seasonality, and possible contributing factors. The final objective is to create precise and trustworthy projections that may help stakeholders, energy planners, and legislators make defensible choices about infrastructure development, resource allocation, and environmental issues.

Table 4.1 Electricity Generated between 1970 and 2020

Years	Electricity Generated (Mwh)	Years	Electricity Generated (Mwh)	Years	Electricity Generated (Mwh)
1970	2824500	1987	17653500	2004	34447600
1971	2980200	1988	12486600	2005	43192500
1972	2920800	1989	20269500	2006	46649500
1973	3243600	1990	20181300	2007	53430900
1974	3871300	1991	21561500	2008	57715600
1975	4113300	1992	24570800	2009	55685100
1976	4327300	1993	23759900	2010	55046400
1977	4892000	1994	28234700	2011	66217900
1978	5569200	1995	28046900	2012	68013100
1979	6438000	1996	30413600	2013	63786076
1980	5960300	1997	33860000	2014	76262682
1981	6136400	1998	35687500	2015	76165606.5
1982	6441200	1999	37030900	2016	92273097.7
1983	8577000	2000	38186300	2017	97476295
1984	10118300	2001	38417500	2018	113248625.2
1985	15027800	2002	32149100	2019	112894124
1986	19437300	2003	32252900	2020	105812004.1

In the study, we examine historical data on Turkey's coal-fired energy output from 1970 to 2020. The megawatt-hours (MWh) of electricity generated annually over this time period are shown in detail in the table. With the goal of predicting future levels of power generation and assisting in the process of making strategic decisions related to energy planning, this dataset provides a useful basis for the use of forecasting techniques.

4.2.Method Outputs

In the research, four methods of forecasting have been applied such as Exponential Smoothing, Moving averages, Weighted moving averages and Linear regression

4.2.1. Exponential Smoothing

The analysis of exponential smoothing method has been completely prepared in excel software with a smoothing constant of α=0.05 and initial forecast of 2913420 with a MAPE value of 14.3, MSE value of 290 with a paired t-test of 0.

Moreover, related calculation of table is given in the Appendix section.

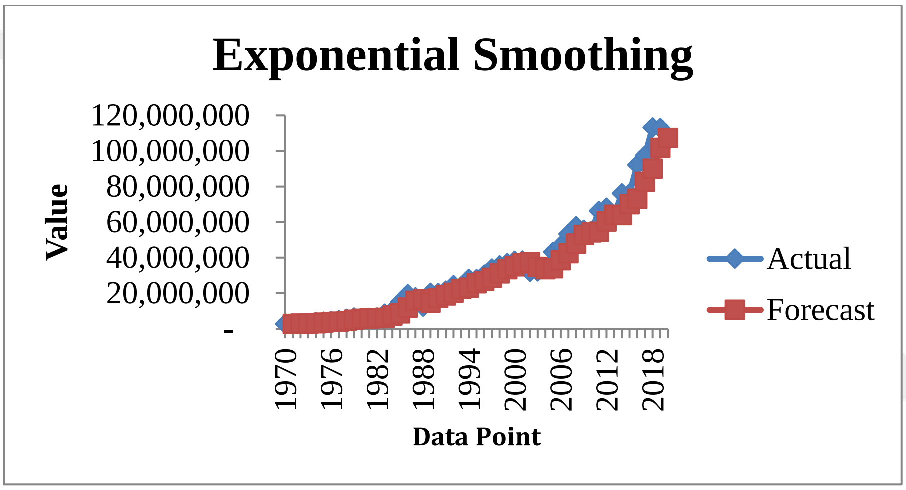

Figure 4.1: Exponential smoothing

Figure 4.1 shows the exponential smoothing of the forecasted electricity generated.

Table 4.2: Paired t-test of Exponential smoothing compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	31287998.12
Variance	9.67554E+14	7.7059E+14
Observations	51	51
Pearson Correlation	0.989184717	
Hypothesized Mean Difference	0	
Df	50	
t Stat	5.387045948	
P(T<=t) one-tail	9.642E-07	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	1.9284E-06	
t Critical two-tail	2.008559112	

The table indicates that there is a substantial distinction between the variable's mean 1 and Variable 2, as evidenced by a high positive correlation and low p-values in both one-tailed and two-tailed tests.

4.2.2. Moving Average 2

With the help of Excel software a successful results have been made with MAPE and MSE values of 5.17 and 48.46 respectively and paired t-test result of 0. As well as related table calculations is given in the Appendix section.

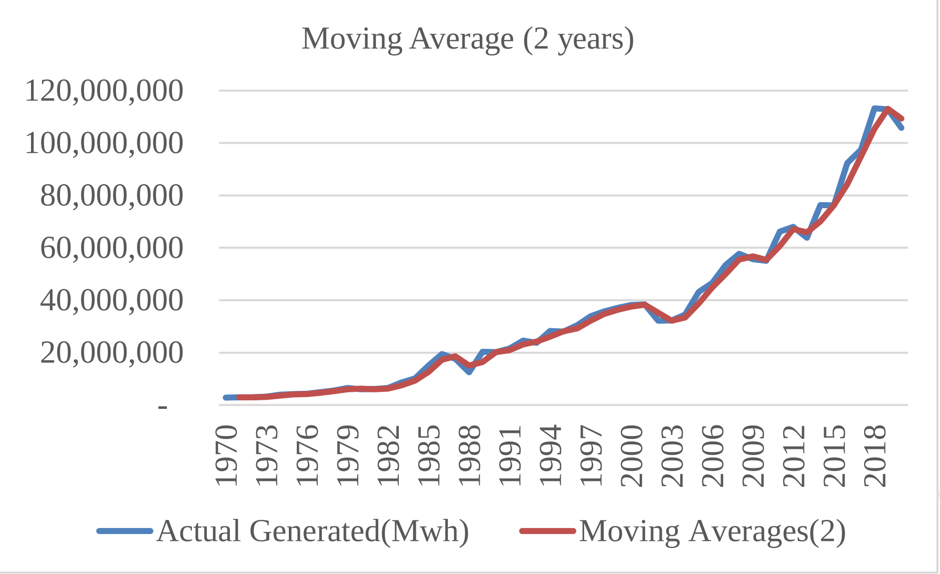

Figure 4.2 Moving Average 2

Figure 4.2 shows moving averages of 2 year.

Table 4.3 Paired t-test of Moving Average2 compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	30236206.92
Variance	9.67554E+14	7.18521E+14
Observations	51	51
Pearson Correlation	0.987456047	
Hypothesized Mean Difference	0	
df	50	
t Stat	5.886633015	
P(T<=t) one-tail	1.64108E-07	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	3.28217E-07	
t Critical two-tail	2.008559112	

The table shows a substantial difference between the means of Variable 1 and Variable 2, which is supported by a very strong positive correlation and exceptionally low p-values in both one-tailed and two-tailed tests.

4.2.3. Moving Average 3

The analysis of Moving Average 3 method has been completely prepared in excel software with a MAPE value of 8.73, MSE value of 119.97 with a paired t-test of 0.

Moreover, related calculation of table is given in the Appendix section.

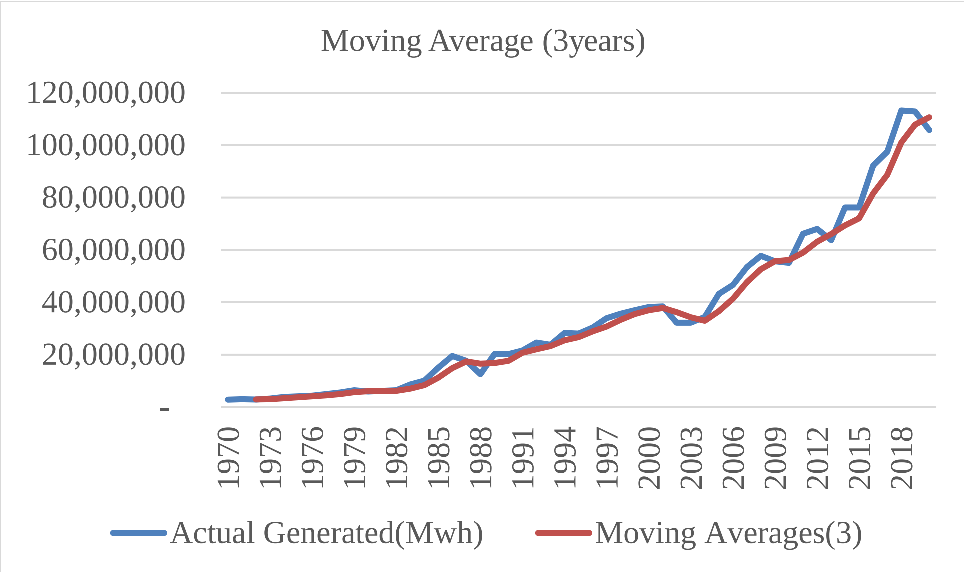

Figure 4.3 Moving Average 3

Figure 4.3 shows moving average of 3 year.

Table 4.4 Paired t-test of Moving Average 3 compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	28234580.5
Variance	9.67554E+14	6.25091E+14
Observations	51	51
Pearson Correlation	0.984912363	
Hypothesized Mean Difference	0	
Df	50	
t Stat	6.576808039	
P(T<=t) one-tail	1.37849E-08	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	2.75697E-08	
t Critical two-tail	2.008559112	

The table shows a substantial difference between the means of Variable 1 and Variable 2, which is supported by a very strong positive correlation and exceptionally low p-values in both one-tailed and two-tailed tests.

4.2.4. Moving Average 4

With the help of Excel software, a successful results have been made for moving average method with MAPE and MSE values of 11.65 and 190.6 respectively and paired t-test result of 0. As well as related table calculations is given in the Appendix section.

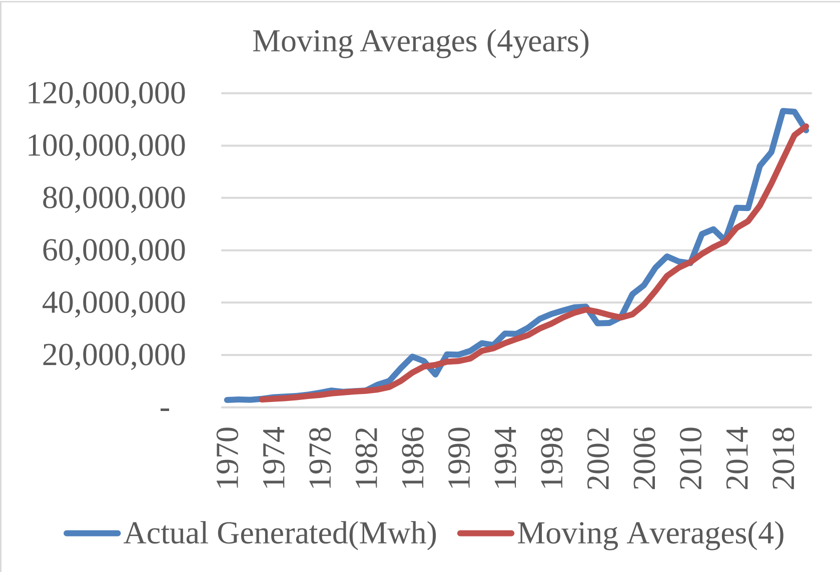

Figure 4.4: Moving average 4

Figure 4.4 shows moving average of 4 year

Table 4.5: Paired t-test of Moving Average 4 compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	25585935.11
Variance	9.67554E+14	5.19897E+14
Observations	51	51
Pearson Correlation	0.983088022	
Hypothesized Mean Difference	0	
Df	50	
t Stat	7.277664255	
P(T<=t) one-tail	1.10436E-09	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	2.20872E-09	
t Critical two-tail	2.008559112	

The table indicates that there is a substantial difference between the means of Variable 1 and Variable 2, as evidenced by a very high positive correlation and exceptionally low p-values in both one-tailed and two-tailed tests.

4.2.5. Weighted Moving Average 3

Excel software has been utilized to implement a weighted moving average with applied weight values of 32%, 50% and 18% and a results of MAPE and MSE values of 45 and 2445.21 respectively, and paired t-test value of 0.

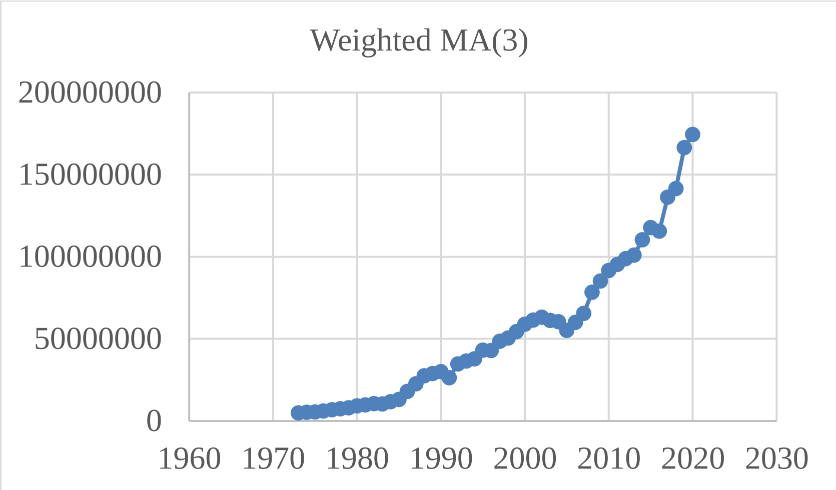

Figure 4.5: Weighted Moving Average 3

Figure 4.5 shows weighted moving average of 3 year

Table 4.6: Paired t-test of Weighted Moving Average 3 compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	51105314.17
Variance	9.67554E+14	2.07246E+15
Observations	51	51
Pearson Correlation	0.985850648	
Hypothesized Mean Difference	0	
Df	50	
t Stat	-7.11750272	
P(T<=t) one-tail	1.96519E-09	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	3.93039E-09	
t Critical two-tail	2.008559112	

The table indicates a notable variation in the means of Variables 1 and 2, with Variable 1 having a significantly lower mean. A very high positive association and exceptionally low p-values in both one-tailed and two-tailed tests corroborate this finding.

4.2.6. Weighted Moving Average 2

Excel software has been utilized to implement a weighted moving average with applied weight values of 50%, and 50% with a results of MAPE and MSE values of 13.09 and 269.9 respectively, and paired t-test value of 0. There is a related calculations in the Appendix section.

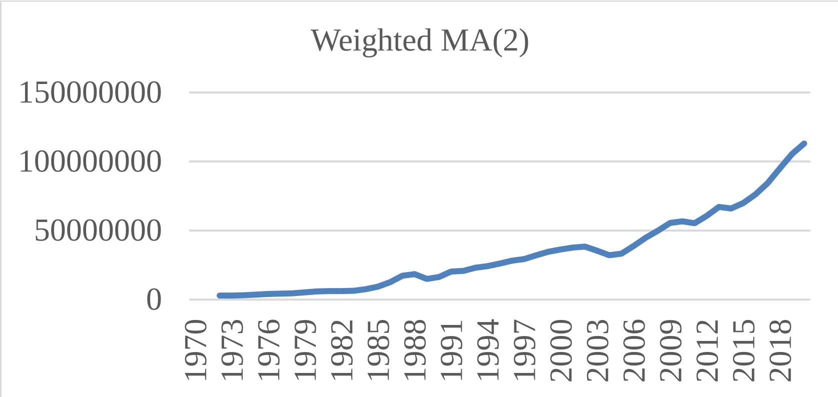

Figure 4.6: Weighted Moving Average 2

Figure 4.6 shows weighted moving average of 2 year

Table 4.7: Paired t-test of Weighted Moving Average 2 compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	32201701.85
Variance	9.67554E+14	8.31237E+14
Observations	51	51
Pearson Correlation	0.988343748	
Hypothesized Mean Difference	0	
Df	50	
t Stat	4.487842849	
P(T<=t) one-tail	2.12044E-05	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	4.24088E-05	
t Critical two-tail	2.008559112	

The table indicates a substantial difference between the means of Variable 1 and Variable 2. This shows evidence against the null hypothesis. The evidence for this conclusion is provided by the extremely strong positive connection.

4.2.7. Weighted Moving Average 1

With the help of Excel software, a successful results have been made for Weighted moving average method with a single weight value of 100% that gave results of MAPE and MSE values of 10.34 and 193.85 respectively and paired t-test result of 0.002 that is equal to the applied alpha α. As well as related table calculations is given in the Appendix section.

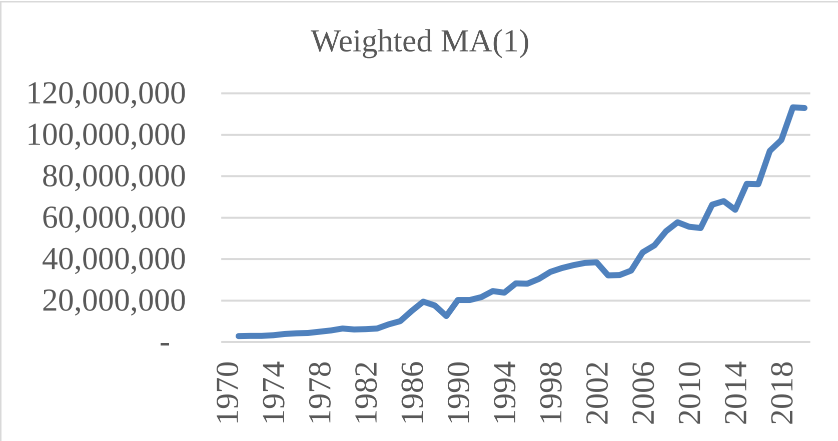

Figure 4.7: Weighted Moving Average 1

Figure 4.7 shows weighted moving average of 1 year

Table 4.8: Paired t-test of Weighted Moving Average 1 compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	33336198.16
Variance	9.67554E+14	8.89116E+14
Observations	51	51
Pearson Correlation	0.989290907	
Hypothesized Mean Difference	0	
df	50	
t Stat	3.193723602	
P(T<=t) one-tail	0.001215748	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	0.002431495	
t Critical two-tail	2.008559112	

The table offers evidence against the null hypothesis, illustrating a substantial difference between the means of Variable 1 and Variable 2. This finding is supported by a very significant positive connection.

4.2.8. Linear Regression

The analysis of Linear regression method has been completely prepared in excel software with a MAPE value of 18.95, MSE value of 459 with a paired t-test of 0.21

Moreover, related calculation of table is given in the Appendix section.

Table 4.9: Regression Statistics

Regression Statistics	
Multiple R	0.97919875
R Square	0.958830191
Adjusted R Square	0.957989991
Standard Error	0.228683785
Observations	51

The table shows with a high degree of explained variance (R Square) and a significant correlation between the variables, these statistics indicate that the linear regression model is a very good fit for the data. The model's accuracy in predicting the dependent variable is further supported by its low standard error.

Table 4.10: Paired t-test of Linear Regression compared to the Actual data

	Variable 1	Variable 2
Mean	35410943.34	36811053.12
Variance	9.67554E+14	1.33182E+15
Observations	51	51
Pearson Correlation	0.985362262	
Hypothesized Mean Difference	0	
df	50	
t Stat	-1.267091576	
P(T<=t) one-tail	0.10549637	
t Critical one-tail	1.675905025	
P(T<=t) two-tail	0.21099274	
t Critical two-tail	2.008559112	

The table shows that according to the analysis, there is insufficient evidence to reject the null hypothesis, indicating that the mean difference between Variables 1 and 2 is not statistically significant. The high positive association between the variables remains.

4.3.Comparison of Results

The provided output of methods present the performance indicators, such as Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and results from a paired t-test, for various forecasting models applied to the dataset. To compare results the table below compares and illustrates the output results in section 4.2.

Table 4.11: Comparison of Results

Methods	Mape	Mse	Paired t-test
Exponential Smoothing	14.3	290	1.9284E-06
MA2	5.17	48.46	3.28E-07
MA3	8.73	119.97	2.75697E-08
MA4	11.65	190.6	2.20872E-09
WMA3	45	2445.21	3.93039E-09
WMA2	13.09	269.9	4.24088E-05
WMA1	10.34	193.85	0.002431495
Linear Regression	18.9	459	0.21099274

The table summarises the results of the different methods applied starting from.

- Exponential Smoothing: MAPE: 14.3, MSE: 290, Paired T-Test: 1.9284E-06
- Moving Averages (MA2, MA3, MA4): MAPE values range from 5.17 to 11.65, showing minimal percentage errors, MSE values range from 48.46 to 190.6, Paired T-Test p-values range from 3.28E-07 to 2.20872E-09, indicating substantial differences from the exponential smoothing model.
- Weighted Moving Averages (WMA1, WMA2, WMA3): MAPE values range from 10.34 to 45, suggesting varied levels of precision, MSE runs between 193.85 and 2445.21, Paired T-Test p-values range from 0.002431495 to 3.93039E-09, indicating substantial differences from the exponential smoothing model.
- Linear Regression: MAPE: 18.9, MSE: 459, Paired T-Test: 0.21099274

So, the results indicate that the minimum values interms of MAPE and MSE obtained by MA2 were 5.17% and 48.46 respectively, and When compared to the significance level (alpha) of 0.05, the paired t-test p-value of 0.21099274 indicates that there is no statistically significant difference in forecasting accuracy between Linear Regression and another model (e.g., Exponential Smoothing).

5. CONCLUSION

Modeling coal-fired electricity generation in Turkey is important for multiple reasons, but it is crucial to highlight that the overall significance is dependent on a variety of factors, including economic, environmental, and social considerations. Here are few points that illustrate the significance of modeling coal-fired energy generation in Turkey.

The researchers conclude by saying that it is vital to remember that the global energy landscape is changing, and decisions regarding coal-based electricity generation must be consistent with long-term development goals and environmental stewardship. Modeling can help you grasp the complex relationships and trade-offs that will shape Turkey's energy destiny.

The purpose of the study was to forecast future electricity Generation based on Coal In Turkiye using time series methods with a given quantity of electricity generated in megawatt-hours for each year.

This study found that low MAPE and MSE in (Moving Average 2) of 5.17 and 48.48 respectively as well as high Paired T-test in Linear Regression after comparison of the different methods.

Future research area could include:

- Technological Innovation and Transition Pathways: Examine technological advancements in coal-fired power generation, such as cleaner combustion methods and carbon capture and storage (CCS). In addition, investigate viable avenues for shifting from traditional coal-based electricity to more sustainable options.
- Global Comparative Study: Compare Turkey's coal-fired electricity generation experience to those of other countries. This research could provide useful insights into best practices, problems, and lessons learned, resulting in a more complete picture of the global situation.

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APPENDIX A_

Table A.1: Forecasting future electricity generation from coal outputs

Years	Actual Generated(Mwh)	Forecast Future Generation(mwh)	Absolute Percentage Error	MSE
1970	2,824,500	#N/A		
1971	2,980,200	2,824,500.00	5.22	27
1972	2,920,800	2,902,350.00	0.63	0
1973	3,243,600	2,911,575.00	10.24	105
1974	3,871,300	3,077,587.50	20.50	420
1975	4,113,300	3,474,443.75	15.53	241
1976	4,327,300	3,793,871.88	12.33	152
1977	4,892,000	4,060,585.94	17.00	289
1978	5,569,200	4,476,292.97	19.62	385
1979	6,438,000	5,022,746.48	21.98	483
1980	5,960,300	5,730,373.24	3.86	15
1981	6,136,400	5,845,336.62	4.74	22
1982	6,441,200	5,990,868.31	6.99	49
1983	8,577,000	6,216,034.16	27.53	758
1984	10,118,300	7,396,517.08	26.90	724
1985	15,027,800	8,757,408.54	41.73	1,741
1986	19,437,300	11,892,604.27	38.82	1,507
1987	17,653,500	15,664,952.13	11.26	127
1988	12,486,600	16,659,226.07	33.42	1,117
1989	20,269,500	14,572,913.03	28.10	790
1990	20,181,300	17,421,206.52	13.68	187
1991	21,561,500	18,801,253.26	12.80	164
1992	24,570,800	20,181,376.63	17.86	319
1993	23,759,900	22,376,088.31	5.82	34
1994	28,234,700	23,067,994.16	18.30	335
1995	28,046,900	25,651,347.08	8.54	73
1996	30,413,600	26,849,123.54	11.72	137
1997	33,860,000	28,631,361.77	15.44	238
1998	35,687,500	31,245,680.88	12.45	155
1999	37,030,900	33,466,590.44	9.63	93
2000	38,186,300	35,248,745.22	7.69	59
2001	38,417,500	36,717,522.61	4.43	20
2002	32,149,100	37,567,511.31	16.85	284
2003	32,252,900	34,858,305.65	8.08	65
2004	34,447,600	33,555,602.83	2.59	7

Years	Actual Generated(Mwh)	Forecast Future Generation(mwh)	Absolute Percentage Error	MSE
2005	43,192,500	34,001,601.41	21.28	453
2006	46,649,500	38,597,050.71	17.26	298
2007	53,430,900	42,623,275.35	20.23	409
2008	57,715,600	48,027,087.68	16.79	282
2009	55,685,100	52,871,343.84	5.05	26
2010	55,046,400	54,278,221.92	1.40	2
2011	66,217,900	54,662,310.96	17.45	305
2012	68,013,100	60,440,105.48	11.13	124
2013	63,786,076	64,226,602.74	0.69	0
2014	76,262,682	64,006,339.37	16.07	258
2015	76,165,607	70,134,510.68	7.92	63
2016	92,273,098	73,150,058.59	20.72	430
2017	97,476,295	82,711,578.15	15.15	229
2018	113,248,625	90,093,936.57	20.45	418
2019	112,894,124	101,671,280.89	9.94	99
2020	105,812,004	107,282,702.44	1.39	2
	Smoothing Constant, α	0.5	**14.30**	**290**
	Initial Forecast	2913420	**MAPE**	**MSE**

The table suggests that a forecasting model, presumably using exponential smoothing with a smoothing constant of 0.5, was used to forecast power generation over the specified time period. The error metrics, smoothing constant, and beginning forecast values are critical for evaluating the forecasting model's success.

Table A.2: Moving Averages 2 outputs

Years	Actual Generated(Mwh)	Moving Averages(2)	Absolute Percentage Error	MSE
1970	2,824,500	#N/A		
1971	2,980,200	2,902,350	2.61	6.82
1972	2,920,800	2,950,500	1.02	1.03
1973	3,243,600	3,082,200	4.98	24.76
1974	3,871,300	3,557,450	8.11	65.73
1975	4,113,300	3,992,300	2.94	8.65
1976	4,327,300	4,220,300	2.47	6.11
1977	4,892,000	4,609,650	5.77	33.31
1978	5,569,200	5,230,600	6.08	36.96
1979	6,438,000	6,003,600	6.75	45.53
1980	5,960,300	6,199,150	4.01	16.06
1981	6,136,400	6,048,350	1.43	2.06
1982	6,441,200	6,288,800	2.37	5.60
1983	8,577,000	7,509,100	12.45	155.02
1984	10,118,300	9,347,650	7.62	58.01
1985	15,027,800	12,573,050	16.33	266.82
1986	19,437,300	17,232,550	11.34	128.66
1987	17,653,500	18,545,400	5.05	25.53
1988	12,486,600	15,070,050	20.69	428.07
1989	20,269,500	16,378,050	19.20	368.58
1990	20,181,300	20,225,400	0.22	0.05
1991	21,561,500	20,871,400	3.20	10.24
1992	24,570,800	23,066,150	6.12	37.50
1993	23,759,900	24,165,350	1.71	2.91
1994	28,234,700	25,997,300	7.92	62.79
1995	28,046,900	28,140,800	0.33	0.11
1996	30,413,600	29,230,250	3.89	15.14
1997	33,860,000	32,136,800	5.09	25.90
1998	35,687,500	34,773,750	2.56	6.56
1999	37,030,900	36,359,200	1.81	3.29
2000	38,186,300	37,608,600	1.51	2.29
2001	38,417,500	38,301,900	0.30	0.09
2002	32,149,100	35,283,300	9.75	95.04
2003	32,252,900	32,201,000	0.16	0.03
2004	34,447,600	33,350,250	3.19	10.15
2005	43,192,500	38,820,050	10.12	102.48
2006	46,649,500	44,921,000	3.71	13.73
2007	53,430,900	50,040,200	6.35	40.27

Years	Actual Generated(Mwh)	Moving Averages(2)	Absolute Percentage Error	MSE
2008	57,715,600	55,573,250	3.71	13.78
2009	55,685,100	56,700,350	1.82	3.32
2010	55,046,400	55,365,750	0.58	0.34
2011	66,217,900	60,632,150	8.44	71.16
2012	68,013,100	67,115,500	1.32	1.74
2013	63,786,076	65,899,588	3.31	10.98
2014	76,262,682	70,024,379	8.18	66.91
2015	76,165,607	76,214,144	0.06	0.00
2016	92,273,098	84,219,352	8.73	76.18
2017	97,476,295	94,874,696	2.67	7.12
2018	113,248,625	105,362,460	6.96	48.49
2019	112,894,124	113,071,375	0.16	0.02
2020	105,812,004	109,353,064	3.35	11.20
			5.17	**48.46**
			MAPE	**MSE**

The table uses a moving averages (2) method to depict actual and anticipated power generation statistics from 1970 to 2020. The anticipated values are notable for their variable accuracy, as demonstrated by the Absolute Percentage Error (APE) and Mean Squared Error (MSE). The overall Mean Absolute Percentage Error (MAPE) is 5.17%, indicating that predicting precision is moderate. Some years, such as 1990 and 2015, have accurate forecasts, whilst others, such as 1988 and 2008, have larger mistakes, indicating possible areas for model improvement.

Table 0.3: Moving Averages 3 outputs

Years	Actual Generated(Mwh)	Moving Averages(3)	Absolute Percentage Error	MSE
1970	2,824,500	#N/A		
1971	2,980,200	#N/A		
1972	2,920,800	2,908,500	0.42	0.18
1973	3,243,600	3,048,200	6.02	36.29
1974	3,871,300	3,345,233	13.59	184.66
1975	4,113,300	3,742,733	9.01	81.16
1976	4,327,300	4,103,967	5.16	26.64
1977	4,892,000	4,444,200	9.15	83.79
1978	5,569,200	4,929,500	11.49	131.94
1979	6,438,000	5,633,067	12.50	156.32
1980	5,960,300	5,989,167	0.48	0.23
1981	6,136,400	6,178,233	0.68	0.46
1982	6,441,200	6,179,300	4.07	16.53
1983	8,577,000	7,051,533	17.79	316.33
1984	10,118,300	8,378,833	17.19	295.54
1985	15,027,800	11,241,033	25.20	634.96
1986	19,437,300	14,861,133	23.54	554.28
1987	17,653,500	17,372,867	1.59	2.53
1988	12,486,600	16,525,800	32.35	1,046.41
1989	20,269,500	16,803,200	17.10	292.45
1990	20,181,300	17,645,800	12.56	157.84
1991	21,561,500	20,670,767	4.13	17.07
1992	24,570,800	22,104,533	10.04	100.75
1993	23,759,900	23,297,400	1.95	3.79
1994	28,234,700	25,521,800	9.61	92.32
1995	28,046,900	26,680,500	4.87	23.73
1996	30,413,600	28,898,400	4.98	24.82
1997	33,860,000	30,773,500	9.12	83.09
1998	35,687,500	33,320,367	6.63	44.00
1999	37,030,900	35,526,133	4.06	16.51
2000	38,186,300	36,968,233	3.19	10.17
2001	38,417,500	37,878,233	1.40	1.97
2002	32,149,100	36,250,967	12.76	162.79
2003	32,252,900	34,273,167	6.26	39.24
2004	34,447,600	32,949,867	4.35	18.90
2005	43,192,500	36,631,000	15.19	230.78
2006	46,649,500	41,429,867	11.19	125.19
2007	53,430,900	47,757,633	10.62	112.74

Years	Actual Generated(Mwh)	Moving Averages(3)	Absolute Percentage Error	MSE
2008	57,715,600	52,598,667	8.87	78.60
2009	55,685,100	55,610,533	0.13	0.02
2010	55,046,400	56,149,033	2.00	4.01
2011	66,217,900	58,983,133	10.93	119.37
2012	68,013,100	63,092,467	7.23	52.34
2013	63,786,076	66,005,692	3.48	12.11
2014	76,262,682	69,353,953	9.06	82.07
2015	76,165,607	72,071,455	5.38	28.89
2016	92,273,098	81,567,129	11.60	134.62
2017	97,476,295	88,638,333	9.07	82.21
2018	113,248,625	100,999,339	10.82	116.99
2019	112,894,124	107,873,015	4.45	19.78
2020	105,812,004	110,651,584	4.57	20.92
			8.73	**119.97**
			MAPE	**MSE**

Using a Moving Averages (3) technique, the table depicts actual and predicted power generation statistics from 1970 to 2020. The Absolute Percentage Error (APE) and Mean Squared Error (MSE) are used to assess forecast accuracy. The total Mean Absolute Percentage Error (MAPE) is 8.73%, indicating that forecasting precision is moderate. While some years, such as 1990 and 2015, have precise projections, others, such as 1988 and 2005, have larger mistakes, indicating possible areas for improvement in the forecasting model.

Table 0.4: Moving Averages 4 outputs

Years	Actual Generated(Mwh)	Moving Averages(4)	Absolute Percentage Error	MSE
1970	2,824,500	#N/A		
1971	2,980,200	#N/A		
1972	2,920,800	#N/A		
1973	3,243,600	2,992,275	7.75	60.04
1974	3,871,300	3,253,975	15.95	254.28
1975	4,113,300	3,537,250	14.00	196.13
1976	4,327,300	3,888,875	10.13	102.65
1977	4,892,000	4,300,975	12.08	145.96
1978	5,569,200	4,725,450	15.15	229.53
1979	6,438,000	5,306,625	17.57	308.82
1980	5,960,300	5,714,875	4.12	16.96
1981	6,136,400	6,025,975	1.80	3.24
1982	6,441,200	6,243,975	3.06	9.38
1983	8,577,000	6,778,725	20.97	439.58
1984	10,118,300	7,818,225	22.73	516.74
1985	15,027,800	10,041,075	33.18	1,101.13
1986	19,437,300	13,290,100	31.63	1,000.19
1987	17,653,500	15,559,225	11.86	140.74
1988	12,486,600	16,151,300	29.35	861.37
1989	20,269,500	17,461,725	13.85	191.88
1990	20,181,300	17,647,725	12.55	157.60
1991	21,561,500	18,624,725	13.62	185.52
1992	24,570,800	21,645,775	11.90	141.72
1993	23,759,900	22,518,375	5.23	27.30
1994	28,234,700	24,531,725	13.11	172.00
1995	28,046,900	26,153,075	6.75	45.59
1996	30,413,600	27,613,775	9.21	84.75
1997	33,860,000	30,138,800	10.99	120.78
1998	35,687,500	32,002,000	10.33	106.65
1999	37,030,900	34,248,000	7.52	56.48
2000	38,186,300	36,191,175	5.22	27.30
2001	38,417,500	37,330,550	2.83	8.00
2002	32,149,100	36,445,950	13.37	178.63
2003	32,252,900	35,251,450	9.30	86.43
2004	34,447,600	34,316,775	0.38	0.14
2005	43,192,500	35,510,525	17.79	316.32
2006	46,649,500	39,135,625	16.11	259.44
2007	53,430,900	44,430,125	16.85	283.78

Years	Actual Generated(Mwh)	Moving Averages(4)	Absolute Percentage Error	MSE
2008	57,715,600	50,247,125	12.94	167.45
2009	55,685,100	53,370,275	4.16	17.28
2010	55,046,400	55,469,500	0.77	0.59
2011	66,217,900	58,666,250	11.40	130.06
2012	68,013,100	61,240,625	9.96	99.15
2013	63,786,076	63,265,869	0.82	0.67
2014	76,262,682	68,569,940	10.09	101.75
2015	76,165,607	71,056,866	6.71	44.99
2016	92,273,098	77,121,866	16.42	269.62
2017	97,476,295	85,544,420	12.24	149.84
2018	113,248,625	94,790,906	16.30	265.64
2019	112,894,124	103,973,035	7.90	62.44
2020	105,812,004	107,357,762	1.46	2.13
			11.65	**190.60**
			MAPE	**MSE**

Using a Moving Averages (4) technique, the table illustrates actual and anticipated power generation statistics from 1970 to 2020. Forecast accuracy is measured using the Absolute Percentage Error (APE) and Mean Squared Error (MSE). The overall Mean Absolute Percentage Error (MAPE) is 11.65%, indicating that forecasting precision is moderate. While some years, such as 2004, have precise projections, others, such as 1988 and 2015, have higher mistakes, indicating possible areas for improvement in the forecasting model.

Table 0.5: Weighted Moving Average 3 outputs

Years	Actual Generated(Mwh)	Weighted MA(3)	Absolute Percentage Error	MSE
1970	2,824,500			
1971	2,980,200			
1972	2,920,800			
1973	3,243,600	4,821,336.32	48.64	2,366.00
1974	3,871,300	5,127,744.32	32.46	1,053.35
1975	4,113,300	5,440,298.32	32.26	1,040.78
1976	4,327,300	5,997,084.32	38.59	1,488.97
1977	4,892,000	6,775,344.32	38.50	1,482.13
1978	5,569,200	7,338,214.32	31.76	1,008.97
1979	6,438,000	7,992,460.32	24.15	582.98
1980	5,960,300	9,113,456.32	52.90	2,798.69
1981	6,136,400	9,708,190.32	58.21	3,388.01
1982	6,441,200	10,579,054.32	64.24	4,126.83
1983	8,577,000	10,285,452.32	19.92	396.77
1984	10,118,300	11,584,316.32	14.49	209.92
1985	15,027,800	13,044,210.32	13.20	174.23
1986	19,437,300	17,912,194.32	7.85	61.56
1987	17,653,500	22,541,954.32	27.69	766.80
1988	12,486,600	27,353,264.32	119.06	14,175.51
1989	20,269,500	28,858,230.32	42.37	1,795.44
1990	20,181,300	30,035,838.32	48.83	2,384.37
1991	21,561,500	26,225,760.32	21.63	467.96
1992	24,570,800	34,682,884.32	41.15	1,693.72
1993	23,759,900	36,347,770.32	52.98	2,806.82
1994	28,234,700	37,864,194.32	34.11	1,163.16
1995	28,046,900	42,964,932.32	53.19	2,829.13
1996	30,413,600	42,865,596.32	40.94	1,676.26
1997	33,860,000	48,489,942.32	43.21	1,866.86
1998	35,687,500	50,451,348.32	41.37	1,711.46
1999	37,030,900	54,352,150.32	46.78	2,187.91
2000	38,186,300	58,799,200.32	53.98	2,913.82
2001	38,417,500	61,446,212.32	59.94	3,593.20
2002	32,149,100	63,113,184.32	96.31	9,276.39
2003	32,252,900	61,176,000.32	89.68	8,041.78
2004	34,447,600	60,330,788.32	75.14	5,645.70
2005	43,192,500	55,178,422.32	27.75	770.06
2006	46,649,500	60,049,718.32	28.73	825.14
2007	53,430,900	65,547,000.32	22.68	514.21

Years	Actual Generated(Mwh)	Weighted MA(3)	Absolute Percentage Error	MSE
2008	57,715,600	78,304,860.32	35.67	1,272.61
2009	55,685,100	85,124,862.32	52.87	2,795.06
2010	55,046,400	91,662,258.32	66.52	4,424.67
2011	66,217,900	95,262,118.32	43.86	1,923.84
2012	68,013,100	98,702,402.32	45.12	2,036.05
2013	63,786,076	100,972,172.32	58.30	3,398.67
2014	76,262,682	110,353,296.32	44.70	1,998.23
2015	76,165,607	117,625,935.00	54.43	2,963.11
2016	92,273,098	115,596,162.33	25.28	638.88
2017	97,476,295	136,109,040.34	39.63	1,570.77
2018	113,248,625	141,512,911.91	24.96	622.89
2019	112,894,124	166,443,143.72	47.43	2,249.89
2020	105,812,004	174,308,109.86	64.73	4,190.46
			45	**2,445.21**
			MAPE	**MSE**

The table displays actual and projected electricity generation data from 1970 to 2020 using a Weighted Moving Averages (3) technique. Forecast accuracy is measured using the Absolute Percentage Error (APE) and Mean Squared Error (MSE). The overall Mean Absolute Percentage Error (MAPE) is 45%, indicating that forecasting precision is moderate. While some years, such as 1973, have higher errors, the model produces reasonable estimates across the dataset in general. Continuous monitoring and subsequent changes to the weighting technique could improve prediction performance even further.

Table A.6: Weighted Moving Average 2 outputs

Years	Actual Generated(Mwh)	Weighted MA(2)	Absolute Percentage Error	MSE
1970	2,824,500			
1971	2,980,200			
1972	2,920,800	2,902,350	0.631676253	0.399
1973	3,243,600	2,950,500	9.036256012	81.654
1974	3,871,300	3,082,200	20.38333376	415.480
1975	4,113,300	3,557,450	13.51348066	182.614
1976	4,327,300	3,992,300	7.741547847	59.932
1977	4,892,000	4,220,300	13.73058054	188.529
1978	5,569,200	4,609,650	17.22958414	296.859
1979	6,438,000	5,230,600	18.75427151	351.723
1980	5,960,300	6,003,600	0.7264735	0.528
1981	6,136,400	6,199,150	1.022586533	1.046
1982	6,441,200	6,048,350	6.099018816	37.198
1983	8,577,000	6,288,800	26.67832575	711.733
1984	10,118,300	7,509,100	25.78694049	664.966
1985	15,027,800	9,347,650	37.79761509	1428.660
1986	19,437,300	12,573,050	35.31483282	1247.137
1987	17,653,500	17,232,550	2.384512986	5.686
1988	12,486,600	18,545,400	48.52241603	2354.425
1989	20,269,500	15,070,050	25.65159476	658.004
1990	20,181,300	16,378,050	18.8454163	355.150
1991	21,561,500	20,225,400	6.19669318	38.399
1992	24,570,800	20,871,400	15.05608283	226.686
1993	23,759,900	23,066,150	2.919835521	8.525
1994	28,234,700	24,165,350	14.41258451	207.723
1995	28,046,900	25,997,300	7.307759503	53.403
1996	30,413,600	28,140,800	7.472972618	55.845
1997	33,860,000	29,230,250	13.67321323	186.957
1998	35,687,500	32,136,800	9.949422067	98.991
1999	37,030,900	34,773,750	6.095314994	37.153
2000	38,186,300	36,359,200	4.784700272	22.893
2001	38,417,500	37,608,600	2.105550856	4.433
2002	32,149,100	38,301,900	19.13832736	366.276
2003	32,252,900	35,283,300	9.395744259	88.280
2004	34,447,600	32,201,000	6.521789617	42.534
2005	43,192,500	33,350,250	22.78694218	519.245
2006	46,649,500	38,820,050	16.78356681	281.688
2007	53,430,900	44,921,000	15.92692618	253.667

Years	Actual Generated(Mwh)	Weighted MA(2)	Absolute Percentage Error	MSE
2008	57,715,600	50,040,200	13.29865756	176.854
2009	55,685,100	55,573,250	0.200861631	0.040
2010	55,046,400	56,700,350	3.004646989	9.028
2011	66,217,900	55,365,750	16.38854449	268.584
2012	68,013,100	60,632,150	10.85224758	117.771
2013	63,786,076	67,115,500	5.21967208	27.245
2014	76,262,682	65,899,588	13.58868286	184.652
2015	76,165,607	70,024,379	8.062992973	65.012
2016	92,273,098	76,214,144	17.40372205	302.890
2017	97,476,295	84,219,352	13.6001711	184.965
2018	113,248,625	94,874,696	16.22441669	263.232
2019	112,894,124	105,362,460	6.671440136	44.508
2020	105,812,004	113,071,375	6.860630381	47.068
			13.097	**269.924**
			MAPE	**MSE**

Using a Weighted Moving Averages (2) technique, the table shows actual and expected electricity generation (MWh) from 1970 to 2020. The accuracy of the model is measured using the Absolute Percentage Error (APE) and Mean Squared Error (MSE). The Mean Absolute Percentage Error (MAPE) is 13.097%, indicating that forecasting ability is adequate. While some years, such as 1973 and 1988, have higher mistakes, the overall predicted accuracy shows a generally accurate model for power generation forecasting. Continuous monitoring and subsequent changes to the weighting technique could improve accuracy even further.

Table A.7: Weighted Moving Average 1 outputs

Years	Actual Generated(Mwh)	Weighted MA(1)	Absolute Percentage Error	MSE
1970	2,824,500			
1971	2,980,200	2,824,500	5.22	27.30
1972	2,920,800	2,980,200	2.03	4.14
1973	3,243,600	2,920,800	9.95	99.04
1974	3,871,300	3,243,600	16.21	262.90
1975	4,113,300	3,871,300	5.88	34.61
1976	4,327,300	4,113,300	4.95	24.46
1977	4,892,000	4,327,300	11.54	133.25
1978	5,569,200	4,892,000	12.16	147.86
1979	6,438,000	5,569,200	13.49	182.11
1980	5,960,300	6,438,000	8.01	64.24
1981	6,136,400	5,960,300	2.87	8.24
1982	6,441,200	6,136,400	4.73	22.39
1983	8,577,000	6,441,200	24.90	620.08
1984	10,118,300	8,577,000	15.23	232.04
1985	15,027,800	10,118,300	32.67	1,067.29
1986	19,437,300	15,027,800	22.69	514.64
1987	17,653,500	19,437,300	10.10	102.10
1988	12,486,600	17,653,500	41.38	1,712.27
1989	20,269,500	12,486,600	38.40	1,474.34
1990	20,181,300	20,269,500	0.44	0.19
1991	21,561,500	20,181,300	6.40	40.98
1992	24,570,800	21,561,500	12.25	150.00
1993	23,759,900	24,570,800	3.41	11.65
1994	28,234,700	23,759,900	15.85	251.18
1995	28,046,900	28,234,700	0.67	0.45
1996	30,413,600	28,046,900	7.78	60.56
1997	33,860,000	30,413,600	10.18	103.60
1998	35,687,500	33,860,000	5.12	26.22
1999	37,030,900	35,687,500	3.63	13.16
2000	38,186,300	37,030,900	3.03	9.15
2001	38,417,500	38,186,300	0.60	0.36
2002	32,149,100	38,417,500	19.50	380.17
2003	32,252,900	32,149,100	0.32	0.10
2004	34,447,600	32,252,900	6.37	40.59
2005	43,192,500	34,447,600	20.25	409.91
2006	46,649,500	43,192,500	7.41	54.92
2007	53,430,900	46,649,500	12.69	161.08

Years	Actual Generated(Mwh)	Weighted MA(1)	Absolute Percentage Error	MSE
2008	57,715,600	53,430,900	7.42	55.11
2009	55,685,100	57,715,600	3.65	13.30
2010	55,046,400	55,685,100	1.16	1.35
2011	66,217,900	55,046,400	16.87	284.62
2012	68,013,100	66,217,900	2.64	6.97
2013	63,786,076	68,013,100	6.63	43.92
2014	76,262,682	63,786,076	16.36	267.65
2015	76,165,607	76,262,682	0.13	0.02
2016	92,273,098	76,165,607	17.46	304.72
2017	97,476,295	92,273,098	5.34	28.49
2018	113,248,625	97,476,295	13.93	193.97
2019	112,894,124	113,248,625	0.31	0.10
2020	105,812,004	112,894,124	6.69	44.80
			10.34	**193.85**
			MAPE	**MSE**

The data presented here reflects actual and projected electricity generation (MWh) from 1970 to 2020 using a Weighted Moving Averages (1) technique. The accuracy of the model is measured using the Absolute Percentage Error (APE) and Mean Squared Error (MSE). The Mean Absolute Percentage Error (MAPE) is 10.34%, indicating that forecasting ability is adequate. The model appears to represent the general trend in power generation, and the majority of the absolute percentage mistakes are within acceptable limits.

Table A.8: Linear Regression outputs

Years	Actual Generated (Mwh)	LN(ELECTRICITY)	Regrated	Forecasted Electricity	Absolute Percentage Error	MSE
1970	2,824,500	14.85384192	15.05532043	3454956.52	22.321	498
1971	2,980,200	14.90750097	15.12881135	3718427.243	24.771	614
1972	2,920,800	14.88736811	15.20230228	4001989.92	37.017	1370
1973	3,243,600	14.99219438	15.2757932	4307176.736	32.790	1075
1974	3,871,300	15.16910093	15.34928412	4635636.723	19.744	390
1975	4,113,300	15.22973618	15.42277504	4989144.663	21.293	453
1976	4,327,300	15.28045435	15.49626597	5369610.683	24.087	580
1977	4,892,000	15.40311178	15.56975689	5779090.572	18.133	329
1978	5,569,200	15.53276198	15.64324781	6219796.893	11.682	136
1979	6,438,000	15.67772849	15.71673873	6694110.935	3.978	16
1980	5,960,300	15.60063137	15.79022966	7204595.58	20.876	436
1981	6,136,400	15.62974881	15.86372058	7754009.155	26.361	695
1982	6,441,200	15.67822542	15.9372115	8345320.332	29.562	874
1983	8,577,000	15.96459476	16.01070242	8981724.17	4.719	22
1984	10,118,300	16.12985622	16.08419335	9666659.379	4.464	20
1985	15,027,800	16.52541238	16.15768427	10403826.9	30.769	947
1986	19,437,300	16.78270446	16.23117519	11197209.91	42.393	1797
1987	17,653,500	16.68644462	16.30466611	12051095.34	31.735	1007
1988	12,486,600	16.34016663	16.37815704	12970097.01	3.872	15
1989	20,269,500	16.82462785	16.45164796	13959180.61	31.132	969
1990	20,181,300	16.82026699	16.52513888	15023690.51	25.556	653
1991	21,561,500	16.88641987	16.5986298	16169378.62	25.008	625
1992	24,570,800	17.0170693	16.67212073	17402435.5	29.174	851
1993	23,759,900	16.98350984	16.74561165	18729523.77	21.172	448
1994	28,234,700	17.15606228	16.81910257	20157814.16	28.606	818
1995	28,046,900	17.14938867	16.89259349	21695024.21	22.647	513

Years	Actual Generated (Mwh)	LN(ELECTRICITY)	Regrated	Forecasted Electricity	Absolute Percentage Error	MSE
1996	30,413,600	17.23040043	16.96608442	23349460	23.227	539
1997	33,860,000	17.33774493	17.03957534	25130061.03	25.782	665
1998	35,687,500	17.39031105	17.11306626	27046448.49	24.213	586
1999	37,030,900	17.42726326	17.18655718	29108977.31	21.393	458
2000	38,186,300	17.45798737	17.26004811	31328792.02	17.958	322
2001	38,417,500	17.46402364	17.33353903	33717887.07	12.233	150
2002	32,149,100	17.28589501	17.40702995	36289171.56	12.878	166
2003	32,252,900	17.28911852	17.48052087	39056539.03	21.095	445
2004	34,447,600	17.35494989	17.5540118	42034942.54	22.026	485
2005	43,192,500	17.58117743	17.62750272	45240475.42	4.742	22
2006	46,649,500	17.65817277	17.70099364	48690458.29	4.375	19
2007	53,430,900	17.79389979	17.77448456	52403532.6	1.923	4
2008	57,715,600	17.87103806	17.84797549	56399761.38	2.280	5
2009	55,685,100	17.83522316	17.92146641	60700737.64	9.007	81
2010	55,046,400	17.82368702	17.99495733	65329701.04	18.681	349
2011	66,217,900	18.00846138	18.06844825	70311663.48	6.182	38
2012	68,013,100	18.03521089	18.14193918	75673544.24	11.263	127
2013	63,786,076	17.97104548	18.2154301	81444315.41	27.684	766
2014	76,262,682	18.14969428	18.28892102	87655158.47	14.938	223
2015	76,165,607	18.14842056	18.36241194	94339632.77	23.861	569
2016	92,273,098	18.34026319	18.43590287	101533856.8	10.036	101
2017	97,476,295	18.39511978	18.50939379	109276703.6	12.106	147
2018	113,248,625	18.54509618	18.58288471	117610010.2	3.851	15
2019	112,894,124	18.54196098	18.65637563	126578804.6	12.122	147
2020	105,812,004	18.47717453	18.72986656	136231548.1	28.749	826
					18.950	**459**
					MAPE	**MSE**

The table represent actual and anticipated energy generation (MWh) from 1970 to 2020, as well as the natural logarithm of electricity generation, regressed values, forecasted electricity, absolute percentage error, and mean squared error.

The given forecast's Mean Absolute Percentage Error (MAPE) is 18.95%, reflecting the average absolute percentage difference between the actual and anticipated values. The MSE (Mean Squared Error) is 459.

keeping in mind that a lower MAPE and MSE generally suggest a better model fit, therefore these metrics can be used to assess the forecasting model's accuracy.