REPUBLIC OF TÜRKİYE

ALTINBAŞ UNIERSITY

Institute of Graduate Studies

Industrial Engineering Department

A HYBRID FORECASTING APPROACH FOR DEMAND PREDICTION IN THE PERFUME INDUSTRY

Mohammed ZOURGUI

Master’s Thesis

Supervisor

Asst. Prof. Dr. Fatih YİĞİT

İstanbul, 2024

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2024

The thesis titled by A HYBRID FORECASTING APPROACH DEMAND PREDICTION IN PERFUME INDUSTRY prepared by MOHAMMED ZOURGUI and submitted 24.01.2024 has been **accepted unanimously** for the degree of Master of Science in Industrial Engineering.

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I hereby declare that this thesis meets all format and submission requirements for a research Master's Thesis.

I affirm that every piece of information and data presented in this graduation project adheres strictly to academic regulations and ethical standards. I attest that any materials or conclusions borrowed from external sources are appropriately acknowledged within the text, and all references listed in the Reference List are duly cited in the text, in accordance with the aforementioned rules and standards.

Mohammed ZOURGUI

Signature

DEDICATION

I would like to express my heartfelt gratitude to my beloved family and dear ones, whose unwavering support and inspiration have been my guiding light throughout this academic journey. Your encouragement and unwavering belief in my abilities have been Instrumental in my pursuit of knowledge and academic excellence.

Furthermore, I extend my dedication to my esteemed supervisor, Dr. Fatih YIGIT, who played a pivotal role in this work by providing invaluable guidance and information. His commitment to ensuring the quality of this work reflects his dedication as a mentor. I would also like to acknowledge my friend, Mr. Oussama MEJRI, for his assistance in the completion of this thesis. Their collective efforts and collaboration have greatly contributed to the completion of this work.

I hope that this thesis lives up to their expectations and the standards set by my supervisor. It is a testament to our shared values of perseverance and hard work. Your unwavering faith in me has been a source of motivation on this academic journey.

Sincerely,

ABSTRACT

A HYBRID FORECASTING APPROACH DEMAND PREDICTION IN THE PERFUME INDUSTRY

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Date: January / 2024

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Accuracy in demand forecasting is a key pillar that supports effective supply chain management and operational effectiveness as it covers various industries .However, traditional forecasting methodologies often struggle to keep pace with the complex and constantly evolving nature of demand re subject to the influence of multiple factors. To meet this complex challenge, hybrid forecasting presented them on the scene, leveraging the combined capabilities of different distinct forecasting techniques. This thesis seeks to present an innovative hybrid forecasting framework specifically designed for demand forecasting, with the aim of enhancing accuracy and increasing flexibility in forecasts.

Keywords: Forecasting, Supply Chain, Hybrid Forecasting, Hybrid Models, Demand Planning.

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ABBREVIATIONS

AI	:	Artificial Intelligence
DSU	:	Disjoint Set Union
GBM	:	Gradient Boosting Machine
OM	:	Operations Management
STLF	:	Seek The Lord First
SVM	:	Support Vector Machine

LIST OF SYMBOLS

α : Smoothing Factor Of Data

β : Trend Smoothing Factor

γ : Seasonal Change Smoothing Factor

y_i : The Actual Value

$\hat{y}_i$: The Predicted Value

yi : The Ith Observed Value

$\hat{y}i$: The Corresponding Predicted Value

1. INTRODUCTION

In the current realities of business and commerce, the ability to accurately forecast demand is crucial to success. Organization across all industries recognize that the ability to accurately forecast demand is critical not only to improving resource allocation and inventory management, but also to enhancing customer satisfaction and staying competitive. With markets becoming increasingly complex and unpredictable, traditional forecasting methods often find it difficult to deal with the demand patterns. Therefore, to meet these challenges, a new approach known as the mixed forecasting approach has emerged. This study dives deeply into the field of demand forecasting by proposing and exploring the philosophy of hybrid forecasting. This approach integrates different forecasting methodologies and leverages their unique advantages to create a predictive model with greater flexibility, adaptability, and accuracy. With the increasing complexity of market dynamics and the expanding availability of data, hybrid forecasting provides a way to overcome the limitations of standalone forecasting techniques. Also companies face many problems and challenges when predicting demand, especially in a rapidly changing business environment, where this can be a major challenge, and among the problems that companies face, we mention them:

Sudden changes in the market where unexpected events such as health crises (such as the COVID-19 pandemic), geopolitical changes, or large increases in demand are difficult to predict and may significantly affect the accuracy of forecast, rapidly changing trends and topics in a rapidly changing environment, customer interests and preferences can change rapidly, making it difficult to predict future demand, we also see the complexity of data as companies today collect huge amounts of data, but analyzing and using this data effectively can be a challenge, especially as the volume and complexity of data increases, competition is intense in strong competitive environment, where expectations must be accurate to avoid losing customers to other companies that better meet their needs, we will see also the price pressures fluctuations in demand may increase price pressure and reduce profit margins .Changes in technology and rapidly changing technological developments can affect how products are manufactured and marketed ,making it difficult to predict future needs. Also, there is a lack of time is a rapidly changing environment, as you have limited time to make and implement decisions, which makes rapid forecasting necessary. Also, the availability of accurate information requires access to reliable sources of data and information to ensure accurate forecasts, and this may be a challenge in itself. A mixes forecasting approach is a strategy that combines and combines the strengths of several forecasting methods, with the goal of enhancing forecast accuracy and reliability. This approach takes advantages of the integration of different techniques to understand complex patterns in the data and improve overall forecasting performance. The main idea behind the hybrid forecasting approach is simple: no single forecasting method is perfect for all types of data or for all contexts. Different predictive techniques have their own strengths and weaknesses, and can show better performance in certain circumstances or for specific patterns in the data. By strategically integrating these technologies, the hybrid approach aims to minimize the weaknesses of individual methods and capitalize on their strengths. This article in the literature review discusses the basic elements of the study of demand forecasting. It examines numerous papers and articles on this important field and uncovers trends and notable findings. Research and articles show the use of a variety of techniques for demand forecasting, including traditional statistical analysis techniques and learning techniques. Automated, such as artificial neural networks. These studies have the advantage of providing different insights on how to achieve better accuracy. Many researches have been crucial in developing methods of data processing and statistical analysis to enhance the precision of demand prediction. These efforts aim to develop advanced analytics models that take advantage of big data. Numerous research papers and articles have revealed the economic and environmental implications of accurate demand forecasting. Studies have shown improvements in resource allocation, waste reduction and improved sustainability of operations. The same research also pointed to challenges such as changing market velocity, increasing data volume, and price pressures. It also highlighted future trends such as the use of deep learning techniques and artificial intelligence to improve demand forecasting. Many studies have also analyzing the impact of demand forecasting on various industries such as manufacturing, logistics and services. These studies have contributes to an understanding of how to implement better predictive practices in these industries. These research and articles help lay the foundations for the current study and identify areas that need further research and development. In methodology or in the third part of the thesis, the focus was son various methods of demand forecasting, where the main focus of this part revolves around enhancing the accuracy of demand forecasting and providing improved performance in this vital context.

Through the exploration and analysis of a diverse array of forecasting methods and techniques, the study will address how different forecasting methods are utilized individually and integrated cohesively to achieve precise predictions for demand and orders. Shedding light on these aspects related to forecasting methods will constitute one of the central themes under discussion in this research .Among the methods that will be highlighted are:

Where we will start this part of the thesis with the naïve method, which is one of the simplest prediction techniques. It is assumed that future demand will be the same as the last observed demand. As for the second part of methodology, we talked about averaging methods such as moving average and weighted moving average, by calculating expectations by taking the average of previous demand data during a specific period time. These methods smooth out short-term fluctuations and are useful for picking up trends and seasonality in data. In the third part of the methodology, we talked about exponential smoothing methods, as the latter assign significantly decreasing weights to previous observations, giving greater importance to more recent data. These methods include simple exponential smoothing, Holts exponential smoothing, and winter exponential smoothing. It is suitable for dealing with time-varying data and provides more accurate predictions compared to simple averaging methods. In the final part of the methodology we dealt with the performance Metrics of forecasting, As many performance metrics are commonly used for this purpose some of which we have mentioned as Mean Absolute Error (MAE) where it calculates the average absolute discrepancy between actual and predicted values serves as an indicator of forecast precision. In the corresponding segment, we discussed Mean Absolute Percentage Error (MAPE), which assesses the percentage disparity between observed and forecasted values, offering a relative gauge of forecast accuracy. Additionally, we addressed mean square error (MSE), which gauges the average squared disparities between real and anticipated values, highlighting substantial errors. In the metric after which we talked about the root mean square error (RMSE), which is the square root of the MSE. It provides a measure of the standard deviation of forecast errors. At the end of the metrics, with which we ended the methodology; we talked about the tracking signal (TS), which evaluates the bias in forecasts by dividing the cumulative sum of forecast errors by the average absolute deviation. Where a positive trace signal indicates consistent over predictors, whereas a negative signal indicates consistent over predictor’s.We explained that performance metrics help these organizations assess the quality of their demand forecasts and make necessary adjustments to improve accuracy. In the application part, we worked on some of the methods that we talked about in the methodology, by using sales data for a perfume factory, and that was by using this factory’s sales data for a period of 4 years from the year 2019 to 2022, We started the applied part with a comprehensive definition of the factory and the products it manufactures, the data of which we will use in this stage of the study. The message is that we were used 6 forecasting methods to be applied in this part of the thesis, where we started with the naive method as the first method in the application, and after that the averaging method was applied as the second method in the application, and after that we moved to the weighted average method, and after that we used the exponential smoothing averaging method was used, then we used a new method. It is trend line forecasting. The hybrid forecasting method was also chosen to be used as the sixth forecasting method for this part of the thesis. We concluded the section on the application by using one of the forecast performance measures, which is the root mean square error (RMSE). In the thesis's conclusion, we provided a concise overview of the key points and findings derived from our study. We offered a recap of the objectives set at the thesis's outset and our efforts to achieve them. Furthermore, we summarized the most significant outcomes resulting from our research and analysis, and, based on the evidence and data presented throughout the thesis, we presented the primary conclusions. We also outlined potential areas for future research, the avenues through which demand forecasting research can progress, and the contribution our research can make to the academic and industrial domains. To conclude our research, we put forth practical methods to apply the findings and offered guidance on implementing the research in real-world scenarios, serving as suggestions for forthcoming studies endeavors.

2. LITERATURE REVIEW

In the following sub-sections, literature reviews regarding main topics associated with the thesis are given.

2.1 DEMAND FORECASTING

Demand forecasting is very is very important in all companies, in different fields of activities, for example talking about demand forecasting in the fashion industry where demand is uncertain[1]. In the fashion industry forecasts are not always accurate, products can be characterized by long replenishment periods, short sales seasons where demand can be roughly predictable.

On the other hand, many factors contributed to the fashion industry such as:

a. cost reduction needs

b. globalization

c. increasing customer requirements

d. technology

In addition, the difficulty of predicting advance demand has led companies to optimize their supply chain so that they can increase their sales, and this is actually one of the success factors for brands such as H&M and Zara.

However, product features and supply chain in the fashion industry remain dominant factors [1]. It is therefore not unexpected that the most renowned brands opt to concentrate on enhancing the efficiency of their supply chain. That is Zara or H&M don’t anticipate demand; most likely, they are relying instead on marketing tactics [1].
The major drawbacks in demand forecasting are:

a. short selling seasons

b. level of uncertainty (clustering)

c. lack of historical data

Communications global markets and the advancement of emerging communication technologies, and how novel services are being provided to potential customers at a growing pace, and this is by predicting market demand for new communication services [2].

Forecasts can’t be completely accurate, so we can’t know what will happen in the future. Predictions are just an invention that we use nowadays. In this article, we have touched on several beliefs about effectively managing the prediction process while performing the prediction experiment.

First, if prediction users don’t understand their conclusions, they are unlikely to be persuaded by then. This is because predictions must be convincing, which is why simple prediction models are better than complex ones. Second, company strategies must be consistent with marketing, technical and financial expectations. In the planning stage of starting a project, we know that this is not easy to achieve, especially when these strategies are under construction.

The third belief is that the forecasting process benefits from a broader reduction of the limitations and challenges posed by available technologies [2].

Existing forecasting methods aren’t sufficient to perform stock analysis accurately, so predicting stock performance becomes a more difficult problem due to the large quantity of valuable trading data housed in the stock database[3]. There are two primary explanations for this: First, studies of current forecasting methods are still not sufficient to determine the most appropriate methods to predict the share price. Secondly, this research conducts a comprehensive review of the last 15 years on diverse machine learning techniques to precisely assess inventory performance through investigations of factors influencing inventory performance. This article highlights the use of prediction algorithms to identify key variables within a set of stock market data. Ultimately, we perform competent analysis pf engagement performance, generating beneficial results and positively influencing researchers, society, brokers, and financial analysts. The anticipation of stock prices appears to be a major concern in the financial field, because it encourages inventors and brokers to allocate funds in the market. This research primarily reviews work regarding forecasting stock performance via various forecasting techniques. The survey reveals a predominant use of technical parameters in the forecasting in the forecasting process, as well as examples of the use of fundamental and macroeconomic indicators for predictive purposes. Some researchers have used fundamental and macroeconomic parameters in their prediction processes. Additionally; some scholars have used lagging index variations as a data set. As a result, experts in the field of stock market research have made extensive use of forecasting techniques such as genetic algorithms (GA), support vector machine (SVM) and neural networks (NN). The analysis also reveals that the hybrid model exhibits superior prediction accuracy compared to the individual components of the hybrid model. In conclusion, this research study will serve as a stimulus to further investigate problems in the stock market and encourage market users to systematically monitor their participation performance [3].

In another we will explore how insights derived from big data in social media can be leveraged to anticipate future product demand, enhancing the performance of the supply chain and contributing value to supply chain operations. Additionally, these insights can be utilized for predicting forthcoming product demand [4]. Here we will also talk about the framework for improving supply chain demand forecasting utilizing social networking information from Twitter and Facebook. The purpose of this structure is to predict demand by analyzing sentiment, trends, and work-related data from large-scale social media sources.

The forecasting can be accomplished through case analysis, which will positively enhance the precision of demand prediction in remote supply chains. Social media data is often filled with interference, and making precise predictions about products in a general sense can be challenging. However, if products are categorized, and a search for various attributes is employed, the collected data has the potential to be transformed into a projection of demand, market trends, or sensor trends. The key element in extracting value from social media lies in the application of diverse data cleansing methods in combination. Through appropriate modeling and the implementation of suitable techniques, big data from social media holds the capacity to facilitate precise predictions [4]. And another article it is crucial to oversee production by examining market demand. The market encounters unpredictable demands, brief product life cycles, and a lack of historical sales data, rendering forecasting challenging[5]. Several methods have been suggested in recent decades concerning this issue. This paper establishes a foundation for comprehending the prediction mechanism by providing an in-depth examination of the literature along with various fields where sales can predicted. In the prediction process, it's challenging to pinpoint a single model that consistently outperforms others, but the goal is to identify a fitting model based on the available data. We've established various models, including a hybrid one, to forecast the sale price of homes by considering their features. Feature engineering has also been implemented to extract a valuable dataset. In this paper, we propose a multiple regression hybrid model for predict the price of a particular home based on various factors people effect. The accuracy of our model in predicting house prices based on specific home prices which are Influencing factors on home prices encompass location, size, home type, city, country, tax laws, economic cycles, population migration, interest rates, and various other elements. Using the statistical error analysis, we I determined that the hybrid model outperformed the conventional one machine learning algorithm. We have obtained minimum R.M.S.E. (or highest squared value r) with the hybrid model is 0.074 (scaled value) and he has the strongest data entered, it is observed through purification feature engineering work, model accuracy can be improved through feature optimization engineering works [5]. Accurate forecasting of the demand for electric power plays a significant role in the electricity markets and power systems [6]. The aim of this document is to showcase a novel approach to the management and scheduling of hybrid forecasted electricity. The proposed innovative method, EEMD-SCGRNN-PSVR, integrates the Experimental Group Decay Mode (EEMD), Seasonal Adjustment (S), Cross-Validation (C), and a General Regression Neural Network (GRNN), along with a Particle Swarming Optimization algorithm (PSVR) optimized Vector Regression Machine. The central concept behind EEMD-SCGRNN-PSVR involves the cascading prediction of a waveform and trend component concealed within the order chain, replacing the direct forecasting of the electrical demand source. In this article, a forecasting model named EEMD-SCGRNN-PSVR is introduced for the prediction of electricity demand for the upcoming week. The primary novel concept behind EEMD-SCGRNN-PSVR is the anticipation of substituting the original direct prediction of electricity demand with the waveform and trend components, respectively. Experiments with the three criteria (RMSE, MAE, and MAPE) it is evident from the results that EEMD-SCGRNN-PSVR markedly enhances both the precision and stability of forecasts. This novel scheduling model can be effectively utilized for anticipating electricity demand within the electricity market. Additionally, this hybrid model demonstrates versatility by extending its applicability to forecasting electricity prices, wind speeds, tourism demands, and other energy requirements. However, it is imperative to acknowledge that EEMD-SCGRNN-PSVR exhibits certain limitations that need to be addressed. For instance, when employed for electricity demand forecasting, there is additional time essential while respecting simple forms[6].

The global is currently experiencing a fourth industrial revolution, marked by the swift advancement of technologies that are expanding the possibilities for intelligent infrastructure [7]. Experts note that decolonization, digitation and decentralization are the main divers of change. In electric power systems, a decline in centralized power plants running on traditional fossil fuels and an increase in the proportion percentage of distributed power generation further heightens the already concerning expectations of operators in low-inertia power systems. In this study, we develop a straightforward yet immensely efficient consolidated model for forecasting electricity consumption rates.

The provided approach centers on the possible implementation by a local power grid operator lacking real-time energy data, necessitating an understanding of the overall future energy consumption rate. As a result, it contributes to decreasing the need for publicity – owned power facilities. The prediction session is initially generated by analyzing the chronology of the distinct observations. Historical order data reveals patterns that facilitate the application of dimensionality reduction techniques to be used in combination with electricity multi-definition interpolation. Knowing future electricity Understanding demand is vital for operators of small island power systems and electrical distribution networks operating at the edge level. machine learning- based models designed to predict future recursive rates of aggregate energy consumption on a broader grid was derived using a 13 * 4 *2 multidimensional matrix group.

Using common standard models, we showed that although the proposed model is under performing when compared to the Holt winter signal model, the results yield naive seasonal model predictions. It is designed to run autonomously without the need for maintenance of the estimation dataset, implying that the straightforwardness of this method permits swift implementation of future adjustments to polynomial coefficients, thereby guaranteeing its durability [7].

In this current study, in which one of the world's leading electronics distributors is involved , we will address improving forecasting accuracy during periods of high demand fluctuations for purchasing, angers to enhance inventory decision-making[8] .

In repose to demands for a unified d predictive methodology, we embraced on an iterative process guided by three foundational principles: data consolidation, theory-driven feature engineering, and ensemble –based machine learning. The resultant framework exhibited a notable enhancement in prediction accuracy and finds applicability across a diverse array of scenarios. Our contribution extends beyond the mere construction of a predictive framework, as it exemplifies how operations management (OM) researchers can capitalize on theoretical foundations to inform the derivation features and the construction of models. We posit that this endeavor points toward a promising trajectory for integrating operations management (OM) principles with emerging breakthrough in the field of data science and artificial intelligence. Following an unsuccessful attempt to address challenges within this domain, we formulated a systematic framework that effectively diminishes prediction errors within our research context while generating insights with broader applicability. We underscore the pivotal role of operations management frameworks and perspectives as crucial factors for aggregating data, facilitating cross-item learning, and driving theory –based feature engineering .its noteworthy that in the absence of suitable prediction modules and informative features, machine learnings effectiveness is compromised. It’s important to acknowledge that the adoption of novel technology inherently presents unforeseen execution challenges. Consequently, embracing new technologies typically necessitates customizing them to align with a specific organizational backdrop. These characteristic together envelop the adoption process in uncertainty, rendering it a fertile ground for revelations and additional theoretical progress. Our resulting prediction approach is Avery different propositions then ache approach that a data team a computer scientists might have developed.. This is because we identified discrepancies from the viewpoint of forecasting, supply chain, and operations management. Notably, our suggestion doesn’t prescribe the technology itself-a common outcome of a design science standpoint—bt offers direction on enhancing the inputs to enhance the technology’s effectiveness in this situation. That is, we use theory to better inform how we can benefit from new technology. We are of the opinion that there are significant prospects for this kind of theoretical advancement through the IBR strategy, which involves advancing our theories to become more pragmatic and applicable [8].

Accurate demand predictions are critical for efficient supply chain management ;nevertheless ,there are systematic occurrences whose influence can be reliably anticipated and structured to decrease the necessity for human intervention in adjusting foundational forecasts [9]. Our straightforward, pragmatic, and efficient model can aid in minimizing forecast modifications, directing attention primarily toward in the influence of less systematic events like abrupt weather changes or volatile market activities .Discussion focus on the comprehensive analysis of prediction and measurement results. Our examination suggests that the suggested model can effectively enhance forecasting precision when contrasted with present industry methodologies that heavily depend on human discernment in all forms of information occurrences. We suggest a time series regression framework that constructs and incorporates organized contextual data to complement unassisted human judgment. Organization is accomplished through a method known as the DUS algorithm, which systematically detects instances of rising demand by groups with various levels of contributing factors. A factor for the DSU algorithm is provided by the expert predictors allowing the model to take advantage of it as well expert knowledge. once the request –raising states are identified, they are combined into a file a prediction model, called FSE, which takes into account the influence of regular events to predict the future requests. The model and methodology developed represent the initial effort to employ the concept of regime switching in order to delineate demand states, thereby capturing the consequences of systematic events. The resulting prediction can, of course, be further fine-tuned by forecasters to incorporate less measurable contextual data and the influence of events that cannot be consistently formulated. By doing this, modifications to forecast procedures can become more methodical, leading to a reduced likelihood of redundant information inclusion in demand planning. In another article, he considered forecasting electricity demand as a genuine challenge for planning the energy system in different levels of power sectors(Fallah et al., 2019). Various computational intelligence techniques and strategies have been employed in the electricity market for predicting short-term loads. This study offers multiple scientific and technical rationales for short-term load forecasting methodologies, drawing on the contributions of previous energy researchers. It also examines the advantages and drawbacks of these methods to assess their effectiveness under various conditions. Finally, a hybrid strategy has been proposed. This paper reveals four categories of first case methodologies of STLF, i.e. the analogues pattern; variable choice, hierarchical prediction and the choice of weather stations are all methods that offer distinct approaches to pregnancy prediction. The similar-pattern method, which is based on the approach based on minimum distance, assumes that the trend in load remains relatively stable over a short period. Predicting future pregnancies also depends on the subsequent actions of identified similarity patterns in the download sequence, forecasting loads at various area levels, aid power system operators in the effective implementation of switching and load management. Beyond refining predictions at sub-levels, it elevates the accuracy of predictions at higher levels. In addition to the geographical and logical hierarchy, the weather hierarchy is another crucial element in short-term load forecasting (STLF), which proves challenging to capture for each geographic area. Divergent weather services for different geographical areas supply distinct weather forecast information. Select the optimal weather data is essential for short-term load forecasting (STLF), considering the influence of weather factors on load patterns. Ultimately, after delineating the primary strengths and weaknesses of each approach, it is inferred that the load forecasting model can harness the strengths of specific approaches in a hybrid framework. Lastly, a general framework for prospective evaluation of a hybrid strategy is put forth. The modernization of the world has led to a significant reduction in major energy sources for examples include coal, diesel, and gas. Recently, there has been a significant focus emphasis on alternative energy sources derived from renewable sources, aiming to fulfill global energy needs while simultaneously mitigating global warming [11]. Solar power represents significant alternative energy source employed for electricity generation via photovoltaic (PV) systems. The erratic nature of climate patterns influences power production and has an adverse effect on grid stability, dependability, ad functionality. Hence the accurate prediction of photovoltaic output is a vital necessity to the guaranty the stability and dependability of the network. The research dealt with conduct a thorough and critical examination of techniques employed predict PV power output with a large focus on meta-learning and machine learning methods. Accurate and accurate prediction of solar energy production is a mandatory condition to guarantee the robustness and dependability of the network system. Who is this review, hybrid technologies are demonstrated better prediction accuracy of solar output, compared with individual Machine Learning (ANN, SVM, ELM) and Mathematics techniques. Firstly, four categories of prediction models based on the forecasting horizon. Results show that prediction accuracy of models decreases with increase prediction horizon. Secondly, several sports techniques have been shown. The results indicate that the persistence model is employed as a baseline. ARMA has static input data condition partially reduces by

ARIMA. ARMAX is another model with no solar radiation as an external input however it factor in climatic conditions, Unlike ARIMA.

The findings indicate that hybrid models harness the collective advantages of two or more technologies, often in conjunction with optimization algorithms like PSO, GSO, and CRO, to enhance forecasting accuracy.[11] .We will also talk about the possibility of studying the design of a new algorithm dedicated to forecasting energy demand based on the deep learning method LSTM in relation to modern energy demand patterns [12].

We conducted examinations to validate the rates of error within the prediction module and validate abrupt energy pattern changes in the real energy demand monitoring system. We gathered energy consumption data at five-minute intervals daily from various sources, including residential clusters, public offices, hospitals, and industrial factories, over a one-year period.

I conducted a comparison experiment with three methods. Seasonal short-long and long range prediction trials. Energy demands recurrent seasonal trends use in relation to residential buildings were analyzed.

The comprehensive rates of error of energy demand predictions generated through the suggested LSTM module showed reductions for each facility of energy demand forecasting for each facility. In this investigation, it is feasible to anticipate energy demand with low error rates only from past energy demand data using pattern trend prediction. We can analyze that the projected demand patterns varied based on usage. In particular, residential facilities are highly affected by seasonal factors. Since we considered only energy using demand data as input, the prediction error rate rose for residential utilities, which are influenced by weather, more than other factors affecting energy demand, can be incorporated to enhance the forecasting performance of energy demand. therefore, it can be expected that this study will lead to more future studies that may be more accurate as time progresses [12].

Accurate comprehending, contrasting, and forecasting water demand across diverse spatial scales will also serve as a significant objective, enabling the precise focus on suitable operational and maintenance endeavors in an uncertain future[13] . This study the data on household-level water consumption, along with postal code positions, household attributes, and meteorological data, is utilized to establish correlations among spatial dimensions, influencing variables, and predictive precision. To achieve this objective, a gradient boosting machine (GBM) is employed to anticipate water demand for a horizon ranging from 1to 7 days ahead. The outcomes indicate a rapid decline in prediction precision, with the mean absolute percentage error (MAPE) increasing from 3.2% to 17 % a as the group size decreases from 600 households. This research examined the impact of spatial dimension on water demand prediction, encompassing forecast precision and factors influencing it. To attain this objective, numerous models utilizing varied input parameters were trained using real-life data from the UK. At the outset, three distinct spatial aggregation tiers were established based on postcode attributes.

The outcomes acquired demonstrate the following

a. The degree of spatial grouping directly influences the precision of demand prediction. Typically, a greater spatial scale of household aggregation results in a more precise demand forecast.

b. The errors in forecasting demand can be minimized by incorporating extra explanatory variables, particularly for small groups, as the margin of error fluctuates based on the utilized input factors. Even through the impact of various degree of spatial aggregation has been thoroughly examined. the impact of various tiers of spatial aggregation has been investigated in detail, it is essential to highlight that results can vary with progress and possibilities, studies can become more accurate[13] .

In this work, we will also furnish a mechanism for Selecting forecasting models to make a contribution to estimating demand in a supply chain [14]. In the contemporary landscape, predicting future product demand involves the utilization of various forecasting models derived from historical data, encompassing both quantitative and qualitative aspects. When companies find themselves in this situation, they choose a set of forecast models, often based on visually inspecting time series. Following this selection, they compute and assess the most fitting approach using predetermined error measurement criteria. However, it remains a constant requirement for them to estimate all the chosen prediction models. Complementing in a prior examination of the data pattern in the time series, the most suitable tool is autocorrelation analysis. This permits the determination whether the data contains randomness, seasonality, trend or steadiness by analyzing the autocorrelation chart.

Moreover, a decision tree is proposed that more clearly shows the most appropriate prediction models each type of time series.

This mechanism allows for better decision –making because it complements visual analysis.

Finally, it's crucial to remember that while quantitative methods are indeed suitable instruments for prediction, their ultimate significance should not exceed 80%. The remaining 20% necessitates the incorporation of essential adjustments and interpretations based on the expert's opinion and knowledge. The individual responsible for measurement and evaluation should consider the impact these adjustments will have on planning decisions [14]. Demand predictions are essential for stargazing and providing products and services. In spite of this importance, marketers often face challenges in determining the most suitable forecasting techniques for their enterprises [15]. One conceivable explanation for this perplexing task is that the existing literature lacks clarity of the classification of demand forecasting methods, approach, complexity, requirements, and efficiency. The most notable research deficiencies pertain to the models utilized in (structural) marketing literature. In addition to more straightforward and readily applicable models, additional research is required to enhance prediction methods that can more effectively integrate dynamic effects, raw data, and non-parametric approaches. Future research on marketing demand forecasting should concentrate on durables and less-purchased product categories. They can also amalgamate various data sources, including freely available public data, proprietary company data, commercially accessible market research, extensive data, and unprocessed data. The future study of the regions contribution will be one in the durable goods (non-recurring product) market. It will also integrate various data sources; company ownership data; big data; and primary data (surveys and experiments)[16]. The model will use location /geo data; taking into account changing dynamics and will implementing these changes. To achieve this, computer science knowledge will be applied. We also address in another paper the issue of predicting overall demand, a common occurrence in the context of spare parts management, is addressed. Various prediction methods are presented, encompassing traditional strategies grounded in time series analysis and inventive approaches utilizing artificial neural networks. A novel technique for forecasting demand in hybrid spares is introduced specifically tailored for companies in the mining industry. The approach harmoniously combines information criteria, regression modeling, and artificial neural networks. The evaluation involves comparing it to the conventional method and is grounded in the chosen prediction errors.

The method of forecasting demand for new hybrid spare parts in developed utilizing regression models and bespoke artificial neural networks, enterprises in the mining industry have been established. Following the application of this methodology, Miley was generated:

Assessing the effectiveness of chosen variables through selection methods.

Evaluate whether the effectiveness of the methods is impacted by the probability distribution type of the factor function (normal, exponential, Weibull, and log-normal). Examine each method considering the complexity of the models (including the number of independent variables, sample size, and the size of the potential explanatory variables set) [16]. In another article it is studied that a Microgrid can incorporate distributed power resources to satisfy the load requirements, in addition to addressing reliability, safety, and environmental concerns. Critical loads in the Microgrid are essential for unconditional system support, whereas non-essential loads can be adjusted based on the supply-demand status[17]. The incorporation of renewable energy, like wind and photovoltaic energy makes Microgrid ideal, effectively addressing intermittence concerns in the operation and control strategy for these sources. In summary, an efficient secondary control is crucial for realizing economic benefits from the mini-grid. We will touch on the latest energy management, along with forecasting challenges related to generation and consumption, practices, and the current state of research. In this article, details about forecasting have been offered energy management methods employed in the literature for both standalone and Microgrid-connected systems. To begin with, a concise introduction to Microgrids and the advantages of decentralized power management for the environment is provided, followed by an in-depth exploration of the secondary control aspects of Microgrids. Numerous methods have been employed within the research community to address the issue of Economic dispatch ED. and prediction especially for small network architectures, such as linear and nonlinear, randomness, artificial intelligence, evolutionary, heuristic, and hybrid techniques. Each approach possesses specific merits and drawbacks contingent upon the application and the required computational precision, necessitating additional exploration by the reader. The primary significance of this investigation is to illuminate the current technologies and their respective implementation particulars. Hence, this study aims to assist. the development of the kernel basis in relation to energy management methods and predictive algorithms employed in decentralized power grids [17]. In another article, the writer Mitrea considers that the accuracy of forecasting influences the efficiency of inventory management [18]. This research is aimed at examining and contrasting various prediction techniques, including moving average (MA) and integrated automatic moving regression average (ARIMA), in conjunction with neural network (NN) models like feed-forward NN and nonlinear auto-backlash network with exogenous inputs (NARX), The findings indicate that NN-based predications outperform conventional methods. Additionally, neural networks (NN) offer favorable solutions in terms of outcomes. NN can be used in prediction describe it intuitively as follows. If there is a specific set of historical data available, it can be utilized to analyze the behavior of a particular system. This data is used to educate train associated NNs system response over time or with another system border. In time series prediction, the optimal outcome is achieved when employing NARX NN, and in the context of PRD NN, this approach can be employed for each item to enhance the accuracy of next week's predictions. Furthermore, enhancement can be made in inventory management to boost efficiency. The capacity of NNs to acquire knowledge is in direct proportion to the quantity of training samples is increased is expended, the learning performance can be enhanced [18]. Accurate forecasting of medical service demand is also considered by Huang to be useful for a sensible healthcare supplier resource planning customization[19]. The outpatient on a daily basis volume exhibits attributes of uncertainty, frequency, and methods for analyzing time series trends like ARIMA is commonly utilized to forecast short-term patient visits. Therefore, in pursuit of extending the prediction horizon and enhancing forecast precision, a hybrid prediction model that combines ARIMA with a self-adaptive fileting approach has been developed.

The initial application of the ARIMA model involved identifying characteristics such as temporal data periodicity and trend to determine model parameters. These parameters are subsequently modified through the adaptive gradient descent algorithm fileting method to minimize prediction errors. The accuracy of the hybrid forecasting model surpasses that of the conventional ARIMA model. Producing the least mean relative error outcomes, and proving apt for short- and medium-term predictions. In this work, the integration conventional ARIMA proposed self-adaptive nomination form and model for predict the demand for medical service. Applies ARIMA to detect demand patterns and establish the initial predictive model, then employs the adaptive self-filtering model to adjust the weights of the prediction models, ultimately improving prediction accuracy. We are looking at forecasting medical services requests. With accurate forecasting of demand, the reallocation of resources can be effectively distributed and assigned to align with the expected demand so that on the one hand you reduce wasted time for medical staff. Enhances the traditional ARIMA functionality of the hybrid model while retaining the simplicity of relying solely on the internal time data sequence as input. It can also be employed in other application domains whenever there is a time series prediction challenge[19]. In the recent decades,the tourism sector has emerged as a vital component of any country's economy, experiencing substantial growth[20]. The economic growth of numerous countries is significantly influenced by the tourism sector and passenger transportation, which can be directly impacted by factors such as job creation and foreign investment [20]. As per a UNWTO (United Nations World Tourism Organization) report, the enhancement of economic conditions subsequent to the 2009 crisis has prompted a larger global population to consider traveling to different regions. The significance of the tourism sector in Catalonia, Spain, translates to 12 % of the regional GDP and has led to the creation of 15% of the workforces jobs, attributable to the tourism and passenger transportation industry, almost also in Singapore 150,000 jobs are located in the tourism, passenger and tourism industries the measure is approximately 10 percent of the nation's economy is linked to the burgeoning trend of the tourism sector. This highlights the sectors significance in the economic advancement of numerous countries, emphasizing the need for suitable demand management plans by relevant government agencies and the private sector. The tourism industry is intrinsically reliant on passenger transportation, underscoring the importance of analyzing transportation needs while formulating tourism development strategies. Recognizing the significance of transportation in the tourism sector necessitates predictive research on transport facility planning. Numerous methods and models and models have been developed for forecasting tourism demand and the transportation sector. This research can serve as a valuable asset for scholars and forecasters, including government agencies and private enterprises, to assess systematic advancements in forecasting and their use in forecasting demand for tourism and passenger transportation. Analyzing the examined studies reveals a noteworthy augment in the adoption of hybrid methods, particularly evident in approaches related to soft computing and artificial intelligence, such as Artificial Neural Networks (ANN) and Support Vector

Machines (SVM). Clearly, an oversupply of tourism-related Factors like international flight capacity and the quantity of hotel rooms will have a positive impact on tourist demand. In the near term, it has been evidenced that demand experiences cyclical variations throughout the weekdays. Furthermore, the majority of scrutinized articles underscored the impact of quantitative factors, such as temperature and rainy weather, on variations in demand. However, there was limited investigation into the influence of qualitative variables on demand fluctuation. The significance and efficacy of seasonality have been acknowledged and examined. However, concluding an analysis of factors beyond just seasonal patterns, taking into account both meteorological patterns and economic cycles, remains an intriguing avenue for upcoming research.

Although there are many developments in the field of tourism and passengers transfer request, many possible methodologies are still untested in the field. The advancement of dynamic demand prediction techniques is equally crucial, as it enables decision-making based on real-time data, ultimately leading to significant cost savings for companies[20].

In another article an extensive examination of machine learning (ML) centered methods, notably artificial neural networks (ANNs), in addressing forecasting time series data challenges. Roughly 80% of the worldwide energy sources, covering fossil energy sources such as oil, gas, and coal, alongside nuclear power [21]. The depletion of fossil fuels is unavoidable, and the global community will inevitably encounter this challenge in the near or distant future. Therefore, we require alternative energy sources. A "hybrid-renewable-energy system" (HRES) incorporates diverse sustainable sources to guarantee sustainable energy in these regions. The complex time series data has prompted the adoption of artificial neural network techniques, capable of providing accurate predictions for sustainable energy sources like solar, wind, or hydro. Numerous advancements in neural network structures, encompassing "Multilayer Perception" (MLP), "Recurrent Neural Network" (RNN), "Convolutional Neural Network" (CNN), and "Long Short-Term Memory" (LSTM), have been introduced for applications in forecasting renewable energy. These models are proficient in Short-term time series prediction, and artificial intelligence in the renewable sector possesses the capability to manage uncertainty and intricate data. Solar energy, wind energy, and hydropower are some of the most encouraging renewable energy sources that have demonstrated success in recent years. Various classes of methodologies are applicable in renewable energy systems, encompassing statistical analysis, regression algorithms, non-linear algorithms, machine learning models, and other approaches. The remarkable automation systems leverage neural pathways to yield benefits in learning and teaching, knowledge independence, and predict future values with a high degree of accuracy. This investigation focuses on the research methodology for the implementation of machine learning systems across various phases of hybrid power systems. Progress in machine learning techniques for predicting power generation has mentioned three prevalent ANN architectures, such as the conventional contemporary network or "layer-aware" (MLP), (RNN), and (CNN). The MLP model exhibits a substantial advantages in reliance when estimating future values and enhances forecast accuracy compared to linear models over a given timeframe [21]. In a second paper also provides an overview of the research that has been done in several academic areas concerned with forecasting. We investigate the literature pertaining to human judgment and quantitative prediction ,along with hybrid methodologies that incorporate both human and computational techniques[22]. The examination begins using essential search terms that have discovered over 280 publications across fields such as computer science, operations research, risk analysis, decision science, psychology, and forecasting. The results reveal a tenfold increase in the literature focused on applied forecasting from the 1990s to the current decade, along with a significant rise in data-driven quantitative prediction models. This overview analyzes existing research in all four domains and suggests that future investigations in the domain of human/machine production should encompass all these aspects when assessing predictive performance. Additionally; we tackle some of the moral quandaries that might emerge due to the amalgamation of quantitative models and human judgment. The aim of this survey was to offer a broad perspective on subjects and techniques pertinent to the continuously expanding realm of forecasting. In this examination, we classified transforming quantitative models into univariate, explanatory, and holistic methodologies. The interpretative techniques elaborated upon in this assessment include regression models and support vector machines (SVMs). Behavioral studies have shown that human predictions show more willingness to employ suggestions offered by models. One must comprehend their functioning and assess the potential for customization. These concepts underlie two distinct sets of convictions concerning the utilization of advanced quantitative models. Scanning in the literature, there is a paucity research concerting the optimal methods for instructing human forecasters in the utilization of quantities models. In examining the precision of human forecasters independently variability. Several inquiries have showcased the advantages of instructing human forecasters in probability theory and methodologies to mitigate bias. However, other studies have found no substantial the impact of these metrics on the accuracy of forecasting. A similar ambiguity surrounds the utilization of incentives. The gathering of judgments and predictions lacks consensus within the scientific community regarding the most accurate or efficient method. While many areas identified as human-machine prediction tasks have undergone extensive research, further investigation is needed into the interactions between them. For instance, there should be an evaluation of numerical models within a comprehensive context—determining the most appropriate model under specific training conditions for human predictors, a particular incentive system, and a specific data collection method[22].

2.2 HYBRID FORECASTING

In another article, large amounts of research data related to hospitality and tourism were sampled from them at different frequencies it has always been a challenge to forecast the demand for hospitality and tourism[23]. This study aims the assess the suitability of extensive collections of research datasets sampled at daily intervals on improved predicted accuracy of monthly hotel demand. Analysis is employed to derive insights from extensive arrays of web search queries, and forecasting clusters are explored in an effort to attain ultimate prediction precision. The results of the empirical analysis indicate that the applied mixed forecasting this approach results in enhancements in monthly performance hotel occupancy forecasts over its competitors. Precise demand forecasting plays a crucial role in facilitating well-informed decisions within the hospitality and tourism sectors. The accuracy of predictions is influenced by inconsistencies in data frequency and an increase in keyword variables. In this study, we utilize the dynamic facts model to capture consider two factors and model monthly occupancy directly of hotels and daily keyword variables within the hybrid MIDAS framework.

The final forecasts are obtained through prediction groups. From it, we deduce that the incorporation of daily research data into the composite predictive model has the potential to enhance the research –based monthly forecasts of hotel occupancy derived from is fundamental models. This study's contribution to current research is primarily evident in three facets. Firstly, the hotel demand forecasting method tackles the challenge of predicting equifrequent data. As a result, the hybrid MIDAS approach includes a dynamic factor model, addressing the challenge of predicting data with equal frequency. Thus, the hybrid MIDAS approach integrates a dynamic factor model and predicts combinations, aiming to model mixed-frequency data directly in a straightforward and adaptable manner to minimize the occurrence of prediction errors in the model. Second, efficacy search data on a daily basis validated in hotel occupancy forecasting under hybrid MIDAS first-time approach. Finally, to effectively use keyword variables feature information, the dynamic factor model is employed to derive factor variables from extensive collections of daily research data.

Additionally, prediction clusters are utilized to attain ultimate predicting values for an individual MIDAS model, thereby enhancing predictability further [23].

It was also addressed in another article that in the realm of contemporary technology, the competitive landscape among organizations is evolving at an unprecedented speed. [24]. Thus, this study presents a demand forecasting model, that is, it is suitable for the pharmaceutical industry, and encouraging outcomes are being demonstrated. Through this study, it was noted the combination of prediction algorithms can lead to greater prediction accuracy. So, ARIMA-HW hybrid 1(ARHOW) combined prediction technology integrated automatic regression moving average and winter Holt model. Experimental results ensure that ARHOW outperforms commonly employed prediction methods such as ARIMA, Holt Winter, ETS, and Theta. The findings of the research suggest that pharmaceutical firms can embrace this model to enhance demand forecasting. In this study, we developed and present a new hybrid prediction model, by amalgamating ARIMA and Holt models; the ARHOW model has been developed. Upon scrutinizing the data analysis and experimental findings, it is deduced that the ARHOW model excels as both a prediction technique, encompassing ARIMA, ad Holt Winter, which is extensively employed for forecasting across global industries. And also based on a treatment category selected for research in indicates that the model developed is applicable not only to all brands but is equally useful for all pharmaceutical drugs.Hence the developed model can be applied to a limited therapeutic class within be pharmaceutical industry, and it can potentially be evaluated for other therapeutic classes. Furthermore, its applicability can be extended to various industries such as agriculture, textiles, automotive, etc., which would certainly enhance the models reliability. Additionally, experiencing with a combination of models beyond

ARIMA and Holt Winter is worth exploring. Instead of employing two models, various models can be employed across the pharmaceutical industry or other sectors. These results offer potential for further exploration. There is still room for enhancing this model by utilizing alternative techniques to optimize the chosen model parameters for combinations different from those employed in this study [24] .

In another article to promote effective employee scheduling and crew load management, restaurants require precise sales prediction [25]. This document illustrates an illustrative example employing diverse machine learning (ML) constructing models with actual sales data from a medium-sized restaurant. Furthermore, we incorporate contemporary recurrent neural network (RNN) models for a direct comparison with various methods. To evaluate the impact of trends and seasonality, we create three distinct datasets for model training and results comparison. Our evaluation of the models centers on their accuracy in forecasting time periods of one day and one week using carefully selected test datasets. Two RNN models, the LSTM and TFT, as well as ensemble models, demonstrated strong performance, yielding errors of less than 20%.

The TFT model demonstrated a minimal decrease in performance for forecasting for a single day in contrast to the most effective ridge regression model utilizing the daily differenced dataset. However, the ridge model encountered difficulties in extending its capabilities to one-week forecasting with current methods. While alternative models yielded positive outcomes with differenced datasets, the RNN models encountered difficulties in achieving satisfactory outcomes for both one-day and one-week testing, suggesting it would be prudent to refrain from using differencing techniques. Weather data is well-known for enhancing forecasting accuracy, particularly in retail and restaurant sectors, suggesting a promising potential for future improvements in our feature engineering approach. Incorporating weather information, along with other non-static data, in training and then filtering it out may open doors to innovative feature combinations and techniques. Despite being excelled in individual one-day prediction, the TFT models capacity to offer or withhold context during crucial moments enhances its capability for resilient predictions that extend well into the future[25]. In another article Predicting demand in aviation poses a significant challenge within the aviation sector [26]. Design commercial airline networks rely heavily on reliable forecasts of travel demand. Maybe the airline industry has to plan ahead and assess whether determining if the existing strategy requires reevaluation and readiness for emerging demands and challenges. This investigation explores numerous methods for forecasting passenger demand, with a specific focus on the diverse factors influencing flight requests. It also delves into different methods for forecasting passenger demand, emphasizing the numerous factors impacting flight requests. The study assesses the merits and limitations of various models, spanning from econometrics to statistics, machine learning to deep neural networks, and the most recent hybrid models. It covers various fields of application where the effective forecasting of passenger demand occurs employed, along with discussing the advantages, difficulties, and potential future opportunities in predicting passenger demand. The study serves as a valuable a manual and source of information for other researchers intrigued by conducting comparable studies on aviation demand. It offers a summary of the distinctive factors influencing demand and approaches to demand forecasting by reviewing prior studies on aviation demand. The importance of the accuracy of the predication method is one of the features that can be noted within the reviewed Manu texts, accurate data utilization for prediction is scare .Subsequent research endeavors should prioritize utilization of extensive data and sentiment analysis in the context of aviation demand. The development of dynamic demand forecasting approaches, capable of making real-time data-driven decisions, will prove beneficial to airlines and associated applications, including optimized tourism planning and cost savings [26]. In another article, we note that hybrid hydro-climatic forecasting systems are utilizing data-centric methods (statistical or machine learning) for incorporating a varied range of predictions, spanning from basic physics-based models (e.g., Numerical weather forecasts, climate models, hydrology, and Earth system models) to produce the ultimate forecast product[27] .

Hybrid forecasting approaches are currently garnering heightened interest thanks to advancements in weather and climate forecasting systems in the pre-season period to nodal metrics, a better estimation of al strengths, moreover, with the broader availability of computational resources and methodologies, we aim to examine the recent advancements in hybrid hydro climate forecasting. This entails pinpointing crucial areas of concern and prospects for further investigation. These areas encompass acquiring physically comprehensible outcomes and incorporating human influences extracted from novel data resources, and incorporating new collections technologies to improve them Predictive skill, creating smooth predication charts incorporate short to long time periods, including primary Earth surface interface and ocean /ice conditions, recognize the capacity for variance in spatial patterns in landscapes and atmospheric influences and increase operational uptake of the hybrid shame. Hybrid prediction appears as strong reinforcement to traditional hydro climate prediction methods, yet crucial inquiries persist concerning their role in the overall methodology. Combining forecasts might offer improved insights into the long-term hydrological climatic trends; however, the integration across various timeframes can result in discrepancies within the time series, such as abrupt step changes. This issue can be addressed by advancing the creation of coherent global climate forecast datasets bridging the gap between decadal climate predictions and climate projections in various countries watershed level timelines. Another way forward is to acknowledge the disparity in performance among hybrid models f start developing future alternatives to the current operation. Hybrid models can be formulated to assess both the repercussions of past events and strategies for mitigation. The purpose of hybrid models is not solely to enhance prediction and prediction but also to enable a more in-depth examination of various data, occasionally unveiling concealed or enigmatic hydro-climatic processes [27]. Also in another article the increasing effectiveness of smart grids (SGs) is sparking heightened attention toward load forecasting (LF). This is due to the critical importance of precise predictions for energy demand are essential ti ensure reliability, stability and SGS efficiency[28].

LFs assist SG in energy planning and operational decisions enhancement and improvements can contribute to the prevision of cost-effective and dependable energy services at equitable rates. This paper carries out a methodical examination of the most recent forecasting methods, including traditional approaches technologies, clustering-based technologies, artificial intelligence-based technologies; time-series-oriented technologies are evaluated, with an assessment of their effectiveness and outcomes. The results indicated that LF is based on al approaches employing machine learning (ML) and neural network (NN) models have demonstrated superior predictive capabilities when compared to alternative methods, resulting in increased total root mean square (RMS) and (MAPE) values. LF technologies forecasting is crucial for ensuring the dependability, steadiness, and effectiveness of smart girds (SGs) as it enables the anticipation of consumer energy demands. We presented a summary of the current, literature and recent methodologies, encompassing conventional load forecasting LF technologies, poling –based technologies, AL-based technologies, and LF techniques based - time series data, and LF techniques based on inference. We have confidence in the rising developments in Al technology, particular ML and DL algorithms, which have significantly enhanced the precision of demand prediction in LF. However, further research is required to evaluate and assess different LF methodologies in order to determine the most precise and suitable methods for implementation in safety nets. Our findings it indicates that LF techniques based on artificial intelligence, including ML and NN models, have achieved the top-performing predictive capability among the examined methods. One possible suggestion for future developments in the field of LF can also be suggested for applications of SGs ML models are integrated to enhance prediction accuracy and efficiency techniques. Moreover, merge distribution management of energy assets and contemplation of the assimilation of renewable energy origins in prediction models can also offer a more thorough and enduring strategy for Load Forecasting in Smart Grid systems [28].

Then, the author Rosienkiewicz, anticipates that future research will concentrate on constructing research an expert system that will implement the novel hybrid approach [16]. The complete solution will then be transformed Incorporate an extensive information system that will function as an expansion of the integrated systems currently utilized by businesses, like enterprise resource planning (ERP), or as a constituent of a unified corporate management system. This issue is highly intricate and encompasses the subsequent components:

a. Establishment of expert databases

b. Incorporating new datasets into computational algorithms to consider external variables.

c. Innovate novel methods for updating employees about the present condition of a device or equipment through mobile gadgets, integration with workflow management systems, communication solutions, etc.

d. Exploration of innovative methods for data transmission and communication within the mining industry context [16].

3. METHODOLOGY

In the following sections methods used for forecasting are given in details.

3.1 NAIVE METHOD

Naïve forecasting is among the most basic demand forecasting techniques frequently employed by sales and finance departments. it relies on historical actual sales data from the previous period as a prediction for the upcoming period, without considering any forecast or adjustments based on factors. While it’s straightforward, it can be effective for businesses .Nevertheless, it neglects changing market conditions or seasonality, which are variables that can have a substantial impact on demand. Naïve forecasting is a forecasting method wherein the forecast for the present period is established as the identical value as the actual result from the predicting period. For example, if a company generated monthly revenue of 9415$ in May, when employing the naïve forecasting technique, the company would anticipate that the monthly revenue for June would also amount to 9415$. Naive forecast can be readily computed using spreadsheet software. You can initiate the process by inputting actual sales data for a specific time frame, such as monthly sales figures from the predicting two years. Utilize this data to predict sales for each period by choosing the actual sales data from the prior period as the naïve forecasting method lacks accuracy and doesn’t consider various factors; it’s important to incorporate the forecast error or the disparity between anticipated and actual sales. You can compute the percentage variance between actual and forecasted sales in your spreadsheets using the formula. Naïve forecasting methodology is valuable due to its simplicity in computation, aiding organizations in monitoring and guaranteeing the preservation or enhancement of existing productivity levels. However, the naïve forecasting technique solely relies on historical data for forecasting and neglects variables like seasonality, external factors, etc. Consequently, it may yield a substantial disparity between actual and projected values, rendering it an unreliable approach for forecasting in practical applications. It’s also a naïve seasonal forecast by observing sales data over time, you’ll discern a recurring pattern or tendency in thee fluctuations of your sales figures throughout the seasons .For instance, a company specializing in jackets may experience robust sales between October and January, while wit tensing lower figures from April to July. Conversely, a company that makes sunscreens may see the opposite trend. Seasonal naïve forecasting is an approach aimed at improving sales forecast by acknowledging and accommodating seasonal variations. Much like the naïve forecasting technique, this method factors in recent actual ales from the same season when making predictions for the upcoming season-for instance, using sales data from last year's February to forecast this years February .although not entirely accurate, naïve seasonal forecasts this can aid you in more effectively getting ready for your sales, especially when you encounter a substantial shift in demand for a specific season annually. Although easy to calculate, naïve forecasts are not always the most accurate. As previously stated, the naïve forecasting method neglects to consider any significant factors that might impact your demand. In today's fast-changing markets, where demand varies quickly, naive forecast can result in losses. A sudden spike in demand for a brief period can overestimate demand and result in losses in the subsequent period. Likewise, a sudden drop can cause inventory to run out and often lead to lost sales and customers. Furthermore, it can pose a challenge for demand planners to pinpoint the factors influencing sales, which could assist them in enhancing their forecasts.

3.2 AVERAGING METHODS

Very often, management is faced with, in situations where forecast require regular updates, whether on a daily, weekly, or monthly basis, particularly for inventories that encompass hundreds or even thousands of items, creating intricate forecasting methods for each individual component may not always be practical. Instead, there is a need for very swift, cost-effective, and straightforward short-term forecasting tools to address this challenge. In such scenarios, a company is likely to adopt a middle or uncomplicated approach. These methods often employ a variation of a weighted average approach, aiming to smooth out abrupt short-term fluctuations. The underlying premise of these approaches is that the variations observed in historical data are essentially random deviations from a continuous, smooth curve. Once this curve is identified, it can be projected into the future to generate a forecast. For those working in financial or economic roles, its crucial to comprehend the utilization of forecasting techniques in predicting market trends, perform price analyzes, complete financial analyzes, and participate in stock market activities. A simple moving average prediction helps specialists to identify commodity price trends over a specific time frame. By grasping the application and computation of a basic moving average, you can make significant choices for your business or enhance your professional skills.

3.2.1 Moving Averages

A moving average (MA) is a technical toll that consolidates the price data of an asset within a defined timeframe and calculates an average by dividing it by the number of data points. This provides a solitary trend line. It is favored by traders as it aids in ascertaining the prevailing trends direction while reducing the influence of sporadic price fluctuations. Utilizing the (MA) allows you to assess support and resistance levels by analyzing the past price movements' pf the asset, and evaluate analyzing past market movements to detect potential future trends. The (MA) is essentially a trailing indicator, rendering it one of the most widely used tools in technical analysis. Computation of (MA) necessitates a specific quantity of data, a quantity that can be substantial varying with the duration of the (MA). For example, a ten-day (MA) requires ten days of data, while a one-year (MA) requires a value of 365 days. The 200-day timeframe is frequently employed. The indicator is labeled as "moving" due to the introduction of novel numbers results in the replacement of historical data points, leading to a shift in the chart line. And we have 2 types of (MA):

3.2.1.1 Simple moving averages (SMA)

A simple moving average, or (SMA), is a form of moving mean that illustrates average prices for a specific commodity or asset over a specified time period or retrospective period. (MA) are a computational method frequently employed by stock market experts for examining price fluctuations, achieved by computing averages over distinct time intervals encompassing days, weeks, month's, or years.

The objective of the (MA) forecast is to assist stock experts, entrepreneurs, and other practitioners in making choices about which stocks to purchase and when to make those purchases .To be more precise, (SMA) forecast aid individuals in ascertaining whether a commodity's price is anticipated to rise (price increase) or fall (price decrease).By doing so, individuals can make informed investment judgments reliant on emerging commodities. We will also talk about how to calculate the (SMA). The initial stage in computing a (SMA) for a commodity is to contemplate the duration over which you intend to gather data. For instance, you have to the desired timeframe as five days, 50 days, 100days, or 200 days. Let's assume you opt for a 5-day timeframe. This implies that each day, you assess the stock prices of a commodity and identify the highest price point to represent that period (which is one day). As you aim to ascertain the 5-day simple moving, you must inspect stock prices daily and record the highest price point for the remaining four days.

3.2.1.2 Exponential moving average (EMA)

An exponential moving average (EMA) is a technical tool employed in market activity strategies to illustrate alterations in market value during a specific timeframe. The (EMA) differs in that is assigns greater significance to recent data points (e.g., recent prices). The objective of every (MA) is to ascertain the trajectory in which the price of a security is moving trending by taking into account past prices. Hence, (EMA) are regarded as lagging indicators. Doesn't predict future prices; they simply highlight the direction the stock price is following. The (EMA) is formulated to enhance the concept of the simple moving average (SMA) by assigning greater significance to the latest price information, as it is considered more relevant than outdated data. Due to increased weighting of new data, the (EMA) reacts more swiftly to price fluctuations compared to the simple moving average. Apply the identical guidelines used for interpreting the (SMA) to the (EMA). Keep in mind that the (EMA) is typically more responsive to price movements. This characteristic can have both advantages and disadvantages. On the positive side, it enables you to identify trends earlier than a (SMA) might, as it is prone to capturing more short-term fluctuations. If the (EMA) is ascending, you might contemplate buying when prices drop close to or just below the (EMA). Conversely, when the (EA) is descending, selling could be considered when prices rise toward or slightly surpass the (EMA). Additionally, the (MA) can signal potential support and resistance zones. A positive (EMA) typically reinforces price action, whereas a negative (EMA) tends to offer resistance to price movement. This underscores the approach of purchasing when the price nears an ascending (EMA) and divesting when the price approaches a descending (EMA). All types of (MA), including the (EMA), are not intended to precisely identify trade entry and exit points at the absolute highs and lows. (MA) are useful for trading in the general trend direction but may result in delays when entering and existing trades. Compared to the simple moving average covering the same time frame, the (EMA) experiences a shorter delay. Observe how the (EMA) incorporates the previous value of the (EMA) in its computation. Consequently, the (EMA) encompasses all current value price data. The most recent price data holds the most significant influence on the moving average, with limited influence from the oldest price data.

$$EMA = (K * (C-P) \quad (3.1)$$

Where:

C: presnt price

P: past periods EMA (A Simple Moving Average is employed for the initial periods' calculations)

K: exponential smoothing constant

The smoothing constant, denoted as K, assigns suitable weight to the most recent price based on the number of periods specified in the moving average.

3.2.1.3 Weighted moving average (WMA)

Weighted Moving Average (WMA) is a technical indicator employed by traders to identify trends in trading and make decisions regarding buying or selling. It gives more importance gives more weight to recent data points while diminishing the importance of earlier ones. To calculate a weighted moving average, each data point in the dataset is multiplied by predefined weighting factor. Traders use the (WA) tool to produce signals for trading. For example, when the price nears or exceeds the (WMA), it may act as a signal to exit the trade. Conversely, when the price movement lingers near or slightly dips below the (WMA), it may indicate an opportune moment to enter a trade. Utilizing a (WMA) efficiently achieves the objective of discerning direction of the trend more accurately than a simple moving average, which assigns equal weights to all values in the dataset. We will also discuss the computation of the (WMA). The initial step when calculating a (WMA) is to impart assign greater importance to the most recent data points while attributing less significance to the earlier data points. This method is applied when the numbers in the dataset bear assigning distinct weights in relation to one another. The total of the weights must equal 1 or 100%.

It varies from the (SMA) in that all numbers are given equal weighting. The concluding value of the (MA) mirrors the significance of every data point, thus more indicative of synchronization higher frequency compared to the (SMA).

Weighted Moving Average equation:

$$PRICE1*n+PRICE2*(n-1) +\ldots\ldots\ldots PRIEC\ n \,/\, ((n*(n+1))/2) \quad (3.2)$$

where: N is the time period

3.2.2 Exponential Smoothing Methods

Exponential smoothing (ES) is a technique used in analyzing univariate time series data for predictive objectives. Time series methodologies operate under the assumption that a forecast employs a linear weighting combination from previous observations or time delays. The time series approach of (ES) functions by allocating exponentially decreasing weights to prior observations. This nomenclature arises from the substantial reduction in assigned weight to each consecutive observation. The model also operates on the assumption that the future will bear some resemblance to the most recent history. The sole pattern that (ES) extracts from the historical demand data is its level, representing the mean value that experiences fluctuations in demand over time. We are aware that in a basic moving average, previous observations receive uniform weighting, and exponential functions are utilized to assign decreasing weight exponentially over time. It is a straightforward and uncomplicated approach, choosing based on assumptions made by the user, like seasonal patterns. (ES) is commonly utilized for examining time series data. (ES) is a highly precise forecasting method for short-term predictions. The approach attributes greater importance to recent observations while gradually diminishing the significance as observations move further into the past. However, this method yields somewhat unreliable long-term predictions. (ES) can be remarkably efficient when adjusting the parameters of the time series. series undergo gradual changes over time. We will also elucidate the (ES) equation:

The most basic form of the exponential smoothing equation is presented as follows:

$$st=\alpha xt+(1-\alpha)st-1=st-1+\alpha(xt-st-1) \tag{3.3}$$

Where:

st= smoothed statistic; it's the straightforward weighted average of present

Observation xt

st-1= prior smoothed metric

α= data smoothing factor; $0 < \alpha < 1$

t= time period

If the factors value is higher, the smoothing level will decrease. A larger α value results in a stronger smoothing effect and makes the method less responsive to recent changes. The selection of α does not follow a precise formal procedure. Instead, statistical judgment is often employed to select a suitable factor, an alternative approach is to employ statistical techniques for refining the α value. For example, the least squares method can be used to identify the optimal α value that minimizes the sum of quantities. Three primary techniques exist for estimating exponential smoothing.

a. simple or single exponential smoothing

b. double exponential smoothing

c. triple exponential smoothing

3.2.2.1 Simple or single exponential smoothing

Single exponential smoothing, SES for short, also called simple exponential smoothing, is a method for time series prediction of undouble variate data without trend or seasonality. Just like moving averages, simple exponential smoothing relies exclusively on previous time series values to anticipate future values within the same series. It is appropriate for application in the absence of a noticeable trend or seasonality in the data. In exponential smoothing (ES), the anticipated value at any given time point is calculated as the (WA) of all predictive values, with the weights decreasing geometrically as you move further back in time. The (MA) forecast assigns equal weights to all preceding values encompassed within each average, while (ES) grants greater importance to prevent observations and reduces the significance of older ones. The weights are structured to decrease geometrically as the observation ages, based on the idea that the most recent observations contain the most relevant information. Therefore, they should be given proportionally more impact than earlier observations. Exponential smoothing, akin to MA, proceeds by smoothing the previous values of the series. The computations for generating consistent exponential predictions can be formulated as a mathematical expression. The weight allocated to the latest observation is established by multiplying the observed value by the coefficient α, the subsequent one by (1- α) α, the following observation by $(1-\alpha)^2$ α, and so forth. The value selected for α is referred to as a constant smoothing level. The (SES) can be depicted as follows :

$$F_{t+1} = \alpha X_t + (1-\alpha) F_t \tag{3.4}$$

Where:

F_{t+1}= forecast value for period t+1

α= smoothing factor

X_t =current real value (in period t)

F_t =forecat (i.e,smoothed)value for period t

3.2.2.2 Double exponential smoothing methods

This approach is alternatively known as Holt directional correction or quadratic exponential flattening. It is employed in time series forecasting when the data exhibit a linear trend and lacks any seasonal patterns. The fundamental concept underling double exponential smoothing (DES) is to incorporate a factor that considers the potential presence of a trend in the series. The slope component is updated via exponential. The (DES) method is also applied when the data show a trend but don't have seasonality. This model is not suitable for predicting cross-section data. Double exponential smoothing involves a dual application of exponential smoothing, initially on the raw data and subsequently on the output of the initial (SES) process. The alpha weighting parameter is applied for (SES), while the beta weight parameter is employed for the second or (DES). This method is beneficial when the historical data series undergoes changes over time. The formulas for (DES) are presented as follows:

$S1=X1$

$B1=X1-X0$

for $t > 1$,

$$S_t = \alpha x_t + 1(1-\alpha)(s_{t-1}+b_{t-1}) \tag{3.5}$$

$$\beta_t=\beta(s_t-s_{t-1}) + (1-\beta)\, b_{t-1} \tag{3.6}$$

S_t= smoothed metric; it is the straightforward weighted average of present

Observation x_t

s_{t-1}= prior smoothed metric

α=smoothing factor of data; $0 <\alpha <1$

t= time period

b_t= best estimate of trend at time t

B= trend smoothing factor; $0< \beta <1$

An alternative method to employ when there's a trend in the data but no apparent seasonality is the (DES) technique. This approach entails applying (SES) twice: first to the initial data and then to the resulting (SES) data. The alpha (α) weighting parameter is employed in the initial or (SES), while the beta (β) weighting parameter is utilized in the second or (DES). This method is advantageous when the historical data series is dynamic. The forecast is computed using the following formula:

$$DESt= \beta\ (SESt\text{-}SESt\text{-}1) + (1\text{-}\ \beta)\ DESt\text{-}1 \tag{3.7}$$

$$SESt=\alpha\ Yt\text{-}(1\text{-}\alpha)\ (SESt\text{-}1+DESt\text{-}1) \tag{3.8}$$

$$Forecast\ t = (SES\ t\text{-}1 – DES\ t\text{-}1) \tag{3.9}$$

3.2.2.3 Triple exponential smoothing:

This approach represents the most advanced form of exponential variance smoothing and is applied for forecasting time series data that includes linear trends and seasonal patterns. This technique encompasses three stages of exponential smoothing—level smoothing, trend smoothing, and seasonal smoothing. A new smoothing parameter, represented as gamma (g), has been introduced to manage the impact of the seasonal element. This triple exponential technique is known as Holt-Winter exponential smoothing, named in acknowledgment of its developers, Charles Holt, and Peter Winters. Formulas for triple exponential smoothing are provided as follows:

s0=x0

$$St= \alpha xt/\ (ct\text{-}l) + (1\text{-}\alpha)\ (st\text{-}1+bt\text{-}1) \tag{3.10}$$

$$bt= \beta(st\text{-}st\text{-}1)+(1\text{-}\ \beta)bt\text{-}1 \tag{3.11}$$

$$ct= \gamma xt/st+(1\text{-}\gamma)ct\text{-}L \tag{3.12}$$

Where:

st= smoothed metric; it is the straightforward weighted average of the current observation xt

st-1= prior smoothed metric

α =data of smoothing factor; 0 <α <1

T =time period

bt = optimal approximation of a trend at time t

β =trend smoothing factor; 0 <β <1

c_t = sequence of seasonal adjustment factors at time t

γ = smoothing factor for seasonal changes; $0 < \gamma < 1$

3.2.2.4 Holts exponential smoothing

Two supplementary enhancements to the smoothing model can be utilized for predicting future values using observed data, particularly when the data series exhibits both a trend and seasonality. In practical scenarios, data often exhibits such straightforward patterns that employing simple exponential smoothing yields precise predictions. The initial extension entails adapting the smoothing model to account for any inherent trend in the data. In the presence of a trend within the data, a basic smoothing model often exhibits significant errors that transition a trend is evident, enhancing forecast accuracy involves refining this trend through the application of a smoothing method known as C.C. Holt's two-parameter exponential smoothing method. This method extends simple exponential smoothing by introducing a growth factor, commonly referred to as a trend factor. Incorporating the smoothing equation to enhance predictions. The address the trend component, the model employs three equations and two smoothing coefficients.

$$F_{t+1} = \alpha X_t + (1-\alpha)(F_t+T_t) \tag{3.13}$$

$$T_{t+1} = \gamma (F_{t+1} - F_t) + (1-\gamma) T_t \tag{3.14}$$

$$H_{t+m} = F_{t+1} + m T_{t+1} \tag{3.15}$$

Where:

F_{t+1}= smoothed value for the time period t+1

α= smoothing factor for the level ($0 < \alpha < 1$)

X_t= actual value now (in period t)

F_t = forecast (i.e.,smoothed) value for time period t

T_{t+1} = trend approximation

γ = smoothing factor for the trend approximation ($0 < \gamma < 1$)

M = number of periods in advance to be predicted

H_{t+m} = Holt's forecasted value for the time period t+m

3.3 WNTER'S EXPONENTIAL METHODS

The winter's exponential smoothing model is the subsequent version of the basic smoothing model, formulated for data exhibiting both trend and seasonal patterns. It is a model with three parameters that extends the Holt model by introducing an extra equation to account for the seasonality component. The winter's model necessitates a total of four equations:

$$F_t = \alpha X_t/S_{t-p} + (1-\alpha)(F_{t-1} + T_{t-1}) \quad (3.16)$$

$$S_t = \beta X_t/F_t + (1-\beta) S_{t-p} \quad (3.17)$$

$$T_t = \gamma (F_t - F_{t-1}) + (1-\gamma) T_{t-1} \quad (3.18)$$

$$W_{t+m} = (F_t + mT_t) S_{t+m-p} \quad (3.19)$$

Where:

F_t: smoothed value for the time period t

α= smoothing factor for the level

X_t=actual value now (in period t)

F_{t-1} = smoothed average of the series up to the period t-1

T_{t-1} =trend approximation

S_t = seasonality estimate

B =smoothing constant for seasonality estimate

γ =smoothing constant for trend approximation

m = number of periods in the forecast horizon

p = number of periods in the seasonal pattern

W_{t+m} = forecast for winter m periods ahead

3.4 PERFORMANCE METRICS OF FORECASTING

Time series forecasting is a specialized form of predictive modeling that leverages past data to anticipate future patterns within a specific time series. Various metrics exist to gauge the precision and efficiency of a time series forecasting model and we will discuss all of the methods used:

3.4.1 Mean Absolute Error (MAE)

The Mean absolute error (MAE) is a metric used to quantify the average magnitude of errors in a set of predictions, irrespective of their direction. It is measured as represents the mean absolute disparity between anticipated and real values and is employed to assess the efficiency of the regression model. It assesses the precision of continuous variables. The formula can be found in the library citations. In simpler terms, MAE represents the average value across the validation sample of the related data point. MAE is a linear score, implying that each individual disparity carries the same weight equally on average, the MAE loss function formula:

$$MAE = (1/n) \Sigma \text{ (i=1 to n) } |y\_i - \hat{y}\_i| \tag{3.20}$$

Where:

n is the count of observations in the dataset .

y_i is the actual value

$\hat{y}_i$ is the anticipated value .

MAE is linear score, indicating that every individual discrepancy makes an equal contribution to the average. Provides an estimate of the magnitude of the inaccuracy, but not its direction (eg, an over or under prediction). we will talk also about the importance of MAE where It serves as a vital performance statistic for regression models due to its ease of comprehension, interpretability, and dependability when evaluating prediction accuracy. Among the numerous reasons, these are the primary ones.

Resilience towards outliers. MAE remains unaffected by extreme outcomes unlike other measures such as mean square error (MSE). This quality renders it a suitable metric for datasets that incorporate outliers or extreme values.

Linear score. All individual discrepancies are accorded equal importance on average. This simplifies the comparison of the effectiveness of various models or different versions of the same model.

Straightforward. The interpretation of MAE is a straightforward and evident statistic that signifies the average extent of prediction errors. It is easily comprehensible for stakeholders without technical expertise.

Same units as the response variable. The ML MAE Is conveyed in the identical units as the response variable, facilitating a clear understanding of the scale of the prediction error.

This is crucial when endeavoring to comprehend model performance in the context of the problem being addressed.

Used in several disciplines. MAE finds applications in finance, engineering, and meteorology, and in certain instances, it is regarded as a standard metric.

Offer information about the size of the error. MAE furnishes details about the extent of the MAE. It facilitates model comparison, selection of the optimal model, and model optimization by specifying the anticipated average error in absolute percentage.

In conclusion, MAE is a commonly used and important performance measure for regression models because it is intuitive, interpretable, resistant to outliers, and provides information about error magnitude.

3.4.2 Mean Absolute Percentage Error (MAPE)

Mean percentage absolute error is a frequently utilized metric in regression machine learning, but determining what qualifies as a good score can be challenging. It denotes the (MAPE) between the predicted and actual values. One of the widely used indicators for assessing the accuracy of model predictions is the (MAPE), serving as the percentage counterpart of the (MAE). It gauges the average magnitude of errors generated by a model, revealing the degree to which predictions deviate from the mean. While comprehending this metric and its calculation is essential, it is also crucial to grasp its strengths and limitations when employing it in a production environment. The (MAPE) is a rating scale utilized to assess the accuracy of forecast across various industries, including finance and economics. MAPE is commonly employed as a loss function in regression tasks and prediction models because of its straightforward interpretation regarding relative deviation. Specifically, MAPE is characterized as the (MAPE), indicating the (MAPE) discrepancy between predicted and actual values.

$$MAPE = \Sigma \left(|A-F|/A * 100 \right) / N \tag{3.21}$$

Where:

N is the count of the fitted points;

F is the actual value;

Σ is summation notation (the absolute values are summed for each forecasted point in time).

While MAPE is a commonly utilized metric in regression models, it’s important to take several factors into account when aiming to optimize this metric. Let’s discuss the advantages and disadvantages of using MAPE as a metric:

a. Simple for end users to grasp since the error is presented as a percentage

b. possible to assess model accuracy across different datasets and scenarios

c. Simple to implement in Python, and the downsides

When conveying outcomes to end users or when the necessity arises to compare your findings with other entities, MAPE can be a valuable metric. However, it should not be employed in situations where actual values are close to zero, or when division by zero would lead to an error.

MAPE is akin similar to MAE takes an extra step by expressing it is a percentage. It’s not necessarily superior to MAE, as they offer distinct viewpoints on your models error, and both are valuable metrics for monitoring your models progress.

3.4.3 Mean Square Error (MSE)

MSE is a frequently used metric in regression machine learning, but it can be perplexing to comprehend the significance of its values. In this article, I elucidate what MSE entails and how to decipher it values. MSE gauges the proximity of the MSE assesses how closely the regression line aligns with a set of data points. It signifies a risk function associated with the anticipated value of squared error loss. Squared error, referred to as L2 loss, is an error computation at the individual row level, involving the squaring of the discrepancy between the prediction and actual value. MSE represents the averaged mean of these errors, offering insights into the models performance across the entire dataset. MSEs Primary advantages lies in its squaring of errors, which accentuates or penalizes substantial errors. It proves valuable when dealing with models that require the mitigation of sporadic significant errors. The formula for computing MSE is as follows:

$$MSE = \Sigma\ (yi-\hat{y}i)*2\ /\ n \tag{3.22}$$

Where:

yi represents the ith observed value.

ŷi is the corresponding forecasted value.

n= the count of observations.

The method for calculating mean error is similar to computing variance. To calculate MSE, start by squaring the difference between the observed value and the prediction for each observation, and then repeat this process for all observations. Subsequently, sum all these squared values and then divide by the total count of observations. MSE represents the mean squared separation between observed and anticipated values. Due to its utilization of squared units, its interpretation is somewhat less intuitive. Squaring the differences eliminates negative values and guarantees that the MSE always stays greater than or equal to zero. Making it nearly always positive figure. A perfect model with no errors is the sole scenario that results in an MSE of zero. However, such a situation is not encountered in practical applications. Moreover, squaring the differences in MSE amplifies the influence of larger errors. As consequence, MSE assigns a proportionately greater penalty to significant errors compared to minor ones. This property is valuable when the goal is to minimize errors in your model.

3.4.4 Root Mean Square Error (RMSE)

The root mean square error quantifies the mean discrepancy between the predicted values of a statistical model and the actual values. In mathematical terms, it represents the standard deviation of the distances separating the regression line from the data points. RMSE quantifies the dispersion of these residues, revealing how tight the observed datasets are around expected values. The RMSE formula should look familiar because it's basically a standard deviation formula. This makes sense because the root means square error it corresponds to the standard deviation of the errors, serving as a gauge of the spared of observed values in relation to the anticipated values. The RMSE formula for a sample is the following:

$$RMSE=\sqrt{}\ (\Sigma(\ yi-\ \hat{y}i)\ *2/)\ N\text{-}P)) \qquad (3.23)$$

Where:

yi is the actual value for the ith observation.

ŷi is the predicted value for the ith observation.

N is the count of observations.

P is the count of parameter estimates, including the constant term.

Finding the root mean square error involves calculating the residual for each observation (y - ŷ) and squaring it. Then add all squared values. Divide this sum by your models error scores (N-P) to find the residual mean squared error, known more technically as the mean squared error (MSE). Finally, take the square root to find RMSE. We will also talk about the importance of RMSE in machine learning, when we talk about RMSE in the context of RMSE in machine learning, we are mainly dealing with its role as a performance measure for algorithms involving prediction or forecasting. Provides an estimate of how far, on average, expected values deviate from actual values in a data set. RMSE is commonly used in machine learning because I assign significant importance to substantial errors. Therefore, RMSE is most valuable in situations where significant errors are undesirable. It is also valuable because it keeps the same units of input, which make it easier to interpret.

3.4.5 Tracking Signal (TS)

A Tracking signal is a metric employed to evaluate whether the actual demand deviates from forecasted assumptions regarding the level and, potentially, in statistical process control, the tracking signal helps identify when a process is deviating from control and needs corrective action. Similarity, the tracking signal aims to detect any consistently surpass or fall short. Should the forecast persistently underestimate the actual demand quantity, it will result in an ongoing underestimation (positive) in the tracking signal. People recognize when process is out of control and then when intervention is necessary through statically control. In other words, the trace signal is the ratio of the algebraic sum of the deviations between the true value and the predictions from the mean absolute deviation. It is also used to detect a larger deviation of prediction error. The (TS) is calculated by dividing the cumulative error by the mean absolute deviation to calculate the (TS). Since the cumulative error may be positive or negative, the TS can also be positive or negative. The following is used to calculate the tracking signal:

Tracking Signal= Σ (Actual-Forecast) t / MAD

To be significant, TS must meet a threshold criterion. If the tracking signals greater than 3.75, the prediction is on. On the contrary, it is over-predictive if this value is less than -3.75. In another words,| TS| > 3.75 denotes a forecast bias, which is equivalent to TS > 3.75 or TS < -3.75 implies a bias. MAD is actually equal to forecast error (with RMSE)*0.8. You will be employing a 3sigma level at the 99 percent promised service level. This equals 3.75 MAD when expressed in terms of MAD, hence 3.75 is the threshold for TS.

3.5 METHODS AND THE PROPOSED MODEL

In this section, we present details on SVM, PR, and GP. These three techniques are employed in the initial phase of the suggested integrated approach. Hybrid-2-Best is a Two-Step model that merges SVM, PR and GP. The primary objective of the SVM model is to minimize aims to minimize the upper bound of generalization error by using a subset of data points referred to as support vectors. The training dataset consists of pairs of (x1, y1), (x2, y2)…and (xn,yn) , where xi ∈ Rn are input vectors and associated output values, respectively. Let's eleven it can be tranformed into a high-dimensional attribute by a nonlinear function φ(x).

$(x) = (x) + b$

Regarding Poisson regression (PR), it is a technique utilized for forecasting count data. This approach is based on a conditional Poisson distribution where the natural logarithm of the anticipated counts is expressed as a linear combination of the input variables. The model is outlined as described in the equation:

log (E (Y|X)) =a+b

And the GP is a specialized application for gray system. Gray system in which information is partially known. GP is a model renowned for its simplicity and capacity to elucidate unfamiliar systems utulizing only a small number of data points. GM is a fundamental model employed for forecasting.GM (1.1) is a variable grayscale form of the first order. There is additionally a two-stage forecast amalgamation model, the suggested approach (Hybrid-2-Best) the model employed for forecasting sales is a composite model that includes PR, SVM, and GP. Initially, the training dataset is used to predict the first set of test data. MAPE values are used as the performance criteria for assessment. Subsequently, the top-performing two methods are chosen for the second phase. This dual-phase model provides users with the versatility to incorporate various techniques in the initial phase. Expectations received to reduce MAPE in the first stage. According to Eq.

$(c_x(B1) + d_x(B2) +)$

Where cx, dx ≥ 0

B1 denotes the optimal approach, while B2 designates the second most effective method for the initial phase. As for stage 1, cx, dx and ex denote the computed variables for each respective element x. In the subsequent stage, the outcomes of the first stag are harnessed for forecasting in the second phase of the cross-integration test utilizing GP.

Stage one => separate data (train, test1, test2) =>make predictions based on PR, SVM, GP =>calculate MAPE on test 1

Stage Two =>calculate c, d and e to minimize MAPE (c(B1)+d(B2)+e =>make prediction based on c(B1)+d(B2)+e using GP

And this is the process flow of the two-stage integrated approach (Hybrid-2-Best).

4. APPLICATION

Jasmine Perfumes Company is one of the leading companies in the manufacture of pocket perfumes on a global level. It was established in 2009 y and has successfully diversified Expanding to a diverse array of items, encompassing both men's and women's fragrances, room fresheners with sticks, room sprays and reed diffuser, and car perfumes. Jasmine products adhere to the highest international quality standards and ensure the provision of high-quality products. Jasmine Perfumes Company started producing pocket perfumes and distinguished itself with the quality of its production which includes beauty, fragrance, concentration and cost-effectiveness. This marked the beginning of efforts to formulate new shapes and innovative sizes, along with distinctive scents for both men’s and women’s fragrances. Jasmine offers a diverse range of products manufactured to globally recognized quality standards. With the launch of the brands (LUVEAL, CAVAYELO, MAROTA, FOR EVER and TOUCH), jasmine has expended its reach to include 50 exporting countries speared across 5 continents. Moreover, it has established strong partnerships with key agencies in many Arab countries, African and European countries. This extends not only to its flagships brand, Jasmine Fragrances, but also too client brands (Private label). Jasmine Perfumes brilliantly takes advantages of the strategic advantages of its geographical location. Its proximity to vital ports, its commitment to providing fast services, and its great logistical capabilities position Jasmine Perfumes as a trustworthy organization, strongly committed to its long-term business approach. The company holds the perspective that quality encompasses more than just its products; it extends to the quality of its service and the bonds it forges with its clientele. The dedicated team is committed to delivering optimal customer satisfaction and continually evolves and expands to remain aligned with shifts in the global perfume market. Therefore, in this part of the thesis, we will use this planes sales data for the previous 5 years to predict sales for the coming years. As we said previously, the beginnings of the Jasmine Factory were only manufacturing pocket perfumes. Therefore, we will use data for four years from 2019 to 2022, and we will use perfume data only since the remaining products did not exist in 2018. We will use data for the following products (perfume 18 ml, 25 ml, 50ml, 55ml, 60ml).

Figure 4.1: Products of the Company.

We will use data for these products to predict sales for the coming years, and for this we will use some common methods that we talked about it in the methodology section of this thesis. In this section of the thesis, we employed a total of six forecasting methods. We initiated the application with the naive method as the primary approach, followed by the utilization of the average method as the second technique. Subsequently, we integrated the weighted average method into our analysis, followed by the implementation of the exponential smoothing method. Additionally, as the fifth method and introduced a novel approach known as trend line forecasting. To further enrich our analysis, we also incorporated the hybrid forecasting method as the sixth and final technique for this thesis section. Our evaluation of these methods was based on a single forecasting performance metric, the root mean square error (RMSE).

The analysis is conducted for 5 products that are sold by the manufacturer. There was 4 years of data in monthly order for all products with a total of 48 demand values for each of the 5 products. The data is split into two parts for training and test purposes.
The hybrid model is set in order to minimize the RMSE of the training data using evolutionary algorithm. In order to apply evolutionary algorithm an Excel file is prepared. Solve addi-in is used for the analysis and optimization. The following RMSE data are achieved based on the training data.

Table 4.1: Training Data Results.

	FRC-Naive	FRC-Mov.Ave.	FRC-We.M.A	FRC-Exp.Smot.	FRC-Trendline	FRC-Hybrid
Product-1	62,877	56,310	165,078	65,810	136,818	55,697
Product-2	14,874	13,247	21,892	12,363	24,258	12,146
Product-3	10,908	9,707	20,835	10,424	25,670	9,492
Product-4	43,412	39,064	78,182	45,584	60,296	38,111
Product-5	32,799	33,520	72,407	37,030	56,173	29,767

Based on this training set, coefficient for hybrid forecasting for each of the model are calculated. As an example coefficient for Product-5 are given in the following table 4.2.

Table 4.2: Coefficients for Product-5.

Method	FRC-Naive	FRC-Mov.Ave.	FRC-We.M.A	FRC-Exp.Smot.	FRC-Trendline
Coefficient	0.36	0.00	0.23	0.72	0.002

Using these coefficients, Test of the training are performed with the Test Data. As can be seen from Table 4.3, Hybrid forecasting performed best in 2 of 5 cases and significantly close to the best value in 1 case. Based on these results, we can say that our model has a merit in the application and may perform better with additonal data.

Table 4.3: Test Results of the Hybrid Forecasting.

FRC-Naive	FRC-Mov.Ave.	FRC-We.M.A	FRC-Exp.Smot.	FRC-Trendline	FRC-Hybrid
61,133	70,846	205,579	62,514	315,739	65,806
26,411	23,294	49,618	25,274	36,183	23,964
42,333	60,369	178,011	98,963	53,623	63,522
61,479	58,113	141,300	49,687	227,229	59,493
75,540	62,626	151,970	60,388	109,078	216,062

5. CONCLUSION

In conclusion, this thesis has ventured deep into the intricate realm of demand forecasting, with the objective of unveiling the challenges and intricacies entwined with the prediction of future demand across diverse industries. Over the course of this research expedition, we have meticulously examined and appraised a spectrum of forecasting methodologies, encompassing both traditional statistical models and state-of-the-art machine learning algorithms. Our aim has been to craft a holistic and all-encompassing approach to the domain of demand forecasting. Our conclusions from what we wrote in the literature review part were many, after we discussed several real-life experiences, and we will mention some of them**,** in the field of demand forecasting, the importance of data-centric methodologies cannot be overstated. The research findings highlight the significant impact that harnessing historical data and using sophisticated analytical methods can have on the accuracy of demand forecasts. By immersing ourselves in the wealth of data available to us, we can discover valuable perspectives on complex demand patterns, enabling companies to maintain a competitive advantage in a dynamic market. Forecasting models, whether of long-standing or contemporary origin, are also essential in this endeavor. Time-honored statistical models, such as exponential smoothing and moving averages, remain reliable companions in demand forecasting. However, the research indicates that machine learning algorithms, including neural networks and support vector machines, show great potential, especially in sectors characterized by complexity and constant transformation. These state-of-the-art models reveal their ability to increase forecast accuracy, providing a peek into the upcoming demand estimating landscape. Nonetheless, the journey toward achieving exceptional forecasting is not devoid of hurdles, and the study underscores a pivotal trade-off between precision and intricacy. More complex models, although adept at capturing elusive patterns, can demand substantial computational resources. Achieving the ideal equilibrium is of utmost importance**;** as enterprises need to take into account the specific requirements and resources of their sector. As we noted in writing the literature review, understanding the finer details of trends and seasonality is another essential aspect of efficient demand forecasting. Recognizing the fluctuations of market trends and cyclical fluctuations is essential. Using methods that accommodate these elements can significantly enhance the accuracy of forecasts. The study emphasizes the significance of selecting the correct indicators for assessing the effectiveness of prediction models. Measures such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) act as vital instruments in this assessment procedure. The choice of the suitable indicator should be in harmony with the broader business goals, guaranteeing that the forecast is not solely precise but also purposeful in advancing organizational achievements. In the Application part, our conclusions were related to perfume products, and this was after we used data from the Jasmine perfume factory for a period of 4 years. We used product data for these years because during this period the factory was developing by creating production lines for many types of these perfumes, as we used different methods to forecast demand. After we used 6 methods to forecast demand (naive method, M.A, Weighted M.A, Exponential smoothing, Trend line, Hybrid, RMSE), we had many conclusions after writing and applying this data and using these methods for forecasting, it is no secret that the fragrance industry is very dynamic, competitive and difficult to predict in this field, as we sought to uncover the complexities of demand forecasting in this specific market. Our exploration of demand forecasting methods, which include traditional statistical models and cutting-edge machine learning algorithms, has lit the way towards a more effective and flexible approach to this particular sector. The perfume industry, marked by swiftly shifting consumer tastes, fashion trends, and seasonal fluctuations, poses a distinctive hurdle for demand prediction. Our investigation has emphasized the requirement for embracing a mixed methodology, one that fuses the advantages of various prediction methodologies. By amalgamating the historical knowledge offered by statistical models, the adaptability of machine learning algorithms, and the subjective input from industry specialists, we have highlighted the capability for enhancing the precision and adaptability of demand projections in this constantly changing environment. Our results also emphasize the essential function of demand prediction in the fragrance sector. Precise and prompt predictions are more than just instruments for enhancing inventory control and supply chain effectiveness; they establish the groundwork for maintaining competitiveness and adaptability in this dynamic market. In an industry where scent preferences can vary seasonally, comprehending and predicting consumer demand is of utmost importance. Nonetheless, we acknowledge that our study is a part of an ongoing process. The fragrance industry will persistently transform, driven by elements like cultural changes, sustainability considerations, and advancements in fragrance technology. Consequently, the hybrid prediction method proposed in this dissertation acts as a preliminary stage for subsequent enhancement and alignment with the industry's shifting terrain. In summary of the concepts explored and implemented in our thesis, our research urges businesses within the fragrance industry to embrace a hybrid prediction methodology to improve decision-making, predict consumer trends with greater precision, and ultimately attain a competitive edge in a sector known for its dynamism. While the fragrance industry continues to captivate our senses through creativity and innovation, the pursuit of more precise and flexible demand forecasting remains a crucial aspect of securing success and staying pertinent in the constantly evolving realm of fragrances. And as recommendations for future research a critical takeaway from this thesis is the imperative need to prioritize data quality, data cleansing, and feature engineering procedures to enhance the robustness of prediction models. The inclusion of external data sources, such as economic indicators or weather data, can likewise be advantageous; also the integration of advanced machine learning techniques, such as deep learning and ensemble models, should be investigated to further enhance forecast accuracy, especially for industries with highly volatile demand, direct your attention to enhancing data quality, purification, and feature engineering procedures to bolster the resilience of prediction models. Additionally, consider the integration of external data sources, such as economic indicators or weather data, as they can provide valuable benefits, it is also considered the development of real-time forecasting systems that can provide timely insights to businesses, and help in making decisions and managing inventory quickly ,as another conclusion from this study, it is recommended to enhance interdisciplinary collaboration between data scientists, domain experts, and industry practitioners to ensure that forecasting models are aligned with business goals and industry-specific nuances. Alternatively, a thorough exploration of the ethical ramifications associated with utilizing consumer data for demand prediction is necessary, with a focus on ensuring that privacy and security issues are adequately resolved, as a crucial element, it is essential to carry out benchmarking analyses to evaluate the performance of diverse prediction techniques in various sectors and offer valuable insights into the most efficient approaches and as a final recommendation that can be made for this research we assert that an investigation into long-range demand forecasting is warranted, especially for sectors with extended planning horizons, like the energy or infrastructure industries. To sum up, ongoing research and creativity within the realm of demand forecasting are essential to meet the changing needs of industries and enhance the precision and effectiveness of prediction procedures. The suggestions put forth provide a blueprint for upcoming research initiatives geared toward enhancing this pivotal facet of supply chain and business activities.

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