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Artículos científicos

Análisis comparativo de modelos tradicionales y modernos para pronóstico de la demanda: enfoques y características

Comparative Analysis of Traditional and Modern Models for Forecasting Demand: Approaches and Features

Análise comparativa de modelos tradicionais e modernos de previsão de demanda: abordagens e características

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Resumen

En estadística inferencial, el pronóstico es un proceso matemático mediante el cual se hace una estimación del valor futuro de una o más variables, como puede ser la demanda. El objetivo de este presente trabajo de investigación documental fue definir la clasificación de los principales tipos de pronósticos. Además, proponer algunos de los modelos más representativos utilizados actualmente para ser implementados por pequeñas y medianas empresas, aquellos que, con base en la literatura consultada, tienen mayor potencial para lograr un pronóstico de demanda exitoso. Se encontró que los pronósticos pueden ser univariados o multivariados; sin embargo, a fin de encontrar las alternativas que impliquen menor costo para la empresa por procesamiento de datos, se consideraron exclusivamente modelos de pronósticos de series de tiempo univariados, ya que requieren únicamente los datos históricos de las ventas de la empresa. Los modelos de pronósticos de serie de tiempo se clasificaron en tres enfoques: *1)* estadísticos o tradicionales, de los cuales se recomendaron el modelo de suavización exponencial triple o de Holt-Winters y el modelo de promedios móviles autorregresivos integrados (Arima), *2)* de aprendizaje automático, de los cuales se destacaron el modelo bosque aleatorio y el modelo de redes neuronales recurrentes de gran memoria a corto plazo (LSTM), *3)* híbridos, de los cuales se sugirieron el modelo Arima-LSTM y el modelo Facebook Prophet.

Palabras clave: inferencia estadística, inteligencia artificial, previsión, series temporales.

Abstract

In inferential statistics, forecasting is a mathematical process by which the future value of one or more variables, such as demand, is estimated. The objective of this paper was to define the classification of the main types of forecasts. In addition, to propose some of the most representative models currently used to be implemented by small and medium-sized companies, those that, based on the literature consulted, have the greatest potential to achieve a successful demand forecast. It was found that forecasts could be univariate or multivariate; however, in order to find the alternatives that would require lower cost for the enterprise by data processing, only univariate time series forecast models were recommended, as they require only historical sales data of the company. Time series forecasting models were classified into three approaches: *1)* statistical or traditional, of which the Holt-Winters or triple exponential smoothing model and the autoregressive integrated moving average (Arima) model were recommended, *2)* machine learning, of which the random forest model and the large short-term memory (LSTM) recurrent neural network model stood out, *3)* hybrids, of which the Arima-LSTM model and the Facebook Prophet model were suggested.

Keywords: statistical inference, artificial intelligence, prediction, time series.

Resumo

Na estatística inferencial, a previsão é um processo matemático pelo qual é feita uma estimativa do valor futuro de uma ou mais variáveis, como a demanda. O objetivo do presente trabalho de pesquisa documental foi definir a classificação dos principais tipos de previsões. Além disso, propor alguns dos modelos mais representativos atualmente utilizados para serem implementados por pequenas e médias empresas, aqueles que, com base na literatura consultada, possuem maior potencial para alcançar uma previsão de demanda bem-sucedida. Constatou-se que as previsões podem ser univariadas ou multivariadas; no entanto, para encontrar as alternativas que implicam no menor custo para a empresa para o processamento dos dados, foram considerados apenas modelos de previsão de séries temporais univariadas, uma vez que requerem apenas os dados históricos de vendas da empresa. Os modelos de previsão de séries temporais foram classificados em três abordagens: 1) estatística ou tradicional, sendo recomendado o modelo de Holt-Winters ou suavização exponencial tripla e o modelo integrado de médias móveis autorregressivas (Arima), 2) aprendizado de máquina, dos quais a floresta aleatória e o modelo de rede neural recorrente de grande memória de curto prazo (LSTM), 3) híbridos, dos quais foram sugeridos o modelo Arima-LSTM e o modelo Facebook Prophet.

Palavras-chave: inferência estatística, inteligência artificial, previsão, séries temporais.

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Introduction

Long denigrated as a waste of time at best, or a sin at worst, forecasting became an absolute necessity throughout the 17th century for those adventurers seeking to build their own future (Bernstein, 1998). Its evolution has been accompanied by the great advances in statistics of the 20th century and the growing computational potential of the first decades of the third millennium (Hanke and Wichern, 2014).

A forecast is a prediction of one or more future events from clues. The level of success of a forecast lies in the accuracy with which it matches reality; Reaching this result is not an easy task, as the Danish physicist Niels Bohr would ironically say: "It is difficult to make predictions, especially about the future" (Montgomery, Jennings and Kulahci, 2015).

Although there is an inherent risk of inaccuracy in predicting the future, forecasting is an important aspect of industrial engineering research and practice as it provides information needed to make good decisions. How would an operations manager establish realistic production schedules without having some estimate of his sales? How could a call center company determine its workforce without some assumption of future demand for its services? The answers to these and more questions require forecasting.

In November 2008, within the framework of the International Congress on Forecasting and Planning in the Supply Chain, held in Mexico City, Anish Jain, president of the Institute of Business Forecasting & Planning (IBF), considered the following:

> At present, at least 80 percent of the companies in Mexico register serious errors in their business forecasts and sales and production planning, which fundamentally affects their profitability, productivity and optimal management of their supply chains, in addition to put at risk their competitive capacity and permanence in international markets, as well as that of the country as a whole (Olavarrieta, 23 de noviembre 2008, párr. 3).

Until the publication of this research, no article or related publication has been found that shows that the percentage of companies with forecast error has decreased at present; However, in the midst of a difficult economic recovery due to the 2019 coronavirus disease (COVID-19) pandemic, forecasting is an important tool for companies to improve their sales and production planning by maximizing profits. profits and the minimization of its costs due to poor optimization of resources. Now, when a business, especially small and medium-sized enterprises, integrate forecasting as an agent in the process of managing their processes and services, the question arises: which forecasting model should be used?

An example of the robust application of forecasting is in the public sector. On November 23, 2017, the Forecast Manual was published in the Official Gazette of the Federation, the purpose of which is to establish the procedures, rules and calculation principles to be followed by the National Center for Energy Control (Cenace) and the market participants for the estimation of demand forecasts and electricity generation forecasts (Secretariat of Energy, November 23, 2017).

According to this manual, the forecast models that can be used by Cenace are: simple moving average, weighted moving average, multiple linear regression and the method of similar days (if the conditions of day A are similar to those of day B, the prognosis is the same for both). The multiple linear regression method considers the five-year historical values of the following variables: real demand by load zone, weather variables by load zone, holidays and atypical days; It is also necessary to consider the current data of: real hourly demand of the day of operation, weather variables forecast for seven days, day of the week to which the forecast corresponds, month to which the forecast corresponds, variation in the demand of the load centers and dates that present schedule change.

Cenace is required to forecast the hourly demand for electrical energy in megawatts/hour for each of its electrical network systems, as well as to use the mean absolute percentage error (MAPE) metric.) to measure the degree of certainty of the model with which it makes its demand forecasts.

Table 1 shows a comparative analysis based on the MAPE metrics corresponding to the month of September 2021 for the interconnected systems of Baja California and Baja California Sur, which were obtained from the Market Information System (SIM) (Cenace, 10 de octubre de 2021)

Tabla 1. Comparación del error de pronóstico con la métrica MAPE de los sistemas interconectados de la península de Baja California para el mes de septiembre del 2021

	Baja California	Baja California Sur
Porcentaje de pronósticos con MAPE > 5 %	10 %	27.50 %
Mayor MAPE	25.36 %	156.36 %
Fecha del mayor MAPE	24/09/2021	09/09/2021

Fuente: Elaboración propia con base en el Cenace (10 de octubre de 2021)

Given the data analyzed, it is fair to ask what is the reason for the large difference in the percentage of ASM between both electrical systems of the Baja California peninsula. The answer is found when analyzing the climatic situation of Baja California Sur. Between September 9 and 10, 2021, Hurricane Olaf made landfall in the municipalities of Los Cabos and La Paz and generated failures in the electricity supply (Editorial Animal Politico, September 9, 2021) that the forecast did not contemplate, which which caused the 36 largest forecast errors of the month to occur on those dates.

It should be noted that Cenace has the freedom to choose the forecast model that it considers best, including multiple linear regression, which among other variables includes the weather of the week; however, the model was unable to react to an atypical event, such as the passage of a hurricane. The case of the use of forecasts by Cenace leaves some lessons to consider when making a model to forecast the demand for any product or service:

- There is no forecast model that can accurately estimate future demand, much less on atypical days.

- • It is convenient to take into account more than one forecasting model, since there is no certainty as to which one may be the most accurate at a given moment; for example, a multiple linear regression model is not necessarily better than a moving average model because it is mathematically more complex, but it is more expensive, since more information needs to be processed as the variables increase and many of them are not statistically significant, in addition that demand does not always adjust satisfactorily to a linear behavior.
- • It is important to consider under which forecast horizon the data performs best; for example, Cenace's energy demand forecasts are better suited hourly rather than daily.
- The robustness of a forecasting model lies mainly in the quantity and quality of the input data. Quality refers to data measurement being as accurate as possible to ensure reliability.

The above deductions are the motivation of this documentary research work, which seeks to define the classification of the main types of forecasts, as well as to propose some of the most representative models of today that are feasible for small and medium-sized companies, which, based on the consulted literature, they have the potential to achieve a successful prognosis.

Method

The methodological approach used was qualitative. For this, the bibliographic research method was taken into account, with a historical-logical analysis of the development of the forecasts. The review of the literature allowed to determine, extract, describe, analyze and compare the most outstanding information obtained from different books to find the theoretical foundation of time series forecasts, as well as to investigate articles from scientific journals and recent research focused on the use of different demand forecasting methods through time series.

Results

There are various classifications of forecasts according to their characteristics. One of the most classic divides forecasts into two approaches: qualitative, based on the opinions, experience, knowledge and values of the forecaster, and quantitative, mathematical models based on a set of historical data and associated values (Heizer and Render, 2014). . Although they are different approaches, they can complement each other.

within the organization. Still, for the purposes of this research, emphasis will be placed here on quantitative forecasts.

Badiru and Omitaomu (2020) propose a classification that satisfactorily encompasses the quantitative approach. According to the data requirement, the forecasts are divided into two types:

- *Intrinsic forecasts.* It is based on the assumption that historical data can adequately describe the scenario of the problem to be forecast. With intrinsic forecasting, forecasting models based on historical data use extrapolation to generate estimates for the future.

- *Extrinsic forecasts*. Look outward and assume that internal forecasts can be correlated with external factors. For example, an internal forecast of the demand for a new product may be based on external forecasts of household income.

Another way to call intrinsic forecasts is as univariate or time series forecasts. While extrinsic forecasting encompasses simple linear regression, multiple linear regression, and multivariate time series forecasting, the latter consists of forecasting two or more time series, which are correlated, simultaneously (Korstanje, 2021).

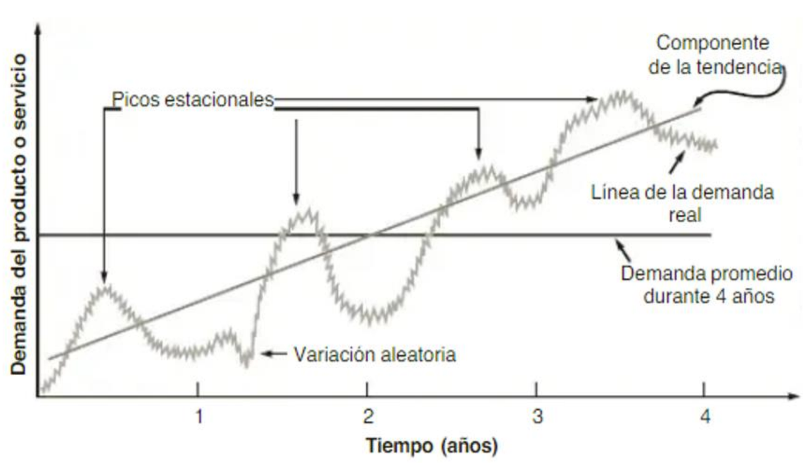
Good forecasts are based on the availability of good data. For a small or medium-sized company, it could be less accessible to obtain the data of the different significant variables to carry out an extrinsic forecast, in addition to the fact that there are cases where having data from multiple variables does not guarantee that a linear regression model is better. than a univariate time series model. Therefore, for the purposes of this research, univariate time series forecasting models are recommended.

Heizer and Render (2014) define that the components of a time series are:

- *Trend*: gradual movement (which occurs successively and continuously) of the data, up or down, in the time series.
- *Seasonality:* data pattern that repeats itself after n periods of time less than one year (days, weeks, months, quarters, semesters), for example, restaurants experience weekly seasons where Saturdays have an increase in sales.
- *Cycles:* are patterns in the data, greater than one year, due to factors other than seasonality. Because they are not periodic, the time intervals of the cyclical variations are not fixed. Cycles usually show periods of boom, slowdown or downturn in economies and are often difficult to forecast, given their multiple causes (political events, international turbulence, etc.)
- *Random variations:* data generated by chance or unusual situations. Since they do not follow any pattern, they cannot be predicted.

Figure 1 shows a time series of demand for a period of four years. The trend, the actual demand line, the average demand, the seasonal peaks and the random variation are shown.

Figura 1. Componentes de una serie de tiempo



Fuente: (Heizer y Render, 2014, p. 109)

The goal of time series analysis is to use the joint density to make probability inferences about future observations; this is more feasible if the time series is stationary. The concept of stationarity implies that the distribution of the time series is invariant with respect to any time shift. Non-stationarity in a time series can be recognized in the trend component. A very scattered plot, with no trend to a particular value, is an indication of non-stationarity. In some cases where stationarity does not exist, some form of data transformation is used to achieve it. For most time series data, the usual transformation used is differentiation. Differentiation implies the creation of a new time series that shows a stationarity, taking the differences between successive periods of the original series (Badiru and Omitaomu, 2020).

The Box-Jenkins method, better known as integrated autoregressive moving averages (Arima), is used for any data pattern, i.e. stationary or non-stationary (via differencing), over a short horizon. term, which results in an advantage when you do not have a clear understanding of the behavior of the analysis data. Therefore, the Arima model is one of the most popular proposals for forecasting (López, 2018; Mills, 2019).

As mentioned above, the mathematical complexity of the models does not guarantee their success (Brighton and Gigerenzer, 2015; Green and Armstrong, 2015); proof of this is that in the year 2000 the third Makridakis competition of the International Institute of Forecasters was held, organized by Dr. Spyros Makridakis of the University of Nicosia. Participants used their preferred method of forecasting. A total of 3003 time series were performed. The conclusions reached were:

1) As in a previous study, advanced or statistically complex methods do not necessarily result in more accurate forecasts than simpler methods.
2) Different measures of precision produce consistent results when used to evaluate different forecasting methods (it is therefore recommended to choose more than one criterion to measure error).
3) The combination of three exponential smoothing methods outperformed, on average, the smoothing methods separately (simple smoothing, Holt-Winters smoothing, and Damped smoothing). This was the only forecast combination method that participated in the competition, achieving the best results of the 24 competing univariate time series methods, including ARIMA models, autoregressive models, trend analysis models and artificial neural networks (Makridakis and Hibon, 2000).
4) 4) The effectiveness of different forecasting methods depends on the length of the forecast horizon and the kind of data (annual, quarterly, monthly) being analyzed. Some methods work more accurately for short horizons, while others are more suitable for longer horizons. Some methods work better with annual data and others are more appropriate for quarterly and monthly data. (Hanke y Wichern, 2014).

It would take 18 years for another of these forecasting competitions, known as M-Competitions, to be organized again. During this long period, the emergence of artificial intelligence and machine learning, called in English machine learning, allowed the development of techniques to enhance the analysis of computer data, which, although it covers fields that had already been treated by inferential statistics , like forecasting, incorporates the complexity of computational logic to help obtain the most accurate result.

It should be noted that, just as mathematical complexity does not guarantee a better forecast, resorting to artificial intelligence does not categorically outperform classic or traditional forecasts. Stoll (2020) made a comparison between traditional and machine learning methods for forecasting the demand of several product families of a company, using MAPE and the root mean square error (RMSE) as criteria, and concluded that the triple exponential smoothing and Arima models performed better than the machine learning forecasting models chosen for comparison.

The conclusion that the triple exponential smoothing model, also known as the Holt-Winters model, is the best is consistent with the results of the Makridakis competition, despite the fact that 20 years have passed between the two comparisons. Said concordance sustains that this model is currently a valid option for carrying out a demand forecast. Even so, it should be remembered that each data series is different and the superiority of one method cannot be predicted with certainty.

But all is not lost for machine learning forecasts. In an extreme scenario carried out in the same investigation by Stoll (2020), high values of standard deviation, the presence of outliers and a small number of observations were used, which affected both types of forecasting methods studied (traditional and machine learning). In fact, in this scenario the random forest machine learning model and the recurrent neural network (RNN) model were worthy contenders and made a good attempt to follow the trend and seasonality of the ensemble. of evidence (Stoll, 2020).

A computer neural network tries to simulate, in a virtual way, the behavior of a biological brain. Similarly, it is composed of simple interconnected units, whose links cause the activation state of neighboring cells to be increased or inhibited. Unlike other computer algorithms, this one can learn on its own as new information is fed into the system. Thus, the model adapts and the weight of the connections varies; this is known as model training from a data set.

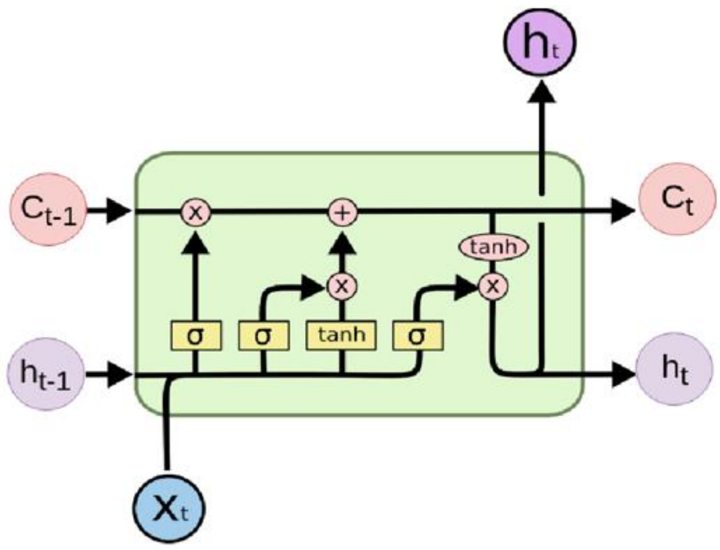
Recurrent neural networks are a type of neural networks whose goal is to detect dependencies in sequential data; this means that they intend to find correlations between different points within a data sequence. Dependencies can be short term or long term. The problem with recurrent neural networks is that they only detect short-term dependencies. To get around this, in the 1990s German scientists developed a variant, now known as a large short-term memory (LSTM) recurrent neural network, which can detect long-term dependencies and greatly improve forecasts. which results in a formidable alternative when it comes to a forecast based on a considerable series of data (Dua, Yadav, Mamgai y Brodiya, 2020; Sherstinsky, 2020).

Supporting the above, a study carried out for the forecasting of carbon stock performance concluded that the LSTM neural network method obtained an average forecast error of 43.75% lower than that of traditional neural networks, as well as lower total CPU time and consumption. energy for calculations (Huang et al., 2021).

Figure 2 shows the structure of an LSTM neural network cell, where the values of c correspond to the memory, h represents the outputs and x the inputs. The rectangles inside the cell are simple neural networks with their activation functions, while the circles are specific operations to discard, update and calculate the new memory state (Ferro, Celis and Casallas, 2020).

Another of the machine learning forecasting models, the random forest, is largely based on the classic decision tree model, but adds more complexity to it. As the name suggests, a random forest consists of a large number of decision trees, each with a slight variation, making it more efficient. Typically, a random forest can combine hundreds or even thousands of decision tree models that fit slightly different data, so they are not exactly the same. When a machine learning model can sometimes be wrong, the average prediction of a large number of machine learning models is less likely to be wrong, as will be argued later. This idea is the basis of joint learning. In the random forest, ensemble learning is applied to a repetition of many decision trees. Ensemble learning can be applied to any combination of a large number of machine learning models. Decision trees have proven to be a high-performance and easy-to-configure model. (Korstanje, 2021).

Figura 2. Celda de red neuronal LSTM



Fuente: Ferro *et al.* (2020, p. 8)

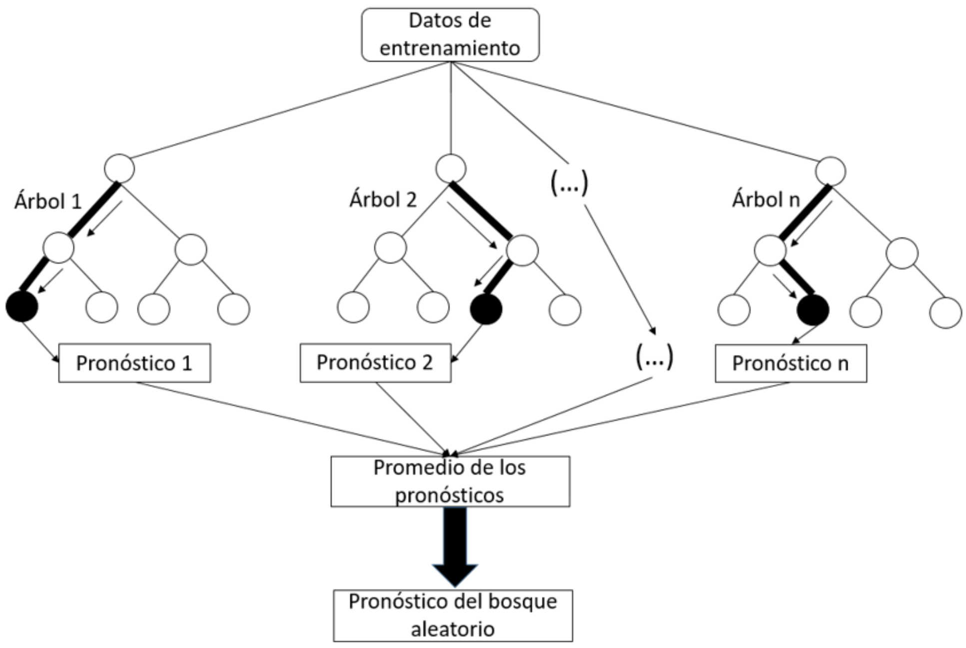
A research work that had the objective of finding a methodology for the prediction of the daily demand for shipments of an electronic commerce company, through the use of both mathematical and machine learning algorithms, concluded that the models that best fit the company's historical data series were the latter, specifically the random forest model, after calibration of its parameters. It should be noted that the second best model was the LSTM neural network model, so it is worth considering both options for comparison (Dalmau Barraza, 2020). Figure 3 presents a basic diagram of the random forest forecasting process, which consists of averaging the forecasts of a large number of decision trees.

To address the issue of improving forecasts through artificial intelligence, research has emerged over the last decade that experiments with the use of hybrid models, that is, that through mathematical formulas combine parameters of a traditional forecast with an automatic learning forecast, whose names are formulated by combining the forecasts that make it up, for example, the ARIMA-LSTM hybrid model (Phan and Nguyen, 2020).

Research by Dave, Leonardo, Jeanice, and Hanafiah (2021) concluded that the hybrid Arima-LSTM model obtained lower MAPE and lower RMSE for forecasting Indonesian export demand during the years 2018 and 2019 compared to the Arima and LSTM models.

LSTM separately. Considering that the Arima model and the LSTM model have already been recommended for comparison, it will not be difficult to combine both, so it is recommended to consider this hybrid model in order to obtain better forecast accuracy.

Figura 3. Diagrama del proceso de pronósticos mediante árbol de decisión



Fuente: Elaboración propia

A research work that had the objective of finding a methodology for the prediction of the daily demand for shipments of an electronic commerce company, through the use of both mathematical and machine learning algorithms, concluded that the models that best fit the company's historical data series were the latter, specifically the random forest model, after calibration of its parameters. It should be noted that the second best model was the LSTM neural network model, so it is worth considering both options for comparison (Dalmau Barraza, 2020). Figure 3 presents a basic diagram of the random forest forecasting process, which consists of averaging the forecasts of a large number of decision trees.

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Years later, Winkler and Makridakis (1983) would also obtain empirical results showing that the combined forecasts of five statistical models, including the Holt-Winters model, are more accurate than the separate forecasts. They also concluded that the weighted averages are superior to the forecasts obtained from a simple, unweighted average of the same models. The article proposes a mathematical model for calculating the weighted average of the forecasts, which can be tested with the models proposed in this investigation.

Returning to Dr. Makridakis, and his renowned forecasting competitions, these were held again from the year 2018. For the fourth competition (M4 Competition), a total of 100,000 time series were made with 61 forecasting models for finance, forecasts for the industry and demographic forecasts, at macro and micro levels, among others. The models were created by the participants, belonging to companies and universities from all over the world. The results showed that 12 of the 17 most accurate models were combinations of other statistical models, which is consistent with previous theories; however, a hybrid model made by Sławek Smyl, from the Uber company, was the winner (Makridakis, Spiliotis and Assimakopoulos, 2020).

Although the fifth Makridakis competition (M5 competition) ended in July 2020, the International Institute of Forecasters has not fully provided the public with the results or the methods used for the forecasts, since on this occasion they worked with sales data provided by the Wal-Mart company (Makridakis et al., 2021); so probably, due to confidentiality, it was not possible to publish the winning model; however, based on the available data, Kolassa (2021) assures that the exponential smoothing methods, with a probability of 92.5%, are the best for the forecast of sales of the Wal-Mart company. What is a fact is that forecasting competitions have had a new boom after 18 years of absence, and each year they seek to focus on a different field; for example, the M6 Competition, to be held from 2022 to 2023, will focus on financial investment forecasts (M Open Forecasting Center [MOFC], 2021).

Discussion

The objective of implementing a forecasting system for a business is to provide information about future changes in the economic environment and the impact of these changes on the company; for example, competitiveness within the market economy causes variability in the demand for certain goods. The level of production must reflect the demands of customers; this demand can be estimated through forecasts (Kurzak, 2012).

This research work has chosen to propose a variety of forecasting models that have demonstrated their effectiveness, according to various recently published comparative studies, for forecasting demand in different economic scenarios around the world. Of the models with a statistical approach, the Arima model and the Holt-Winters triple exponential smoothing model (Stoll, 2020) are proposed, a recommendation that coincides with the results of the Makridakis competitions (Hanke and Wichern, 2014). Of the machine learning models, LSTM neural networks are suggested, instead of a typical recurrent neural network (Huang et al., 2021), and the random forest model, for demonstrating a better fit in predictions (Stoll, 2020).). The results of Dalmau's research (2020) highlight these same proposals. Finally, from the hybrid approach, the Arima-LSTM model is proposed, given that it has shown greater effectiveness than the two forecasts separately (Dave et al., 2021), and the Facebook Prophet model, due to its ease of use and its potential to compete with other models (Kumar Jha y Pande, 2021; López, 2018).

The inclusion of linear regression models was omitted since the research focused exclusively on univariate time series forecasting models. The main reason is that the implementation of linear regression models requires a larger amount of data as the variables increase, as well as the need for statistical tests to choose the significant variables for the model. Another reason is that linear models are limited when the analysis variable does not behave linearly, such as demand, sales, the price of a product, inflation or other variables related to the economic environment (Binner, Bissoondeeal , Elger, Gazely and Mullineux, 2005). An example of the above statement is the research by Morales, Ramírez and Rodríguez (2019), where the multiple linear regression model was overwhelmed by nonlinear machine learning models for forecasting sales of different food companies. On the other hand, the Arima model, with single-variable data, has the potential to match and even exceed a multiple linear regression model in certain scenarios (Correia, d'Angelo, Almeida, & Mingoti, 2021).

Once the models of each approach have been proposed, this research proposes to go beyond the competitions or comparisons of forecasts, such as the M-Competitions described by Makridakis et al. (2020), and not only conclude which model has better behavior with the data. Like Rao and Gao (2021), it has been concluded that, once the forecasts of each of the models have been obtained, it is recommended that they be combined through some method of weighted averages, and obtain a model of final forecasts that achieve higher accuracy than the separate models. Currently, the main free programming software for time series analysis, R and Python, offer different libraries and algorithms to automatically perform the combination of various forecast models. (Dutta, 2020; Hyndman, 2016).

Conclusions

Based on the literature consulted, it is concluded that there is no forecasting model that can perfectly determine future demand and its accuracy will depend on the quantity, quality and particular behavior of the time series data. There are also no methods that allow knowing in advance which forecasting model will work best, so the trend in the industry is to increase the number of options to make a comparison, relying on the current power of computers. An ideal time series is one that has a pattern in the behavior of the data, that is, it is a stationary series, which allows a forecast to be made with less precision error.

When a time series is not stationary, a mathematical transformation, known as difference, is used to work with it. Traditional time series forecasting models encompass methods that have a purely statistical approach; On the other hand, modern models cover forecasts under two approaches: machine learning approach and hybrid approach. Evidence was found to support that the combination, using weighted average methods, of several forecast models usually gives better results than the forecast of the models separately.

Table 2 shows the forecast models that this research proposes to make a comparison and determine which model behaves better for forecasting demand. The MAPE and the square root of the RMSE were used as evaluation criteria.

Tabla 2. Modelos propuestos a pequeñas y medianas empresas para el pronóstico de la demanda

Modelo	Tipo	Características
Suavización exponencial triple (Holt-Winters)	Modelo tradicional. Enfoque estadístico.	Se busca encontrar los valores óptimos de las constantes de atenuación del promedio de los datos (α), de la tendencia (β) y la componente estacional (γ) para construir la serie de tiempo del pronóstico que mejor se ajuste a los datos, por lo que se requiere de patrones de variación regulares.
Promedios móviles autorregresivos integrados (Arima) o Metodología de Box-Jenkins	Modelo tradicional. Enfoque estadístico.	Se conforma de las componentes autorregresiva (*p*), integrada (*d*) y de media móvil (*q*) que utilizan las variaciones y correlaciones existentes dentro de la serie de tiempo para determinar patrones y, a partir de ellos, generar un pronóstico, para lo cual a veces es necesario transformar la serie a fin de volverla estacional.
Redes neuronales recurrentes de gran memoria a corto plazo (LSTM)	Modelo Moderno. Enfoque de aprendizaje automático.	Funciona a través de celdas que simulan ser una neurona biológica, las cuales realizan operaciones lógicas que le permiten memorizar patrones y dependencias de una serie de datos a corto y largo plazo para de esta forma generar un pronóstico.
Bosque aleatorio	Modelo Moderno. Enfoque de aprendizaje automático.	Con base en la serie de datos, el programa crea una gran serie de árboles de decisión con un pronóstico similar para cada uno. El algoritmo promedia todos los pronósticos para obtener un pronóstico final, con menor error que los pronósticos individuales.
Arima-LSTM	Modelo moderno. Enfoque híbrido.	Es la combinación del modelo Arima y el modelo de redes neuronales LSTM.
Facebook Prophet	Modelo moderno. Enfoque híbrido.	Un modelo fácil de usar que busca que las tendencias no lineales se ajusten a la estacionalidad anual, aun cuando se tengan datos faltantes. Matemáticamente se sustenta en series de Fourier y en la regresión aditiva.

Fuente: Elaboración propia

Contributions to future lines of research

This research work constitutes an analysis of the state of the art of demand forecasting through time series analysis, and makes the recommendation of six of the most effective models that are currently used, which can be implemented in any company with a free software, such as R and Python, or even Excel, if you choose to test only statistical forecasting models. Finally, it is recommended that, once the forecasts have been made, a seventh option be considered: the combination, through weighted averages, of all the proposed models, and give greater weight to the method with the best results, in order to corroborate that the combination of several forecasts is better than separately.

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