A Model to Prevent Stockouts in Retail using Time Series Sales Forecasting

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ABSTRACT

Stockouts have a huge impact on retailers and customer satisfaction. In recent years, machine learning has proved useful for accurate time series sales forecasting. And accurate forecasts help retailers make accurate purchasing decisions. But a lot of retailers still rely on an old-fashioned way of forecasting. In this paper a model is proposed that aims to tackle this problem and provide retailers worldwide with a methodology to make time series sales forecasting using machine learning accessible. The proposed model is created and verified based on a case study at a large retailer. All steps needed for a retailer to gain valuable business understanding and make decisions that help to prevent stockouts are discussed, from data exploration, processing to the actual forecasting techniques. The research shows that every article needs to be handled individually to get the optimal results. While the implemented forecasting technique in the case study is more successful in maintaining a healthy inventory level, it is not able to prevent stockouts in all cases. The model could easily be extended with more advanced techniques, making it a valuable tool for retailers worldwide.

Keywords
Stockouts, Retail, Machine Learning, Sales Forecasting, Time Series, ARIMA

1. INTRODUCTION

The goal of retailers worldwide is to provide the right products at the right time while maintaining a healthy stock. Retailers need to have a good overview of how many items they have in stock and when they need to re-stock their merchandise. Despite modern sales forecasting techniques using machine learning, retailers still use a very traditional way of resupplying their stores [9]. To prevent stockouts, retailers often have large safety stocks [19]. But despite the safety stocks, the chance of a stockout is huge, with potentially a big impact on customer satisfaction and sales [7, 11]. To prevent stockouts and increase profitability, retailers need to have an accurate prediction of customer demand [19].

In recent years, many machine learning techniques have been used successfully for sales forecasting in retail. But because of the diversity of the retail sector, it is difficult for retailers to pick the optimal technique depending on the article and business domain. This could potentially lead to less accurate forecasts and ultimately to a stockout.

This research aims to tackle this problem and provide retailers worldwide with a methodology to make sales forecasting using machine learning accessible and effective. All steps needed for a retailer to gain valuable business understanding and make decisions that help to prevent stockouts will be discussed, from data exploration, processing to the actual forecasting technique(s).

The goal of this research is therefore to find out if and to what extent we can help in preventing stockouts in retail. The results will form the basis of a new model that can help retailers from different business domains make adequate decisions on when and which machine learning technique to use to tackle their inventory or sales problem. The proposed model will be based and verified on a case study at a large retailer.

Based on the aforementioned problems, this paper addresses the following research question:

How and to what extent can retailers prevent stockouts using sales forecasting?

The research question consists of sub-questions, based on the case study:

RQ1 What important details can be identified from the data set?
RQ2 Which methods are applicable for processing the data to be able to make a sales forecast?
RQ3 What machine learning techniques are applicable for sales forecasting and to what extent?
RQ4 To what extent can these forecasting techniques help to prevent stockouts?
RQ5 How can other retailers use the proposed techniques?

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2. RELATED WORK

A lot of literature has been published regarding sales forecasting, the causes and the impact of stockouts and opportunities for retailers when a stockout occurs.

Sales forecasting has always been a popular subject in literature, which makes sense because of the importance for retail to maintain a healthy inventory. Xia et al. (2012) identified two groups of forecasting methods, the classical methods based on mathematical and statistical models, and modern methods that use artificial intelligence like machine learning [19]. The classical methods are not always satisfactory when it comes to complex real-world problems. They proposed an extreme learning algorithm (ELM) with adaptive metrics of inputs to improve forecasting accuracy. The method outperformed other modern methods like auto-regression. Wong et al. (2010) also used ELM for medium-term fashion sales forecasting but integrated a harmony search algorithm to improve the network generalization performance [18].

Lastly, Chen et al. (2011) used a sales forecasting system based on Gray Extreme Learning Machine (GELM) [5]. The experimental results showed that GELM outperformed several sales forecasting methods which are based on back-propagation neural networks.

Chu et al. (2003) compared different linear and nonlinear models for retail sales forecasting and found that nonlinear models are able to outperform their linear counterparts [6]. The overall best model in their research was the neural network built on deseasonalized time series data. A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time [2].

A model that is often used in sales forecasting is the Bass model, which describes how products get adopted in the population, often used for new products. Lee et al. (2014) proposed a machine learning based approach to find the two most difficult and important variables of the Bass model [13]. Fan et al. (2017) also used the Bass model, but in a different context. They combined the Bass model with a sentiment analysis based on online reviews and historical sales data and found that it has a higher accuracy than the standard Bass model [10].

The causes of these stockouts also have been examined. Ehrenthal et al. (2013) indicate that the causes of retail stockouts are specific to the retailer, store, category and product [9], there is no solution that works everywhere. This partially explains why stockouts still occur today.

The impact of a stockout is more costly than most competitors imagine, Consten et al. (2004) found that in a study with more than 600 retail outlets [7]. Campo et al. (2004) researched what consumers buy in a category during a out-of-stock period and found that these periods can affect all three purchase decisions: reducing the probability of purchase incidence and lead to purchase of smaller quantities. One year later these researchers discussed the differences and similarities of stockouts and permanent assortment reductions [3]. Sloot et al. (2005) identified what effect brand equity and the hedonic level of products have on the decision making of consumers in case of a stockout [15]. Intended behavior during a stockout can however differ from the actual behavior, Zinn et al. (2008) found that the intended behavior is a good indicator when the customer quits the search but rather poor when customers delay the search [20].

Ehrenthal et al. (2013) proposed a procedure to help store managers in reducing the change of a stockout to below the global average of 8.3 percent [9]. Peinkofer et al. (2016) investigated the impact of limited inventory availability disclosure on customer responses, but in contrast to their hypothesis that it would increase customer competition and therefore decrease the negative impact, the results showed that customers were actually more dissatisfied. Improvements to store operations, coordination of store delivery and shelf replenishments are described as key factors in reducing stockouts [14]. Breugelmans et al. (2006) investigated three scenarios in a stockout period and found that suggesting a replacement slightly reduces the purchase cancellation rate. This effect however disappears when replacement products are significantly more expensive [1].

3. METHOD OF RESEARCH

This research is based on a case study at a large fashion retailer with more than a 100 stores. The retailer selected so-called ‘continuity articles’, which means that they may never be out of stock. In order to forecast sales and prevent stockouts, one first needs to explore the data. The aim of the data exploration is to discover important details and correlations that might be of interest later on, this is done by visualizing the data. The data will be aggregated to fixed periods, so the forecasting can be treated as a time series problem.

To make the data set ready for forecasting, one needs to process the data. A data warehouse will be created that contains all the important sales facts, such as the respective article and store. With the data warehouse in place, one is more flexible to experiment with different approaches. Many time series forecasting models rely on the model to be stationary, so multiple techniques and transformations will be tested to see which one fits a particular article and yields the best results.

When the data is processed and ready to be used for forecasting sales, a forecasting method will be used to see to what extent it can accurately forecast sales. The results will be compared to other forecasting techniques such as the ELM proposed by Xia et al. (2012) [19]. Validation of the results is a crucial part in this research. By dividing the available data in a training and testing set, the accuracy of the forecasting techniques can be identified. This will be done using the root mean squared error (RMSE), because it gives retailers a logical impression of the performance if compared to other forecasting techniques. The RMSE will also be combined with the average sales to give retailers an idea of the actual accuracy of the technique.

Based on the results of the previous steps, a model will be constructed that can help retailers from all branches to implement and use time series forecasting techniques. The model should be self explanatory. The results will be discussed and also how the model can be implemented and extended. To be able to answer the research question, the model and sales forecasting technique are validated. This is done by checking whether the sales forecasting model is able to lower the chance of a stockout, by combining and comparing the sales forecasting technique with the actual stock level data.

The final step is to conclude the research and to validate to what extent other retailers could benefit from the proposed model. But also to identify its limitations and what future work is needed to make the model more applicable for retailers worldwide.
Table 1. Articles used in this data set.

<table>
<thead>
<tr>
<th>Article</th>
<th>Target Group</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Article 1</td>
<td>men</td>
<td>pants</td>
</tr>
<tr>
<td>Article 2</td>
<td>men</td>
<td>t-shirts</td>
</tr>
<tr>
<td>Article 3</td>
<td>men</td>
<td>t-shirts</td>
</tr>
<tr>
<td>Article 4</td>
<td>men</td>
<td>denim</td>
</tr>
<tr>
<td>Article 5</td>
<td>men</td>
<td>denim</td>
</tr>
<tr>
<td>Article 6</td>
<td>women</td>
<td>denim</td>
</tr>
<tr>
<td>Article 7</td>
<td>boys</td>
<td>t-shirts</td>
</tr>
<tr>
<td>Article 8</td>
<td>boys</td>
<td>denim</td>
</tr>
<tr>
<td>Article 9</td>
<td>girls</td>
<td>denim</td>
</tr>
<tr>
<td>Article 10</td>
<td>girls</td>
<td>denim</td>
</tr>
</tbody>
</table>

4. DATA EXPLORATION

The first step in data analysis is to explore and visualize the data, gaining valuable insights.

The data set consists of weekly sales and stock data from a large fashion retailer operating in The Netherlands, Belgium and Luxembourg. The time period of the data ranges from July 2016 till May 2017. Ten articles have been selected that are labeled as ‘continuity articles’, which means they should always be in stock, making those the most interesting for this case study. The details of the ‘continuity articles’ can be found in Table 1.

For the remainder of this section, three articles have been selected to increase the readability.

As can be seen in Figure 1, the pieces sold are very different per article. Whereas article 9 and 10 have a minor positive trend, article 3 is sold at a steady rate. The graph also shows that the seasonality for article 10 is very high. The peaks in October and November can partially be explained by the fact that those articles where sold with a discount in that period, as shown in Figure 2. However, a discount does not necessarily imply that article sales will increase during a sale period, a high discount on article 3 did not significantly increase the sales.

These insights indicate that not all articles can be treated equally, because of their huge differences in trend, seasonality and discount dependence.

5. DATA PROCESSING

The next step in the analysis is the processing of the data. In this section the data processing is discussed, starting in section 5.1 with an initial processing step namely creating a data warehouse and in section 5.2 stationarity techniques are discussed.

5.1 Data Warehouse

A data warehouse was created containing all the facts. The star schema can be found in Figure 3.

5.2 Stationarity

A time series is said to be stationary if its statistical properties such as mean and variance remain constant over time. This is important because most time series models work on the assumption that the data is stationary. Let \( \{X_t\} \) be a stochastic process and let \( F_X(x_{t_1+\tau}, \ldots, x_{t_k+\tau}) \) represent the cumulative distribution function of the joint distribution of \( \{X_t\} \) at times \( t_1 + \tau \). Then \( \{X_t\} \) is said to be stationary if, for all \( k \), for all \( \tau \), and for all \( t_1, \ldots, t_k \), \( F_X(x_{t_1+\tau}, \ldots, x_{t_k+\tau}) = F_X(x_{t_1}, \ldots, x_{t_k}) \). Since \( \tau \) does not affect \( F_X(\bullet) \), \( F_X \) is not a function of time [2].

To test the stationarity of a time series the Augmented Dickey-Fuller (ADF) test is used [8].

The ADF test for a unit root assesses the null hypotheses of a unit root using the model:

\[
y_t = \epsilon + \gamma t + \omega y_{t-1} + \beta_1 \Delta y_{t-1} + \ldots + \beta_p \Delta y_{t-p} + \epsilon_t
\]

Where:

- \( \Delta \) is the differencing operator, such that \( \Delta y_t = y_{t-1} \).
- The number of lagged difference terms, \( p \), is user specified.
- \( \epsilon_t \) is a mean zero innovation process.
The null hypothesis of a unit root is: \( H_0 : \varphi = 1 \).

Under the alternative hypothesis, \( \varphi < 1 \). Variants of the model allow for different growth characteristics. The model with \( \varphi = 0 \) has no trend component, and the model with \( c = 0 \) and \( \varphi = 0 \) has no drift or trend. A test that fails to reject the null hypothesis, fails to reject the possibility of a unit root.

A lot of products in the data set are far from stationary. That is why in this paper multiple techniques are implemented which aim to transform the original time series to a more stationary version. The underlying principle is to model or estimate the trend and seasonality in the series and remove those to get a stationary series [2].

Transformations are used first to reduce trend in a simple but sometimes effective way, the log of a time series for example can be useful for series with a positive trend, because it penalizes higher values more than lower values. The following transformations are used: none, the log of the series or the square root of the series.

The transformed series with the highest confidence of a stationary series (tested with the ADF test) will be used in the techniques that are mentioned next.

A common approach is the Moving Average (MA). This approach takes the moving average based on the frequency of the time series. Note that if this approach takes the average of the last \( n \) values, then the rolling mean will not be defined for the first \( n - 1 \) values. This technique can be used in combination with the log transform. A drawback of the aforementioned technique is that the time period has to be strictly defined. This makes the technique less useful in complex situations [2].

An alternative for the MA is the Exponentially Weighted Moving Average (EWMA), where a weight is assigned to all previous values with a decay factor. The difficulty in this technique is determining the halflife or amount of exponential decay. This depends strongly on the business domain [2].

Differencing is a more advanced technique which works better in cases with high seasonality. Differencing is taking the difference of an observation with that of the previous one. An example of how differencing was used successfully in the case study can be found in Figure 4 where the rolling mean became much more stable therefore increasing the stationarity of the series. A window of 10 was used, that explains why the first 9 weeks have no rolling mean and standard deviation [2].

What is interesting about the data set when using these trend and seasonality eliminating techniques is that every article requires a different technique and transformation. As can be seen for three articles in Table 2. The results for all articles can be found in Appendix A. The techniques are very successful in making the series stationary, for all articles, the stationary confidence levels can be increased to at least 98%. To illustrate the importance of this adaptive approach, Table 3 contains the confidence levels if the worst technique were used. While the confidence levels are still high, the confidence of article 4 declined.

**Table 2. Transformations (TR) and trend/season techniques (TS) used to get the highest level of confidence the series is stationary.**

<table>
<thead>
<tr>
<th>Article</th>
<th>ADF</th>
<th>TR</th>
<th>TS</th>
<th>ADF end</th>
</tr>
</thead>
<tbody>
<tr>
<td>Article 1</td>
<td>70.59%</td>
<td>log</td>
<td>MA</td>
<td>99.96%</td>
</tr>
<tr>
<td>Article 6</td>
<td>86.23%</td>
<td>log</td>
<td>EWMA</td>
<td>100.00%</td>
</tr>
<tr>
<td>Article 7</td>
<td>51.70%</td>
<td>as is</td>
<td>MA</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

**Table 3. Techniques and transformations used that return the worst result.**

<table>
<thead>
<tr>
<th>Article</th>
<th>ADF</th>
<th>TR</th>
<th>TS</th>
<th>ADF end</th>
</tr>
</thead>
<tbody>
<tr>
<td>Article 1</td>
<td>70.59%</td>
<td>as is</td>
<td>EWMA</td>
<td>95.19%</td>
</tr>
<tr>
<td>Article 4</td>
<td>99.87%</td>
<td>log</td>
<td>Differencing</td>
<td>98.87%</td>
</tr>
<tr>
<td>Article 7</td>
<td>51.70%</td>
<td>log</td>
<td>EWMA</td>
<td>99.96%</td>
</tr>
</tbody>
</table>

6. RESULTS

In this section the forecasting results are discussed in section 6.1. The forecasting results combined with the results from the previous sections are combined into the proposed model discussed in section 6.2.

6.1 Sales Forecasting

Having the techniques and transformations in place to make any time series stationary, one can start using models to forecast the sales for a particular article. In this paper, the Autoregressive Integrated Moving Average model (ARIMA) is used. ARIMA is generally the model used to forecast times series and other more complex models are often compared with the results of the ARIMA model [2]. For validation purposes the training data consists of the data from 2016 and the test data will be the available data in 2017.

The ARIMA model is a popular technique used for time series forecasting. The model can be defined as:

\[
y_t = c + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} + e_t
\]

Where \( y_t \) is the differences series. The predictors on the right hand side include both lagged values of \( y_t \) and lagged errors. We call this an ARIMA(\( p, d, q \)) model, where:

- \( p \) = order of the autoregressive part;
- \( d \) = degree of first differencing involved;
- \( q \) = order of the moving average part;

![Figure 4. Two figures that illustrate the rolling mean and standard deviation of the sales of article 7, both originally and after differencing.](image-url)
Table 4. The RMSE of the ARIMA(2,1,1) model.

<table>
<thead>
<tr>
<th>Article</th>
<th>Average RMSE</th>
<th>RMSE %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Article 1</td>
<td>42.59</td>
<td>12.08</td>
</tr>
<tr>
<td>Article 2</td>
<td>443.13</td>
<td>72.81</td>
</tr>
<tr>
<td>Article 3</td>
<td>103.02</td>
<td>18.05</td>
</tr>
<tr>
<td>Article 4</td>
<td>555.71</td>
<td>217.57</td>
</tr>
<tr>
<td>Article 5</td>
<td>517.41</td>
<td>241.07</td>
</tr>
<tr>
<td>Article 6</td>
<td>395.83</td>
<td>286.64</td>
</tr>
<tr>
<td>Article 7</td>
<td>201.54</td>
<td>52.83</td>
</tr>
<tr>
<td>Article 8</td>
<td>413.10</td>
<td>143.67</td>
</tr>
<tr>
<td>Article 9</td>
<td>384.54</td>
<td>162.37</td>
</tr>
<tr>
<td>Article 10</td>
<td>591.98</td>
<td>397.95</td>
</tr>
</tbody>
</table>

Selecting appropriate values for $p$, $d$ and $q$ can be difficult. Often the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are plotted to determine $q$ and $p$, $d = 1$ because the series is differenced once [2]. In Appendix B, the ACF and PACF plots of article 10 can be found as well as an explanation on how to pick the optimal values for $p$ and $q$. The implementation used in this paper is ARIMA with $p = 2$, $d = 1$ and $q = 1$, because it was able to produce good results for all articles. It is important to note that it would be better to fit different ARIMA models for different time series. Using this implementation the root mean squared errors (RMSE) of the articles were found, see Table 4. The RMSE is only useful when comparing the accuracy of multiple techniques, because it is scale dependent [12]. Therefore the RMSE % reflects the average error percentage of the average pieces sold in a week.

For all articles in the data set the forecasts can be found in Appendix C. It is important to note that the stock levels are also taken into account, assuming there is no initial stock. This way one is able to see the impact on the stock if the purchasing department would buy according to the sales forecast. When starting with no initial stock, 6 articles would go out of stock.

If one takes the implemented ARIMA model and the stock at the end of the last week of 2016, the forecasts show promising results. Even though the forecast is somewhat off, the stock levels remain more constant over time with the forecasts than the actual stock levels in 2017. The forecast of article 4, 6 and 10 can be found in Figure 5. Almost all articles reduced the amount of stock needed for these articles. Therefore, if the forecasting model was used as the only input for the purchasing department, costs of stock would decrease substantially. All stock forecasts can be found in the Appendix D.

There is a side note however, the model forecasts the sales of an article but does not take into account the different variations of the articles, such as colors and sizes. It also does not forecast the distribution for hundreds of stores. This is because if all article variations and stores were taken into account, forecasting would become very difficult as the sales of a specific article in a specific store would most of the time be zero. But despite the precision, this forecasting technique could help the retailer maintain a healthy inventory on a country or region wide level. To be able to make a forecast for all variations and stores, a more complex and complete sales forecasting technique needs to be implemented, for example the (G)ELM techniques proposed by Xia et al. (2012) and Wong et al. (2010) [19, 18].

Figure 5. The actual and predicted sales, as well as the stock levels for article 4, 6 and 10.

6.2 Model for retail sales forecasting

The aim of this research was to give retailers worldwide a model or approach to tackle time series problems. Based on the steps taken in the case study, a model has been created. The proposed model can be found in Figure 6 and is partially based on the CRISP-DM model [17], a model that is a data mining process model that describes commonly used approaches that data mining experts use to tackle problems. The following subsections discuss the steps in the model in more detail. The goal of the model is for retailers to gain business understanding that help in making important business decisions.

In order to be able to process the article data efficiently, retailers should construct a data warehouse containing all the important and changing facts. This makes faster analysis and on-line analytical processing (OLAP) possible, crucial for retailers with hundreds or even thousands of articles. Chaudhuri et al. (1997) provide an overview of data warehousing and OLAP technologies that retailers could use [4]. The model is build on the assumption that there is a data warehouse in place before continuing.
one needs to transform the time series back to its original mean squared error (RMSE). It is important to note that given time series problem concerning an article. To implemented and tested to see which one works best for the Here one or multiple forecasting techniques could be im-
phased and the optimal technique is always used.

Another recursive step in the model is forecasting phase. The results of the ARIMA forecast where different based count to see whether it could help in preventing stockouts. (RQ4) The actual stock levels and the forecast of the articles were taken into ac-

7. CONCLUSION

In this paper, the following research question is addressed: 

How and to what extent can retailers prevent stockouts using sales forecasting?

(RQ1) The most important details that could be identi-

(RQ3) The Autoregressive Integrated Moving Average (ARIMA) model has been used to make sales forecasts for the articles. The model showed promising results as it performed quite well in forecasting sales. However, more advanced techniques proposed in the literature have the potential to outperform it and make the forecast more reliable. (RQ4) The actual stock levels and the forecast of the articles were taken into account to see whether it could help in preventing stockouts. The results of the ARIMA forecast where different based on the article. This can partially be explained because just the basic implementation of the ARIMA model was used, without any optimization. Most forecasts however would lead to a lower stock levels, which means lower in-

6.2.4 Evaluation

Even though the previous step automatically picks the optimal forecasting technique. It is important to evaluate the steps taken and the accuracy of the forecasts, because even though the optimal steps are taken, the results could still be unsatisfactory. The accuracy can be tested by combining and comparing the sales forecast with the actual stock levels to see the impact. Before proceeding to the deploy-

6.2.5 Deployment

When one knows which data preparation and forecasting techniques work well for a given article, one can deploy the technique to support business decisions. Depending on the requirements, the deployment phase could be generating a report, but also more complex such as creating an algorithm that the retailer could use to make forecasts.
color and store would be taken into account. More advanced techniques are required to make proper forecasts on such a small scale. (RQ5) In this paper a model is proposed that takes all steps taken in this case study into account. The model is adaptive, which means that it is able to pick the most accurate path for making time series forecasts. The model needs to be repeated for each article, because no article is the same and to make it compatible with retailers from different sectors. The model can easily be implemented in the form of an algorithm and can be extended to use more techniques if required.

The used forecasting technique is far from perfect, the proposed model however, provides retailers with a method to handle advanced time series problems in a concise and easy to understand manner.

8. LIMITATIONS

The proposed model is based on the assumption that not one forecasting method fits all and that multiple should be implemented to get optimal results. This holds true for making the data stationary, but its not implemented and tested for forecasting. The model is tested on aggregated weekly sales data across all stores in the case study and has not been tested on a store level, or variants of the articles.

9. FUTURE WORK

Based on the limitations mentioned in the previous section, future work is needed to:

• validate the model with more different retailer data sets.
• improve the current sales forecasting technique.
• add new, more advanced forecasting techniques.
• create an algorithm that is able to make forecasts based on the model.
• include article variants and aggregation techniques.

10. ACKNOWLEDGEMENT

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11. REFERENCES

APPENDIX

A. STATIONARITY TABLE

In Table 5 the results of the Augmented Dickey-Fuller test (ADF) can be found if the optimal transformation and technique are used. Apart from article 4, all articles would reach a ADF confidence of more than 99%.

<table>
<thead>
<tr>
<th>Article</th>
<th>ADF start</th>
<th>Transformation (TR)</th>
<th>Trend and seasonality (TS)</th>
<th>ADF end</th>
</tr>
</thead>
<tbody>
<tr>
<td>Article 1</td>
<td>70.5858146283</td>
<td>log</td>
<td>MA</td>
<td>99.9640817419</td>
</tr>
<tr>
<td>Article 2</td>
<td>93.3127505709</td>
<td>log</td>
<td>MA</td>
<td>99.9999897913</td>
</tr>
<tr>
<td>Article 3</td>
<td>99.9995666287</td>
<td>log</td>
<td>MA</td>
<td>99.9999999862</td>
</tr>
<tr>
<td>Article 4</td>
<td>99.8696573623</td>
<td>as is</td>
<td>MA</td>
<td>98.8683384923</td>
</tr>
<tr>
<td>Article 5</td>
<td>51.4311988562</td>
<td>log</td>
<td>MA</td>
<td>99.9311811191</td>
</tr>
<tr>
<td>Article 6</td>
<td>86.2275066794</td>
<td>log</td>
<td>EWMA</td>
<td>99.998564317</td>
</tr>
<tr>
<td>Article 7</td>
<td>51.703000125</td>
<td>as is</td>
<td>MA</td>
<td>99.9999998881</td>
</tr>
<tr>
<td>Article 8</td>
<td>99.880438209</td>
<td>log</td>
<td>MA</td>
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B. ACF AND PACF PLOT

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of article 10 can be found in Figure 7. In this plot, the two dotted lines on either sides of 0 are the confidence intervals. The plot can be used to pick the optimal $p$ and $q$ values for the ARIMA($p, d, q$) model [2]:

- $p$ - The lag value where the PACF chart crosses the upper confidence interval for the first time.
- $q$ - The lag value where the ACF chart crosses the upper confidence interval for the first time.

![Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)](image)

Figure 7. The ACF and PACF plot of article 10.

For article 10, this would mean ARIMA(1,1,1) would be optimal, assuming the series is differenced once ($d = 1$).
C. FORECASTS WITHOUT INITIAL STOCK

In Figure 8 the forecasts without initial stock are visualized. The stock level is therefore defined as the sum of the sales forecast minus the sum of the actual sales to see what will happen over time.

Figure 8. Sales forecast and the effect on the stock level assuming there is no initial stock.
D. ACTUAL VS. FORECASTED STOCK LEVELS

In Figure 9 the actual stock levels of the retailer are visualized, but also the stock levels if the retailer would decide to purchase exactly according to the sales forecast. The forecasts can be found in Appendix C.

Figure 9. Impact of the sales forecast on actual stock.