

**DEMAND FORECASTING: AN APPLICATION OF THE HOLT WINTERS
METHOD IN A MEDIUM-SIZED TEXTILE INDUSTRY**

**PREVISÃO DA DEMANDA: UMA APLICAÇÃO DO MÉTODO HOLT WINTERS
EM UMA INDÚSTRIA TÊXTIL DE MÉDIO PORTE**

**PREVISIÓN DE LA DEMANDA: UNA APLICACIÓN DEL MÉTODO HOLT
WINTERS EN UNA INDUSTRIA TEXTIL DE TAMAÑO MEDIANO**

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Diego Milnitz¹, Jamur Johnas Marchi², Robert Wayne Samohyl³

ABSTRACT

Demand forecasting is a fundamental process for supporting strategic and operational decisions in industrial companies, especially in seasonal sectors such as textiles. This article aims to evaluate the application of the additive Holt-Winters method in a medium-sized textile company located in Santa Catarina, considering forecasting as a dynamic process that requires continuous evaluation, data processing, and periodic adjustments. The research was developed based on a monthly time series of children's clothing production between 2008 and 2011, initially using classical decomposition to identify trends and seasonality, followed by the application of the Holt-Winters model. Forecast quality was measured using the mean absolute percentage error (5.97%) and Theil's U statistic (0.346), indicating satisfactory model adherence. However, outliers were identified in November and December 2010, associated with delays in raw material supply, which distorted the results. After processing these data, performance indicators improved significantly, with a reduction in the mean error to 5.08% and a Theil's U of 0.312. These findings reinforce the importance of understanding forecasting as an iterative process, which depends on both model selection and the quality and consistency of the information used. As a contribution, the study highlights the applicability of the Holt-Winters method to the textile sector, highlights the importance of anomaly treatment, and suggests the future integration of hybrid and digital approaches to increase reliability and support planning practices aligned with Industry 4.0 principles.

Keywords: Demand Forecasting. Holt-Winters. Outliers. Textile Industry. Time Series.

RESUMO

A previsão de demanda é um processo fundamental para apoiar decisões estratégicas e operacionais em empresas industriais, especialmente em setores sazonais como o têxtil. Este artigo tem como objetivo avaliar a aplicação do método de Holt-Winters aditivo em uma indústria têxtil de médio porte localizada em Santa Catarina, considerando a previsão como um processo dinâmico que exige avaliação contínua, tratamento de dados e ajustes periódicos. A pesquisa foi desenvolvida a partir de uma série temporal mensal da produção de vestuário infantil entre 2008 e 2011, empregando inicialmente a decomposição clássica para identificação de tendência e sazonalidade, seguida pela aplicação do modelo Holt-

¹ Dr. in Production Engineering. Universidade Federal do Paraná (UFPR). E-mail: Diego.milnitz@UFPR.br

² Dr. in Production Engineering. Universidade Federal de Santa Catarina.

E-mail: jamur.marchi@unipampa.edu.br

³ Dr. in Production Engineering. Universidade Federal de Santa Catarina. E-mail: samohyl@deps.ufsc.br

Winters. A qualidade das previsões foi medida por meio do erro percentual absoluto médio (5,97%) e da estatística U de Theil (0,346), indicando aderência satisfatória do modelo. Contudo, foram identificados outliers nos meses de novembro e dezembro de 2010, associados a atrasos no fornecimento de matéria-prima, que distorceram os resultados. Após o tratamento desses dados, os indicadores de desempenho melhoraram significativamente, com redução do erro médio para 5,08% e U de Theil de 0,312. Esses achados reforçam a importância de compreender a previsão como processo iterativo, que depende tanto da escolha do modelo quanto da qualidade e consistência das informações utilizadas. Como contribuição, o estudo evidencia a aplicabilidade do método Holt-Winters ao setor têxtil, ressalta a relevância do tratamento de anomalias e sugere a integração futura de abordagens híbridas e digitais para aumentar a confiabilidade e apoiar práticas de planejamento alinhadas aos princípios da Indústria 4.0.

Palavras-chave: Previsão de Demanda. Holt-Winters. Outliers. Indústria Têxtil. Séries Temporais.

RESUMEN

La previsión de la demanda es un proceso fundamental para la toma de decisiones estratégicas y operativas en empresas industriales, especialmente en sectores estacionales como el textil. Este artículo tiene como objetivo evaluar la aplicación del método aditivo Holt-Winters en una empresa textil mediana ubicada en Santa Catarina, considerando la previsión como un proceso dinámico que requiere evaluación continua, procesamiento de datos y ajustes periódicos. La investigación se desarrolló con base en una serie temporal mensual de producción de ropa infantil entre 2008 y 2011, utilizando inicialmente la descomposición clásica para identificar tendencias y estacionalidad, seguida de la aplicación del modelo Holt-Winters. La calidad de la previsión se midió mediante el error porcentual absoluto medio (5,97 %) y el estadístico U de Theil (0,346), lo que indica una adherencia satisfactoria al modelo. Sin embargo, se identificaron valores atípicos en noviembre y diciembre de 2010, asociados a retrasos en el suministro de materia prima, que distorsionaron los resultados. Tras el procesamiento de estos datos, los indicadores de rendimiento mejoraron significativamente, con una reducción del error medio al 5,08 % y un índice U de Theil de 0,312. Estos hallazgos refuerzan la importancia de comprender la previsión como un proceso iterativo, que depende tanto de la selección del modelo como de la calidad y consistencia de la información utilizada. Como contribución, el estudio destaca la aplicabilidad del método Holt-Winters al sector textil, destaca la importancia del tratamiento de anomalías y sugiere la futura integración de enfoques híbridos y digitales para aumentar la fiabilidad y respaldar prácticas de planificación alineadas con los principios de la Industria 4.0.

Palabras clave: Previsión de la Demanda. Holt-Winters. Valores Atípicos. Industria Textil.

1 INTRODUCTION

Making predictions has been an increasing challenge for companies that want to be competitive. The merit of a good forecast may lie in smoothing out market turbulence, providing a slightly safer horizon for business decision-making. For Hill (1994), the existence of a demand forecasting process allows production strategies to be satisfactorily operationalized. However, many companies still do not have a structured and organized method to perform forecasting. Instead, there is even a certain distrust in the business environment when it comes to forecasting. Some of the factors that contribute to this problem are the issues of power and politics that involve the business environment, or even the lack of knowledge of effective forecasting methods that produce misjudgments (SAMOHYL, *et al.* 2008).

One of these apparent mistakes can be noticed when the forecast fails and becomes discredited in the company. At least three points must be considered: first, it happens that predictions are not made to get it right, they only indicate possibilities, which are based on the analysis of the behavior of past data. In this sense, forecasting is best used when its numbers are analyzed not in isolation, but also considering its context. Another point to be considered is that prediction models need to be continuously evaluated and improved through methods of measuring forecast error. With these measures, the model can be adjusted, becoming adaptable according to the changes that occur in the company. (SAMOHYL, *et al.* 2008). The third point is that the quality of the data series can also have problems, for various reasons ranging from a typing error to a delay in the delivery of a product. When this occurs, prediction models are generally unable to explain or treat such data.

This article aims to contribute to a better understanding of these three points through the application of a demand forecasting model as a business process in a textile company located in the state of Santa Catarina. For this study, a series of data was taken that represents the monthly production of pieces in the children's segment of this company. Due to the short life cycle of the products, the data collection represents the total production of the products between March 2008 and February 2011. The work addresses the concept of demand forecasting and exponential smoothing, focusing on the *Holt-Winters method*, and including discrepancy measures, which are fundamental for the evaluation of the forecasting model. Next, the study is presented, where the application of the model to the data series is reported and, finally, some considerations are made about the work.

2 RELEVANCE OF DEMAND FORECASTING

According to Gaither and Frazier (2001), demand forecasting is future estimates of a product or service. It can be said that a model that can better perform such estimates contributes significantly to the company not having unnecessary costs. In other words, SAMOHYL, *et al.* (2008) highlights that demand forecasts with little precision make the company burdened with costs. A classic example is the influence that demand forecasting has on inventories. Inventory levels beyond what is necessary make it difficult for the company to manage and costs, having its origin in inaccurate forecasts.

Making predictions then involves a certain risk, but worse would be not to make any predictions at all. For Makridakis *et al.* (1998), the demand forecasting process is relevant for companies because it fundamentally helps in resource planning. According to Martins and Laugeni (1998), this process involves statistical, mathematical or econometric models or even more subjective models. It is important that the company chooses the method that best suits its reality.

For Davis (1997), the selection process involves some factors such as the nature of the product, the availability of data, the long, medium or short forecast horizon, the necessary precision, the available budget and the pattern of the existing data (horizontal, seasonal, cyclical or trend). Specifically, this last factor has been studied for a long time through the decomposition method applied in time series (MAKRIDAKIS *et al.*, 1998).

2.1 METHOD OF DECOMPOSITION

The decomposition method assumes that a time series can be represented by its components separately. Thus, the main series is decomposed into series for seasonality (S), trend (T), mean (L), cycle (C) and random noise (a).

Table 1 shows the representations of the decomposition, additive and multiplicative methods. After the data series has been decomposed, it is possible to make predictions by regrouping the individual components.

Table 1

Representation of the time series and decomposition methods

Characteristic	Mathematical representation
Time series	$f(S_t, T_t, L_t, C_t, a_t)$
Additive Method	$z_t = S_t + T_t + L_t + C_t + a_t$
Multiplicative Method	$z_t = S_t \times T_t \times L_t \times C_t \times a_t$

Source: Adapted from Makridakis *et al.* (1998).

In this prediction model, random noise is considered equal to zero for additive decomposition and one for the multiplicative model. Generally, data decomposition is used to observe each component of the series separately, thus facilitating the identification of patterns in the data collection for later use of more representative prediction models.

2.2 METHODS OF FORECASTING BY EXPONENTIAL SMOOTHING

According to SAMOHYL, *et al.* (2008) The exponential smoothing methods consist of decomposing the series into components (trend and seasonality) and smoothing its past values, that is, giving differentiated weights whose values decay exponentially to zero the older. In this article, the *Holt-Winters* method with additive seasonality will be applied to perform demand forecasts. The choice of this method is justified by the fact that forecasts made through exponential methods value the most recent data. This appreciation is fundamental for data related to the textile segment, as they are influenced in short periods such as seasons of the year or the "fashion of the moment". Also, according to Makridakis *et al.* (1998), Pellegrini & Fogliatto (2001) and SAMOHYL, *et al.* (2008), there are other methods, however, given the objective of this work and the characteristic of the series used, it was limited to addressing only the *Holt-Winters model*.

2.3 HOLT –WINTERS FORECASTING

The exponential model is one of the best known forecasting methods for allowing the adaptation of seasonality over time (LAWTON, 1998). In companies, it is quite common to use moving averages to make predictions. The *Holt-Winters* method is a method that also uses the moving average, but transformed from simple to exponential, in order to better represent the trend and seasonality of the data. As a result, it generally produces better forecasts than those made with simple moving averages such as classic decomposition (SAMOHYL, *et al.* 2008).

Exponential models are divided into two groups: additive and multiplicative. In the additive model, the amplitude of seasonal variation is constant over time; That is, the difference between the highest and lowest demand value within the stations remains relatively constant over time. In the multiplicative model, the amplitude of seasonal variation increases or decreases as a function of time (LAWTON, 1998). For this article, the Holt-Winters type exponential model with Additive seasonality will be used.

The equations for the additive method are shown in Table 2.

Table 2

Representation of the components of the Holt Winters Additive model

Component	Holt Winters Additive
Average	$L_t = \alpha \cdot (Z_t - S_{t-s}) + (1 - \alpha)(L_{t-1} + T_{t-1})$
Tendency	$T_t = \beta \cdot (L_t - L_{t-1}) + (1 - \beta) \cdot T_{t-1}$
Seasonality	$S_t = \gamma \cdot (Z_t - L_t) + (1 - \gamma) \cdot S_{t-s}$
Forecasting Model	$\hat{Z}_{t+k} = L_t + k \cdot T_t + S_{t-s+k}$

Source: Adapted from Makridakis *et al.*, (1998)

Its mathematical representation is given by Makridakis *et al.* (1998), where it is a complete season of seasonality (for example, it is equal to 12 when we have monthly data and annual seasonality); , and represent the level, trend and seasonality of the series, respectively; it is the forecast for periods ahead; and, finally, it is the smoothing constant that controls the weight relative to seasonality, ranging from 0 to 1. $SSL_t T_t S_t \hat{Z}_{t+k} k \gamma$

3 ASSESSMENT OF THE FORECAST DISCREPANCY

Predictions always get it wrong, but it's preferable to get it wrong with small discrepancies rather than big ones. Measures of forecasting errors are very useful in the sense of continuous improvement of the forecasting process. Since discrepancies will always be present, the identification and investigation of this inaccuracy can, in many cases, lead to improved future outcomes (SAMOHYL, *et al.* 2008). This method is widely used by engineers and administrators to verify the percentage of error in relation to the observed value is the calculation of the mean absolute percentage discrepancy (DPAM). This method does not consider the sign of the values in the calculation, the objective of this measure is to know the distance between the forecast and the value observed in the series. The formula can be seen in Table 3.

Table 3

Mathematical representation of the calculation of errors

Discrepancy Measure	Formula
DPAM	$DPAM = \frac{1}{n} \sum_{t=1}^n \left \frac{P_t - O_t}{O_t} \right $
U of Theil	$U = \sqrt{\frac{\sum_{t=1}^{n-1} \left\{ \left(\frac{P_{t+1} - O_t}{O_t} \right) - \left(\frac{O_{t+1} - O_t}{O_t} \right) \right\}^2}{\sum_{t=1}^{n-1} \left(\frac{O_{t+1} - O_t}{O_t} \right)^2}}$

Source: Adapted from Samohyl (2008).

Another method used to measure the adherence of the model used for prediction is the U of Theil. This measure plays a decisive role in determining the use or not of a specific forecasting technique, be it quantitative, qualitative, formal or informal, as it has the ability to demonstrate whether such effort is worthwhile and makes sense to spend it, or whether better results could be achieved using the simplest of techniques, that is, naïve forecasting (SAMOHYL, *et al.* 2008). On the other hand, Makridakis, Wheelwright & Hyndman (1998) define that the closer the value of this statistic is to zero, the better the prediction technique will be, i.e., the model generates a smaller error than the error of the naïve method.

4 CASE STUDY

The case study reports the application of the exponential forecasting model in a textile company located in the state of Santa Catarina. The chosen company had its origin in early 1964, focused on the production of children's baptism sets and currently its production is directed to children's clothing.

The data series used in this study represents the monthly production of pieces in the children's segment of this organization. Due to the short life cycle of the products, the data collection represents the total production of the products between March 2008 and February 2011. The application of demand forecasting can help to understand the growth of the organization in terms of product sales, allowing early decisions to be made in order to improve the production structure and optimize the acquisition of raw materials. Table 4 shows the data series that represents the production of the products.

Table 4

Textile Company Data Series

	2008	2009	2010	2011
January		661.739	728.643	843.348
February		821.654	884.565	1.158.469
March	814.552	755.350	873.754	
April	779.349	693.069	865.629	
May	1.038.955	901.356	1.176.554	
June	1.079.083	1.075.301	1.082.864	
July	1.277.628	1.244.583	1.310.673	
August	1.274.927	1.251.458	1.298.396	
September	1.082.136	1.088.239	1.292.469	
October	1.211.421	1.359.611	1.353.218	
November	995.827	1.283.188	1.557.801	
December	721.082	671.148	710.803	

Source: Data from the analyzed company.

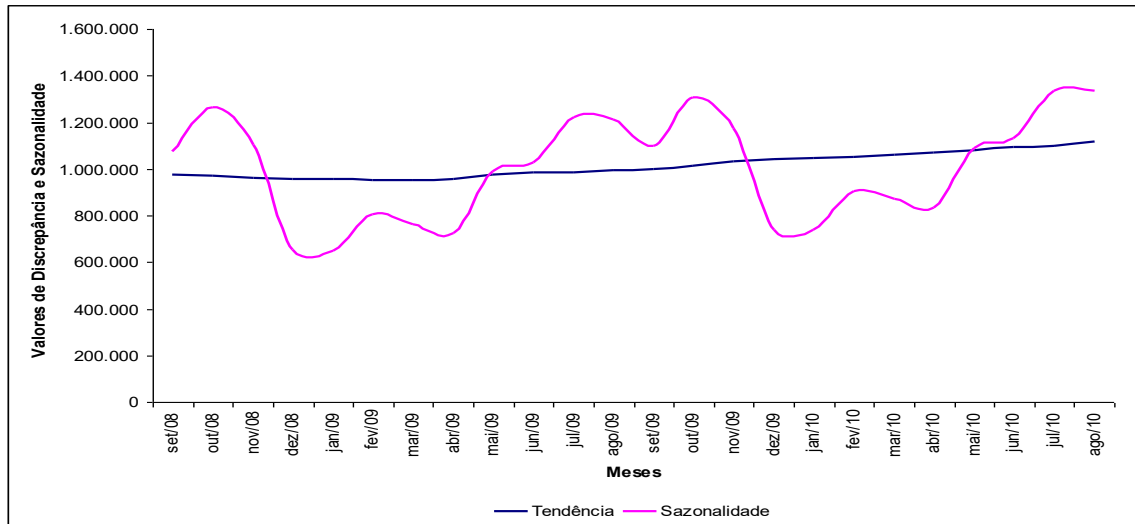
4.1 APPLICATION OF THE ADDITIVE DECOMPOSITION METHOD

The application of the decomposition method, in addition to generating forecasts, helps in choosing the forecast model to be used. By decomposition, you can check the trend and seasonality components separately from the data series. According to SAMOBYL, *et al.* (2008), the trend is an easy-to-visualize component, as its presence is perceived when the values of the series increase or decrease in a given time interval. The seasonality component, according to Wallis & Thomas (1971), can be defined as the set of movements or fluctuations with a period equal to or less than one year, systematic, but not necessarily regular, that occur in a series of data.

In the case of the decomposed series, it is possible to verify a slight positive trend and a marked seasonality. As shown in Figure 1, the extent of the seasonal variation is equal over time. Thus, there is no difference between the highest and lowest value of demand within the stations.

Figure 1

Graph of the Trend and Seasonality Components



Source: developed by the Author.

A good forecasting model must consider a linear trend and a constant seasonal variation over time, i.e., an additive seasonal component. Thus, the Holt *Winters* Exponential Additive model is a suitable model for such a purpose.

4.2 APPLICATION OF THE FORECAST BY THE *HOLT METHOD – WINTERS* ADDITIVE

The forecast through the exponential model presents better trend and seasonality results compared to the classic decomposition model that uses simple moving averages. According to Hanke, Reitsch and Wichern (2001), the *Holt Winters* Method is more indicated when working with seasonal data, without necessarily parking them, and with which one intends to make short-term forecasts. Table 5 shows the values calculated for the exponential smoothing model, and the formulas shown in Table 2 were used to perform the calculations.

Table 5

Calculated data from the Holt Winters Additive forecast

Months	Série Obs.	Prev. Series	Discrepancy
March/2010	873.754	867.606	6.148
April/2010	865.629	840.408	25.221
May/2010	1.176.554	1.104.244	72.310
June/2010	1.082.864	1.163.018	-80.154
July/2010	1.310.673	1.362.113	-51.440
August/2010	1.298.396	1.354.877	-56.481
September/2010	1.292.469	1.232.135	60.334
October/2010	1.353.218	1.450.690	-97.472

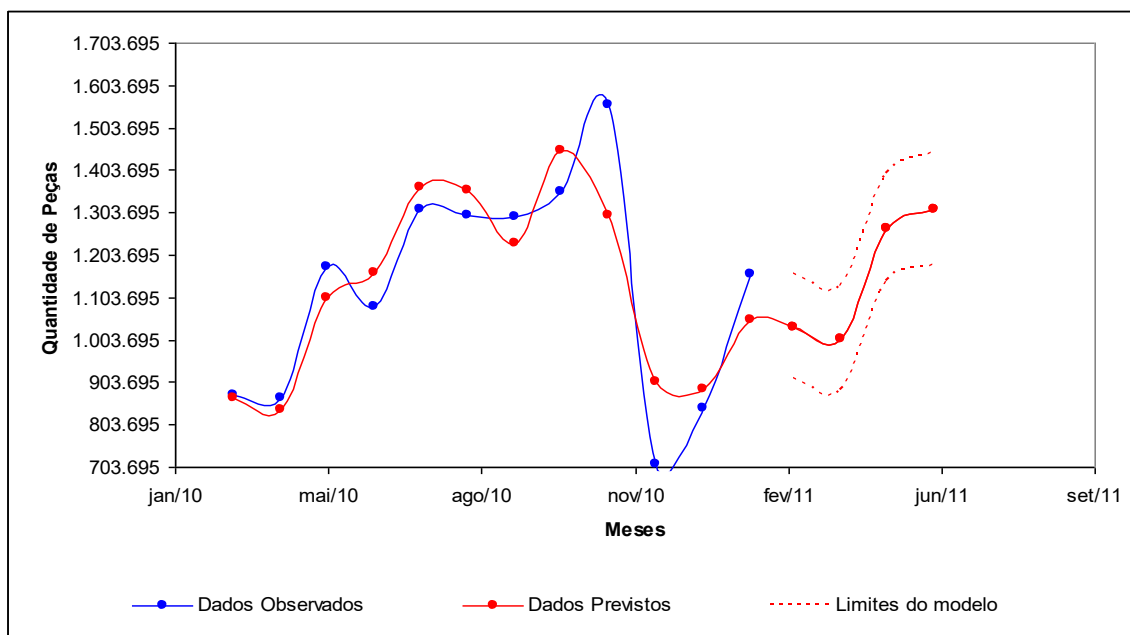
November/2010	1.557.801	1.295.900	261.900
December/2010	710.803	904.925	-194.122
January/2011	843.348	888.984	-45.636
February/2011	1.158.469	1.049.424	109.045
March/2011		1.034.970	
April/2011		1.007.289	
May/2011		1.267.272	
June/2011		1.310.749	

Source: Data from the analyzed company.

After the calculations of the forecasts, the data of the last seasonal period were placed in a line graph for analysis of the perspective of adherence of the model in the series. Observing Figure 2, it is possible to understand that the model presented a certain adherence, but with prediction errors, thus reinforcing the statement of SAMOBYL, *et al.* (2008) that forecasts always generate errors. Visually it is not possible to know what the values of these errors are, that is, the difference between the predicted and observed values in the analyzed data collection. However, using the suggestion of SAMOBYL, *et al.* (2008), in the area of forecasting, the discrepancy between the predicted and the observed value is an excellent measure of the quality of the predicted values. For a more accurate evaluation of the model, calculations of the discrepancy measurements are performed using the formulas contained in Table 3. The model applied, *Holt Winters* Additive, showed a mean absolute percentage error of 5.97%, with a U of Theil value equal to 0.346, very close to zero. Thus, demonstrating that, despite the errors, the model used represents the data of the series well.

Figure 2

Forecast Graph of the Holt Winter Additive model

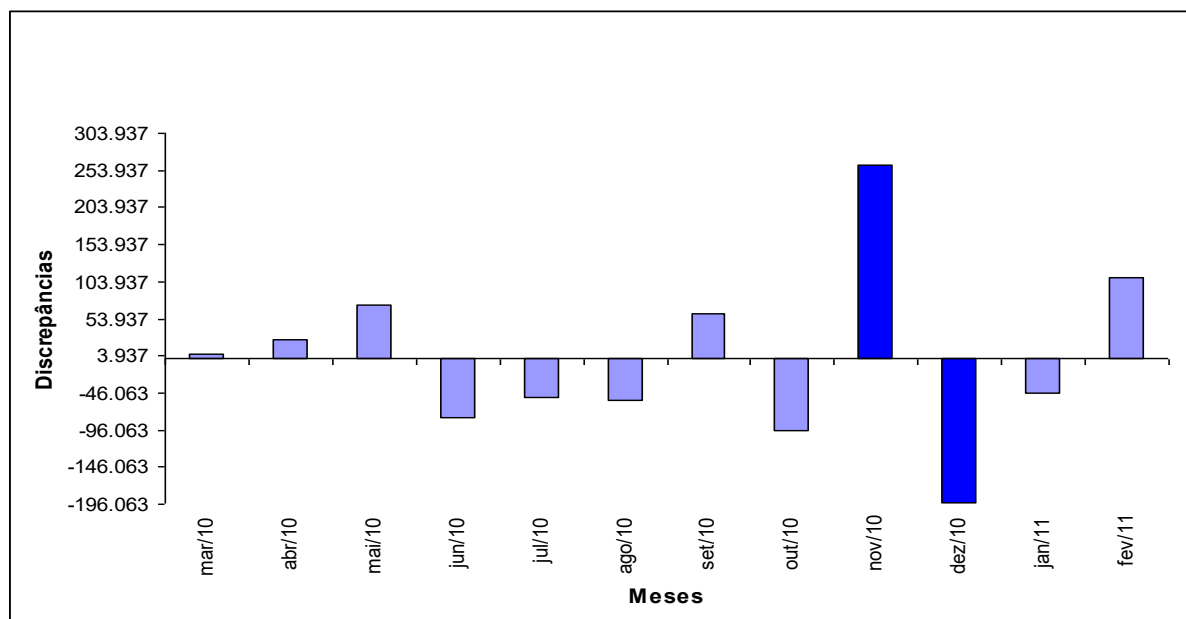


Source: developed by the Author.

However, two points that draw attention in the graph in Figure 2 are the months of November and December, in these two periods there is a very large distance between the observed point and the forecast. If we compare it with the same months of previous years, it is possible to see that in November 2010 there was a peak in the production of parts. This finding is reinforced by Figure 3, a bar graph of the forecast errors. In this Figure it is clear that the biggest errors occurred in the months of November and December 2010.

Figure 3

Graph of the discrepancies in the demand forecast



Source: developed by the Author.

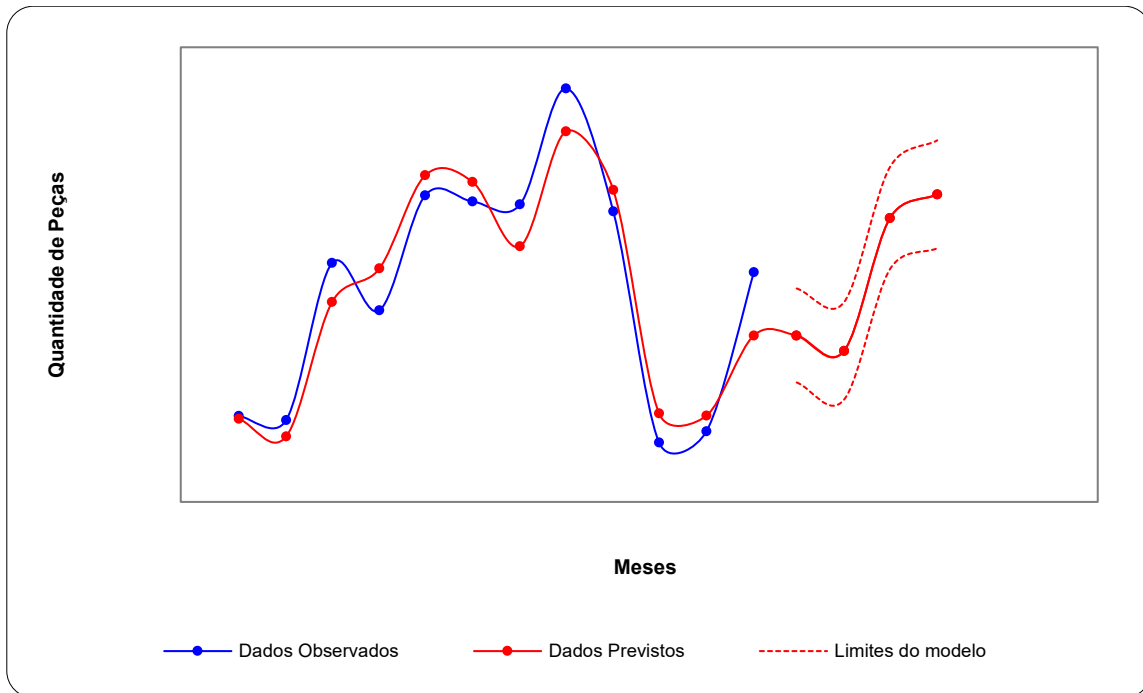
This anomaly, or *outlier*, as some authors refer to, can deteriorate the quality and assertiveness of the model used. According to SAMOHYL, *et al.* (2008), this data should be analyzed and worked on in the series to enable the model to have a better grip. Also according to this author, this analysis should be carried out at the source that generates the data, that is, the textile company studied.

When evaluating the reasons that caused this excess of production in November 2010, it was found that an important raw material for making the products was not delivered on the correct date, thus generating a delay of almost 11% in October. In this way, increasing the amount of production in the following month by an average of 18%.

Then, the data from the series were worked on in order to improve the model's adherence. These amounts were distributed according to the factory's production forecast, without considering the lack of raw material, between the months of October and December 2010. Thus, with a new data series, the demand forecast was redone and distributed in the graph, as shown in Figure 4.

Figure 4

Forecast Graph of the Holt Winter Additive model with new data series

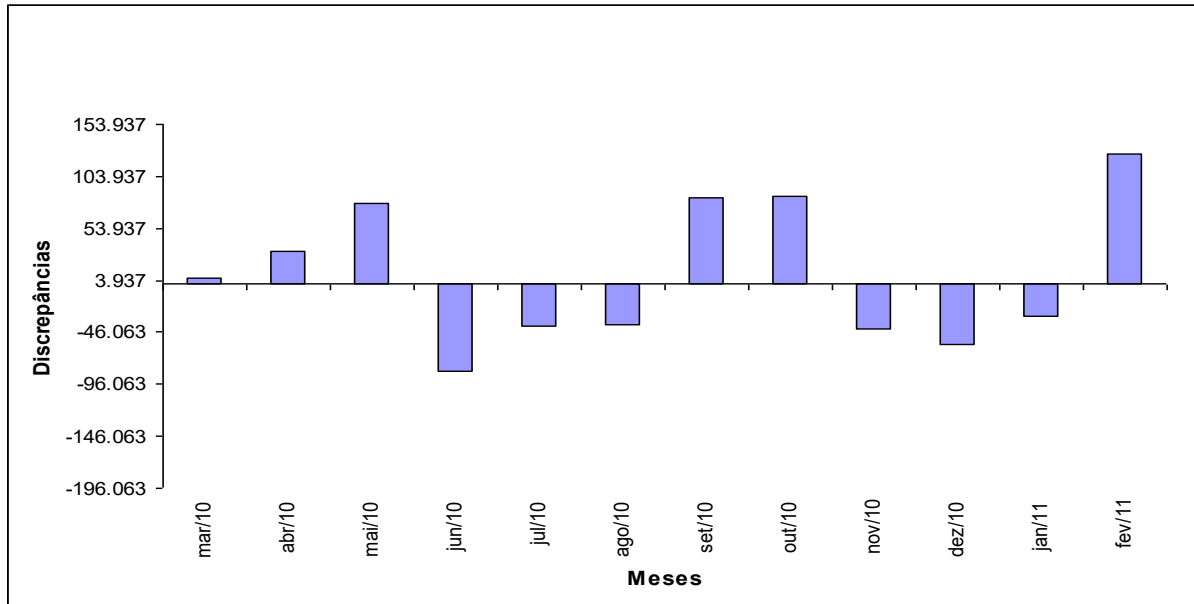


Source: developed by the Author.

Through the improvement of the data, the exponential model proved to have an even greater adherence to the analyzed series. Looking at Figure 5 and comparing it with Figure 3, it is possible to conclude that the errors generated with the optimization of the forecast are smaller and more consistent with the company's reality. According to Churchill *et al.*, (2003), an accurate demand forecast, which can be measured by the difference between what was predicted and what was accomplished, has a considerable impact on the organization's results. Thus, if the improvement in the forecast generates smaller errors, the company will be able to base its decisions with greater confidence on the data calculated by the method.

Figure 5

Graph of the discrepancies of the new demand forecast

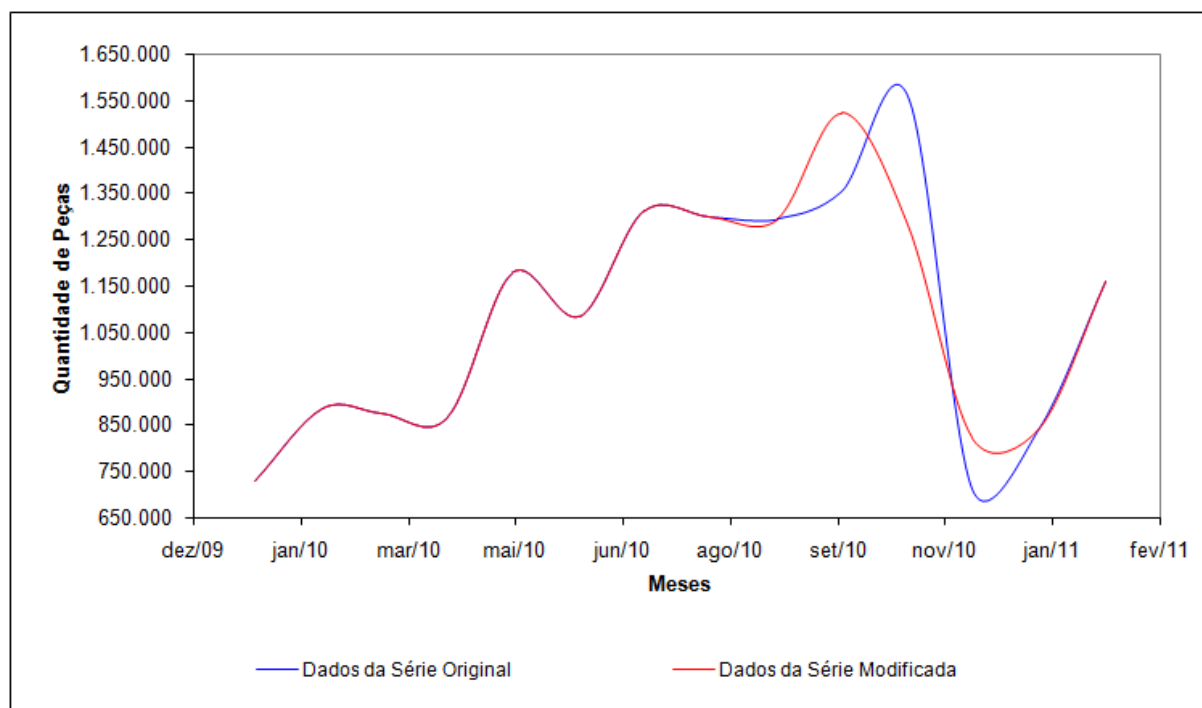


Source: developed by the Author

To evaluate the discrepancies of the model applied to the new series, the formulas in Table 3 were used again. The new forecast showed a mean absolute percentage error of 5.08%, with a U of Theil value of 0.312. These are significantly better values than the original series.

Figure 6

Graph of the data of the series



Source: developed by the Author.

Through figure 6 it is possible to evaluate the difference between the original data and the data worked. Thus, it is noted that the size of the amplitude between October and December was reduced, this decrease is smoother than in the original series, getting closer to the normal production conditions in the organization. Thus, the weighting of this figure reinforces the statement that performing demand forecasting activities is not limited to collecting data and using a solver to generate forecasts. Rather, collect, criticize and improve the data in order to represent well the situation to be analyzed.

5 FINAL CONSIDERATIONS

Performing demand forecasts is important to assist in determining the resources needed by the company, according to Makridakis *et al.* (1998). In times of fierce competition, this activity becomes fundamental, as it can contribute significantly to better decisions, avoiding unnecessary expenses. This work sought to demonstrate through an application of the Holt-Winters model how forecasting can be seen as a process in the company, that is, as something dynamic. The case of the demand forecast of the textile segment company served as an example that a forecasting model cannot be static. On the contrary, it necessarily needs

to be evaluated and improved, so that it can produce reliable forecasts, which really serve as support for managerial decision-making.

It was possible to observe in the data series that the textile sector has a very particular characteristic with very characteristic seasonal patterns in the annual cycles with periods of increasing and decreasing production that are repeated. The model chosen proved to be suitable for this type of data series. Having an optimal adherence, this opinion is reinforced through the calculations of the DPAM and Theil U discrepancy measures. During the data analysis, the data series showed to contain an anomaly in November 2010, this data was carefully evaluated with the company. After the understanding of this *outlier*, the data of the series were worked on and a new forecast was made. The results of the data treatment generated better predictions compared to the original series, with a reduction in the mean absolute discrepancy of 3% and also reducing the U of theil measurement by more than 6%.

From the study carried out, three implications can be drawn that deserve the reflection of those who are interested in predictions as a process:

- The prediction model needs to be continuously evaluated and improved through methods that contribute to identifying errors. With this, the results of the model can be adjusted, becoming adaptable to the changes that occur in the company.
- Data error analysis can be important to identify anomalies, thus making it possible to make the prediction model more effective.
- The analysis of the source of the data series also becomes relevant, because as in the case presented, it can generate discrepancies that negatively influence the model.

The task of making predictions is not just about applying models in data series, and thus generating results that will be used in important decisions within the company. This activity is more complex than it seems, because the people involved must understand the behavior of the data series and seek through critical observations, the improvement of the model. Thus, make predictions that demonstrate a behavior closer to the reality of the organization, increasing the credibility of the model and generating confidence in its use. Without this, the results can lead to decisions that do not match the market and the company.

REFERENCES

- Churchill, A. G., Jr., Ford, N. M., Hartley, S. W., & Walker, O. C., Jr. (2003). Sales force management (7th ed.). McGraw-Hill.
- Davis, M. M., Aquilano, N. J., & Chase, R. B. (1997). Fundamentos da administração da produção (3rd ed.). Bookman.
- Gaither, N., & Frazier, G. (2001). Administração da produção e operações (8th ed.). Pioneira.
- Hanke, J. E., Reitsch, A. G., & Wichern, D. W. (2001). Business forecasting (7th ed.). Prentice Hall.
- Hill, T. (1994). Manufacturing strategy: Text and cases (2nd ed.). Irwin.
- Lawton, R. (1998). How should additive Holt–Winters estimates be corrected? *International Journal of Forecasting*, 14(3), 393–403. [https://doi.org/10.1016/S0169-2070\(98\)00037-8](https://doi.org/10.1016/S0169-2070(98)00037-8)
- Makridakis, S. G., Wheelwright, S. C., & Hyndman, R. J. (1998). Forecasting: Methods and applications (3rd ed.). John Wiley & Sons.
- Martins, P. G., & Laugen, F. P. (2005). Administração da produção (2nd ed.). Saraiva.
- Pellegrini, F. R., & Fogliatto, F. S. (2001). Passos para a implantação de um sistema de previsão da demanda. *Revista Produção*, 11(2), 5–14. <https://doi.org/10.1590/S0103-65132001000200002>
- Samohyl, R. W., Souza, G., & Miranda, R. (2008). Métodos simplificados de previsão empresarial. Ciência Moderna.
- Wallis, K. F., & Thomas, J. J. (1971). Seasonal variation in regression analysis. *Journal of the Royal Statistical Society: Series A (General)*, 134(1), 57–72. <https://doi.org/10.2307/2343877>