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Seasonal Data Cleaning for Sales with Chase Demand Strategy

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Abstract: The intricate process of planning production, involving product life cycle management and the synthesis of manufacturing information, is crucial for coherence in manufacturing. Manufacturing companies, operating in a high-mix, low-volume production environment, integrate production planning with management to focus on production processes, emphasizing high-quality, rapid product delivery. This includes material item planning to anticipate future demands and ensure sufficient raw material and finished product quantities, considering purchasing, production, and sales capacities. This study explores the electro technical sector, specifically a manufacturing entity specializing in low-voltage plastic cable distribution boxes. It scrutinizes the vital role of seasonal data cleaning in optimizing production planning, with a targeted focus on three products. The implementation of a chase demand strategy is related to capacity planning, taking into account the change in production capacity linked to demand over time. The problem in implementing this strategy is related to the fluctuating level of quality due to changes in demand for specified products.

Keywords: seasonal data cleaning; production planning; sales prediction; chase demand strategy

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1. Introduction

The significance of data cleaning, especially in time series analysis, where outliers wield considerable influence on data quality, cannot be overstated. Ref. [1] emphasizes the critical role of effectively identifying and handling outliers as a core objective of data cleaning, highlighting its application in the case study company. This approach aims to enhance overall data quality, subsequently improving the precision of forecasts—an indispensable factor for decision-making processes, enabling more effective planning, resource allocation, and risk management.

Time series analysis, vital for understanding indicator trends, necessitates attention to both overarching patterns and the intensity of fluctuations, be they seasonal or cyclical, across various economic phenomena. Addressing and, if feasible, mitigating the underlying causes of these fluctuations becomes crucial.

In the realm of production lines, short-term fluctuations occurring during specific hours often require organizational interventions in planning processes. However, in sectors like agriculture, construction, and tourism, intrinsic seasonality poses challenges that may be impractical to completely eliminate. Here, production planning's primary goal is to meet product demand, manage inventory, and ensure appropriate pricing.

2. Literature Review

The topic of seasonal data cleaning is of paramount importance, as it directly impacts the quality and reliability of data used in various domains. Several key articles focus on the nuances and challenges associated with seasonal data cleaning. Ref. [2] presents a case study in the automotive industry, where machine learning is applied to predict the sales of four-wheeler (4W) units. This demonstrates the relevance of seasonal data cleaning in optimizing sales predictions and distribution strategies.

Sales forecasting is a pivotal aspect of business strategy, and recent research sheds light on enhancing accuracy and understanding the multifaceted factors influencing sales dynamics. Ref. [3] tackle the intricacies of forecasting by addressing the challenge of integrating multiple drivers into traditional models, proposing innovative techniques like dimensionality reduction and shrinkage estimators. The study's empirical results demonstrate the effectiveness of these approaches in improving forecast accuracy, with considerations for both promotional and non-promotional periods. Ref. [4] further underscore the strategic importance of accurate sales predictions, advocating for positive operational cash flow, continuous client pursuit, and diversification to navigate seasonal fluctuations.

Additionally, ref. [5] utilizing the example of cosmetic industry, analysing factors influencing product sales using statistical methods and emphasizing the significance of accurate sales forecasting across various aspects of the supply chain. Meanwhile, ref. [6] explores the unsustainable practice of product destruction, highlighting the downstream factors contributing to this phenomenon and reinforcing the critical role of accurate sales forecasts in efficient inventory management and waste reduction. Together, these studies contribute to a comprehensive understanding of sales dynamics, emphasizing the need for advanced forecasting techniques and strategic planning to navigate the complexities of modern business environments.

Ref. [7] explores the broader context of cleaning big data streams, emphasizing the challenges posed by continuous data generation and the limitations of traditional data cleaning methods. They highlight the importance of addressing common issues in data cleaning, including missing values, duplicated data, outliers, and irrelevant data, within the context of big data streams. Ref. [8] survey delves into the specific challenges and methods of cleaning time series data. Their work underscores the importance of data cleaning in time series data, which often exhibit seasonal patterns. They categorize time series errors, including those related to seasonality, and discuss the necessity of minimizing modifications to the original data.

Ref. [9] delve into the domain of short-term load fore-casting (STLF) in the electric power industry. Accurate STLF is crucial, and the article emphasizes that data cleansing is an initial step to improve data quality. The article showcases the practical application of data cleaning techniques, including addressing outlier detection and missing data, within a domain that experiences seasonality in energy demand. Ref. [10] focuses on the forecasting of seasonal time series data using machine learning methods. They discuss the significance of accurately forecasting parameters with seasonal variability and the application of various machine learning techniques to address seasonal data. This research highlights the practical use of data cleaning in achieving accurate and efficient short-term forecasts in real-time control systems.

In the domain of manufacturing operations, effective production planning is crucial for ensuring efficiency and competitiveness. Ref. [7] emphasizes the importance of real-time data cleaning in managing large volumes of data, particularly in high-mix, low-volume production environments. Their insights address challenges in data analysis, aligning with the precision needed for production planning amidst structural changes and data quality issues. Ref. [9] provide valuable insights into data-driven modeling for short-term load forecasting, emphasizing the significance of data cleansing techniques. Their focus on outlier removal and imputation methods contributes to enhancing data quality, crucial for accurate forecasting in large-scale manufacturing projects where production plans heavily rely on predictive models.

Ref. [8] survey on time series data cleaning techniques is relevant to anticipating future demands during production planning. Their classification of errors in time series data, including continuous errors, aligns with the need for precision in forecasting to avoid disruptions in the production process. The exploration of challenges and future directions in time series data cleaning emphasizes adapting techniques to evolving data patterns, crucial for dynamic production planning. In the realm of qualitative data, ref. [11] stress the importance of coding for decision-making. Their systematic approach to the coding process resonates with the meticulous handling of diverse information in production planning. As production plans involve a mix of qualitative and quantitative data, their insights provide a valuable perspective for ensuring the reliability of information used in production decision-making.

The importance of seasonal data cleaning is evident across diverse domains, from automotive sales to energy forecasting and beyond. These review collectively underscore the significance of data cleaning in addressing the unique challenges posed by seasonal data, ensuring the reliability and utility of the information for a wide range of applications.

The process of planning production is a critical aspect of manufacturing operations, requiring careful consideration to ensure efficiency and competitiveness in the market. In the context of high-mix, low-volume production environments, production planning takes center stage as companies strive to meet the challenges of delivering high-quality products swiftly.

The diverse domains, ranging from automotive sales to energy forecasting, collectively emphasize the criticality of seasonal data cleaning. This review underscores the paramount significance of data cleaning in addressing the unique challenges posed by seasonal data, ensuring the reliability and utility of information across a myriad of applications.

3. Problem Formulation

Inventory optimization represents a complex project that spans across all parts of the company's value chain. Inventories are a crucial aspect of management, and their proper configuration influences the efficiency of procurement, production, logistics, sales, and asset management. For the successful implementation of inventory reduction projects, it is essential for the company to thoroughly understand where and why inventories arise and subsequently involve and motivate all relevant departments. The overall success of the project depends on proper project management and effective collaboration between different areas of the business.

Inventory management is therefore an interdisciplinary task that requires collaboration from various departments. To achieve optimal results, it is essential for each department to fulfill its role in the overall context of the project. Properly motivating employees in the purchasing, production, logistics, sales, and asset management departments is crucial for fostering cooperation and engagement that lead to effective inventory reduction and overall improvement in the company's performance.

A high level of inventory freezes the movement of financial resources, necessitates the creation of continually new storage spaces, leading to the depreciation of long-stored materials and finished products (examples include corrosion, aging of certain materials, exceeding expiration dates, and many other forms of deterioration), which can result in production stoppages. This, in turn, leads to a loss of sales revenue and a loss of customer trust. The goal of a manufacturing company is to manage/optimize its inventory in a way that ensures smooth production operations, meets customer demands, and minimizes storage costs.

The problem addressed (Figure 1) in the presented contribution focuses on identifying the seasonal component with a focus on product sales. In solving this problem, it is necessary to identify the periods of decline and increase in product sales. In the case of detecting significant seasonal fluctuations, it is essential to eliminate these fluctuations and equalize the sales of products.

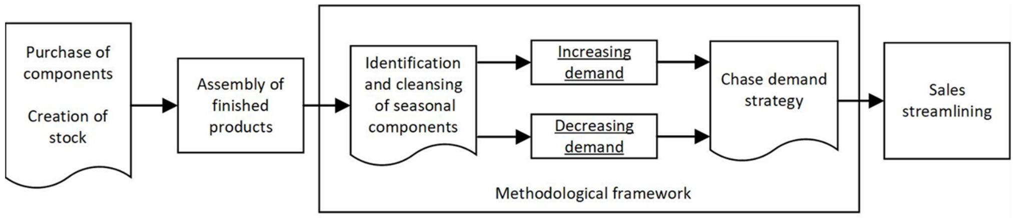

Figure 1. Sales imbalance.

The proposed methodological framework aims to bridge the gap between cleansing data from seasonal influences and implementing the chase demand strategy. By providing steps for effective data cleansing to eliminate seasonal biases, this framework provides organizations with a structured approach to optimize demand tracking. It emphasizes accurately identifying and mitigating the impact of seasonal fluctuations while integrating insights into the chase demand strategy for enhanced operational efficiency. This development signifies an advancement in demand management and strategic planning, offering valuable insights into leveraging these practices for more accurate demand forecasting and streamlined sales processes. Overall, this framework contributes to academic literature, providing actionable strategies for businesses to optimize operational processes amid seasonal variations.

4. Materials and Methods

The decomposition method (Figure 2) is a fundamental approach for analysing time series. It involves decomposing a time series into four components: trend (T), seasonal (S), cyclical (C), and random (ε). A good decomposition reveals underlying insights and aids in further analysis, including anomaly detection and forecasting. Decomposition helps identify patterns and fluctuations in different components, such as spikes and dips corresponding to changes in the remainder or mean anomalies corresponding to changes in trend [12]. The trend component (T_t) represents the long-term pattern in the values of the analyses indicator over time. It captures the overall tendency, which can be falling, rising, or stagnant.

The seasonal component (S_t) represents the regular, recurring patterns that occur within a specific period. Seasonal changes are influenced by factors like changing seasons, holidays (such as Christmas and Easter), vacations, and other periodic events. Seasonal patterns in time series data pose challenges for analysis, and a good seasonal-trend decomposition is crucial for revealing insights and facilitating anomaly detection and forecasting [12].

The cyclical component (C_t) represents fluctuations around the trend caused by cyclical influences with a duration longer than one year. Examples include the production cycle, economic cycles, and varying lengths and rates of growth and decline in the time series. This component is particularly relevant for macroeconomic analysis. The occurrence, intensity, and duration of cycles are not precisely predictable. The random (or irregular) component (ε_t) captures random fluctuations that do not follow a systematic pattern. Even after removing the trend, seasonal, and cyclical components, random influences remain in the time series. These fluctuations are unrelated to specific factors and exhibit no discernible pattern. They result from unpredictable events such as epidemics, strikes, earthquakes, major droughts, or other unidentified influences of a random nature.

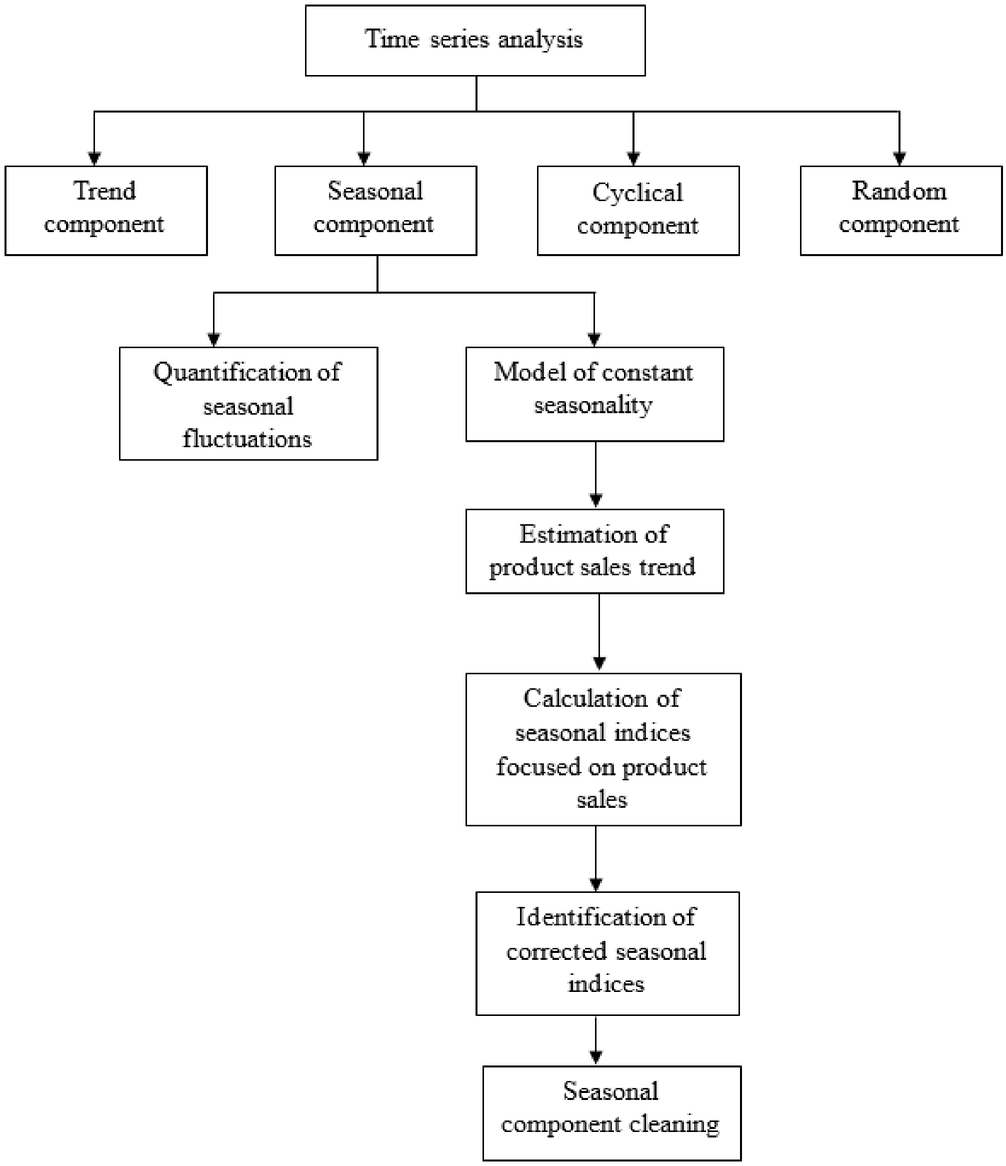

Figure 2. Specification of time series components.

When choosing between an additive or multiplicative model for decomposition, an additive model is suitable if the magnitude of the seasonal fluctuations remains constant regardless of the time series' level, while a multiplicative model is appropriate if the seasonal fluctuations increase or decrease proportionally with the level of the series. In economic series, the multiplicative decomposition is more prevalent as seasonal variations tend to increase with the level of the series. Alternatively, instead of deciding between additive and multiplicative decomposition, one can opt to transform the data before performing the decomposition [13]. The sum of the seasonal and cyclical components represents the periodic component of the time series:

$$P = S + C \tag{1}$$

when analysing a time series, it is common to assume an additive model to describe its behaviour. In this model, the value of the indicator in the t-th period is given by the sum:

$$y_t = T_t + P_t + \varepsilon_t,\ t = 1,\ 2,\ \ldots,\ n \tag{2}$$

If the time series follows the form (2), it can be classified as a periodic time series. In practical applications, the periodic component P_t is typically represented solely by the seasonal component S_t. Therefore, the model can be written as $y_t = T_t + S_t + \varepsilon_t$ representing the time series as a seasonally weighted series. If $P_t = 0$, it indicates a non-periodic time series:
where:
T_t, S_t, ε_t—are estimates of the trend, seasonal variation, and random component.

4.1. Model of Constant Seasonality

The specification of this model assumes a constant amplitude, meaning that the magnitude of the seasonal component fluctuation remains the same. It does not consider the trend direction, implying that the size of seasonal fluctuations can be assumed to be constant within the same season across different years. The model equation takes the following form [14]:

$$y_{ij} = T_{ij} + b_j + \varepsilon_{ij},\ S_{ij} = b_j\ for\ \forall\ i = 1,\ 2,\ \ldots,\ k; j = 1,\ 2,\ \ldots,\ n \quad (3)$$

where:
b_{ij}—unknown seasonal parameters.
The model equation is based on the inclusion of unknown seasonal parameters. These parameters are represented by a dimensional seasonal constant, measured in the same units as the values of the time series. This constant is added to the trend component. It is assumed that the following holds true for the seasonal parameters:

$$\sum_{j=1}^{m} b_{ij}\ for\ \forall\ years\ i = 1,\ 2,\ \ldots,\ k \quad (4)$$

that means, the regression analysis reveals both positive and negative fluctuations relative to the trend, which ultimately offset each other throughout the year.

Due to the regular annual cycle, seasonal effects occur from year to year within each season, resulting in repeated seasonal fluctuations represented by b_{ij}. These fluctuations show variations between different years. The model assumes that the trend component T_{ij} takes on different values a_{ij} in all periods j = 1, 2,. . ., r of each respective year i. The sequence of these values across the years i = 1, 2,. . ., m forms a staircase trend. In this scenario, the season is described by a model of constant seasonality. The equation is given in the form [14]:

$$y_{ij} = a_{ij} \cdot sin\omega_{ij} \cdot t + b_{ij} \cdot cos\omega_{ij} t + \varepsilon_{ij},\ i = 1,\ 2,\ \ldots,\ m; j = 1,\ 2,\ \ldots,\ r \quad (5)$$

where:
ω_{ij}—frequency of periodic functions of time
The solution involves estimating the parameters a_{ij}, b_{ij}:

$$\hat{a}_{ij} = \frac{1}{r} \cdot \sum_{j=1}^{r} y_{ij} = \overline{y}_i \quad (6)$$

$$\hat{b}_{ij} = \overline{y}_j - \overline{y} \quad (7)$$

$$\overline{y}_j = \frac{1}{m} \cdot \sum_{i=1}^{m} y_{ij} \quad (8)$$

where:
$\overline{y}_j$—partial average.

$$\overline{y} = \frac{1}{r \cdot m} \cdot \sum_{i=1}^{m} \sum_{j=1}^{r} y_{ij} \quad (9)$$

where:

$\bar{y}$—overall average of the analysed set.

Estimates for the m + r parameters of the model can be obtained by solving a system of m equations:

$$\sum_{j=1}^{r} y_{ij} = r \cdot \hat{a}_{ij} + \sum_{j=1}^{r} \hat{b}_{ij} \tag{10}$$

along with other equations:

$$\sum_{j=1}^{r} y_{ij} = \sum_{ij}^{m} \hat{a}_{ij} + m \cdot \hat{b}_{ij} \tag{11}$$

where:

$\hat{a}_{ij}$, $\hat{b}_{ij}$—the best estimate of the parameters

4.2. Analysis of the Seasonal Component of a Time Series

Various approaches have been used to model the seasonal component, emphasizing the complexity and the need for effective estimation and forecasting techniques [14]. This contribution aims to analyse the seasonal component of the relevant production process time series. Firstly, it is important to determine whether the examined time series exhibits actual seasonal fluctuations. Graph analysis is one method that can be used to identify the seasonal (cyclical) component of a time series. Other methods include spectral analysis, periodogram analysis, and so on.

The seasonal data are displayed in one chart. The visualization of trend and seasonality data in one chart can bring several benefits. Firstly, it enables the identification of any synchronization or misalignment between trends and seasonal patterns. This can be particularly useful in detecting anomalies or unusual behaviour that might not be evident when analysing the components separately. Additionally, it provides a clear visual representation of the relationships between trends and seasonal fluctuations, aiding in the interpretation and interpretation of the data [15].

The tasks involved in addressing the seasonal component of the time series are as follows [16]:

- Quantifying seasonal fluctuations;
- Cleaning the time series by excluding the seasonal component.

In mathematical models, two types of seasonal influences can be considered: constant seasonality and proportional seasonality. When modeling periodic time series, both a cyclical component and a seasonal component are taken into account, collectively forming the periodic component. In this discussion, our focus is on time series models with a constant trend [17,18]. If the trend is not constant, it becomes necessary to remove the trend component from the time series values. The resulting series, after removing the seasonal component, can be expressed in the following form [14]:

$$y_t - S_t = T_t + \varepsilon_t \tag{12}$$

The multiplicative time series model is expressed as [14]:

$$y_t = T_t \cdot S_t \cdot \varepsilon_t \tag{13}$$

Following that, the series needs to be cleansed of its seasonal component and expressed in the following form:

$$\frac{y_t}{S_t} = T_t \cdot \varepsilon_t \tag{14}$$

Various models can be employed to describe the seasonal component [14]:

1. Constant seasonality model: This model assumes that seasonal fluctuations remain the same within each season but differ across seasons;

2. Proportional seasonality model: Based on the assumption that the seasonal component changes in direct proportion to the trend component's value for the corresponding period;
3. Hidden period model: This model is a part of spectral analysis.

To remove seasonality from the time series, one can start with the multiplicative time series model with constant seasonality, where the cyclical component is integrated into the trend component. The procedure for eliminating seasonality involves:

1. Estimating the trend of the time series and calculating the theoretical values;
2. Removing the trend component from the time series using the relationship.

$$\frac{y_t}{T_t} = S_t \cdot \varepsilon_t,\ t = 1,\ 2,\ \ldots,\ n \tag{15}$$

To eliminate the seasonal component from the random component, seasonal indices can be calculated:

$$\overline{S}_i,\ i = 1,\ 2,\ \cdots,\ n \tag{16}$$

For a time series consisting of quarterly values, four seasonal indices need to be calculated. In the case of monthly data, up to twelve seasonal indices are required. The value of the seasonal component is determined by a specific seasonal index. In the case of constant seasonality, this value remains the same for the corresponding quarter of each year in the observed time series. Thus, the seasonal component for the first quarter of each year is assigned the logarithm of the seasonal index specific to that quarter. This relationship must hold for the sum of all the seasonal indices:

$$\sum_{i=1}^{k} \overline{S}_i = k \tag{17}$$

where:

k—the number of reasons.

If the condition is not met, it is necessary to calculate the corrected seasonal indices according to the following relationship:

$$\overline{S}(cor)_i = \frac{\overline{S}_i \cdot k}{\sum_{i=1}^{k} \overline{S}_i},\ for\ i = 1,\ 2,\ \ldots,\ k \tag{18}$$

The series of seasonally adjusted values should be derived from the original time series by dividing each value of $\mathrm{y_t}$ by the corresponding seasonal index [19].

4.3. Chase Demand Strategy

The essence of the chase demand strategy lies in adjusting output according to demand fluctuations, either by increasing or decreasing sales in response to changes in demand levels. The significance of implementing this strategy is underscored by its ability to control production levels and optimize inventory management in line with changes in demand. Management's primary focus is to effectively respond to shifts in demand by implementing sales adjustments aimed at minimizing inventory and maximizing profits. However, a challenge associated with the chase demand strategy is that all output changes are reactive to demand fluctuations. The strategy's objective is to maintain minimal inventory levels while ensuring customer satisfaction, yet it may lead to overproduction during periods of low demand. The disadvantage of this strategy is that excessive production will be realized during periods of low demand [20].

Specific characteristics of the chase demand strategy include [21]:

1. Uncertainty regarding demand timing.
2. Maximizing profits based on market requirements.
3. Sales depending on sales changes.
4. Production and sales adjusting according to demand changes over time.

5. Variable costs due to demand fluctuations.
6. Flexible and immediate decision-making in pursuit strategy.
7. Important factors influencing demand changes include inflation, price fluctuations, consumer preferences, and trends.
8. Application of the chase demand strategy aligns company decisions with immediate customer needs.

However, there are several disadvantages associated with the chase demand strategy [21]:

1. Requires investment opportunities.
2. Potential decrease in variable and input costs without increasing production levels may lead to an increased break-even or equilibrium point.
3. Likelihood of declining product demand over time.
4. Immediate and simplified problem-solving required for unexpected changes in production or assembly processes.
5. Variable process requiring sales forecast calculations to anticipate demand changes.

5. Results

The analysed company is a manufacturing entity with a focus on the production of low-voltage plastic cable distribution boxes in the field of electro technical sector. Their primary activity revolves around the manufacturing, completion, and supply of these cable distribution boxes. Additionally, they provide technological equipment, protective elements, and accessories that complement their core products. The company operates within a competitive environment, facing both domestic and international competitors within the same strategic group. They cater to the market demand for interchangeable products with similar purposes but varying designs and materials. This analysis focuses on three specific products, namely product A—fuse bases, product B—junction boxes up to 100 A, product C—junction boxes up to 400 A. Figure 3 displays the time series depicting the average number of manufactured junction boxes for product A, capable of handling up to 100 A of electrical current. The time series exhibits a clear upward trend. Additionally, seasonal effects are observed within each cycle, and after a 12-month period, there is a significant decrease in the average number of manufactured products. This decline can be attributed to the company's practice of settling contracts exclusively in January. The presented seasonal influence needs to be eliminated or adjusted for accurate analysis.

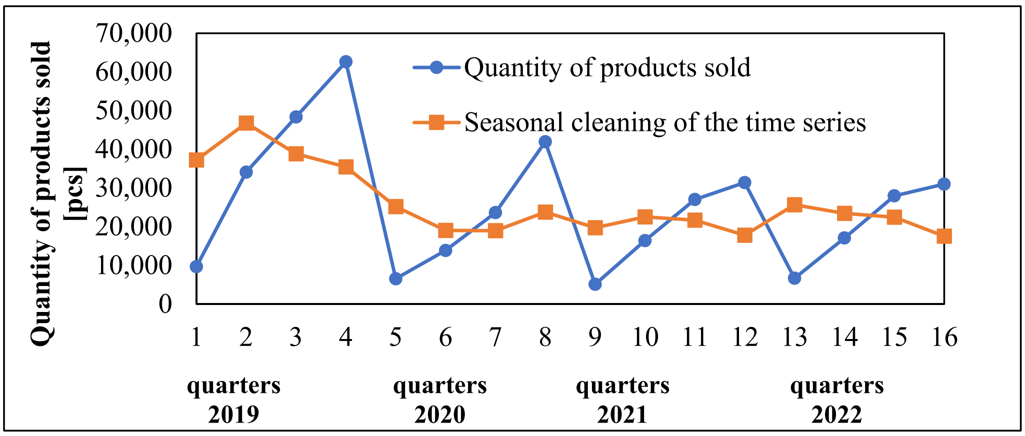

Figure 3. Seasonal cleaning of the quantity of products (fuse bases).

The charts clearly show a significant decline, especially in the first quarters of each year. This can be attributed to companies focusing on supplier and customer contracts at the beginning of the year. On the other hand, the last quarter of each year experiences a significant increase, indicating substantial growth in products sold.

The overall average of products sold in the fuse base reached 25,199 units. However, during the first quarters of the periods 2019 to 2022, there was a significant decrease in sales by 72.26%, representing a drop of 18,210 units. This downward trend also manifested in the second quarters, where seasonal influences caused another decline of 19.24%, equivalent to 4848 units compared to the overall average of 25,199 units. Nevertheless, this decline was subsequently offset by positive growth in sales during the remaining two quarters compared to the overall average of 25,199 units. Sales increased by 25.91% in the third quarter, representing a rise of 6530 units. The fourth quarters showed a substantial increase of 65.59%, meaning an increase of 16,528 units compared to the overall average.

The sale of junction boxes up to 100 A products (Figure 4) is significantly jumpy, especially at the beginning of the calendar year. The sale of this type of product must be equalized. Due to the real situation, when companies empty their warehouses at the end of the calendar year, due to the lack of financial capital. They use this capital to purchase input components for the following calendar year. Using the method of seasonal cleaning, it is possible to see the even sales of products.

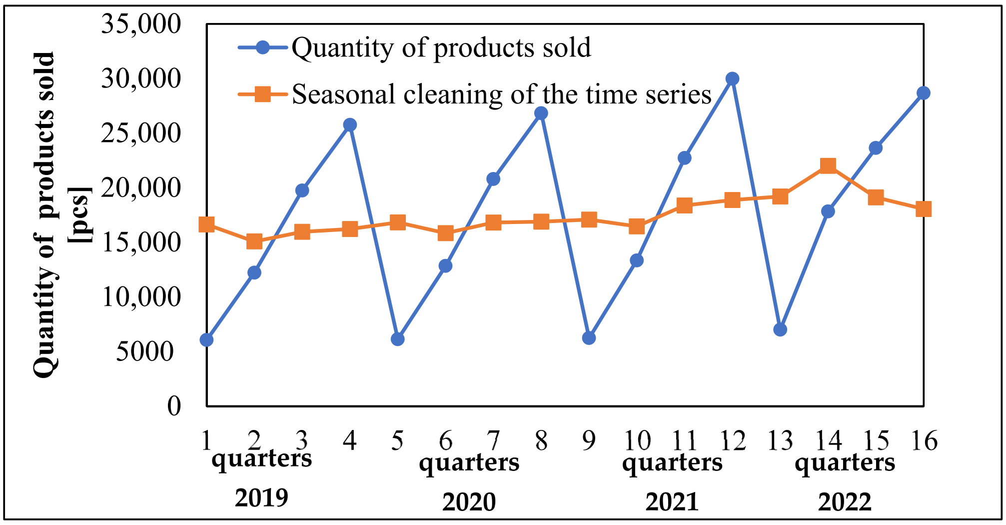

Figure 4. Seasonal adjustment of the quantity of products sales (junction boxes up to 100 A).

The overall average of sold junction boxes up to 100 A is 17,485 units. The decrease in product sales during the 1st quarters of the years 2019–2022 compared to the overall average is 63.63%, amounting to a decrease of 11,126 units. Due to seasonal influences, there was a decline in sales in the 2nd quarters of the years 2019–2022 compared to the overall average by 19.60%, representing 3427 units. This decline was offset by an in-crease in the quantity sold during the other 2 favourable quarters compared to the overall average of 17,485 units.

The increase in product sales during the 3rd quarters of the years 2019–2022 is 24.23%, indicating an increase of 4238 units. In the 4th quarters of the years 2019–2022, compared to the overall average of 17,485 units, there is an increase of 59%, equivalent to an increase of 10,316 units.

The primary concern of management is to ensure an increase in demand in the first quarters of 2019–2022 by implementing the chase demand strategy. Within this strategy, adjustments to demand are made to minimize inventory and maximize profits. This strategy operates on the principle that all changes in output are responses to changes in demand. The chase demand strategy incorporates the "decision on the spot" strategy, necessitated by the rapid changes in market demands, allowing for immediate decision-making.

The overall average sales of junction boxes up to 400 A reach 590.40 units. In the first quarters of the years 2019–2022, there was a significant decrease in sales, amounting to 65.96% compared to the overall average, which represents a decrease of 389.40 units. This decline in sales during the 2nd quarters of the same period was further accentuated by seasonal influences, causing an additional decrease of 16.62%, equivalent to 98.15 units. However, this decline was successfully offset by an increase in sales during the remaining two quarters.

In the 3rd quarters of the years 2019–2022, there was an increase of 24.14%, indicating a sales increase of 142.52 units relative to the overall average. In the last quarters of this period, there was an even more significant increase of 58.44%, representing an increase of 345.02 units, bringing the sales above the overall average.

These adjusted quantities provide a better representation of the current state of the company. The largest increase Figure 5 in the amount of manufactured products (junction boxes up to 400 A) was recorded in the second quarter of 2022.

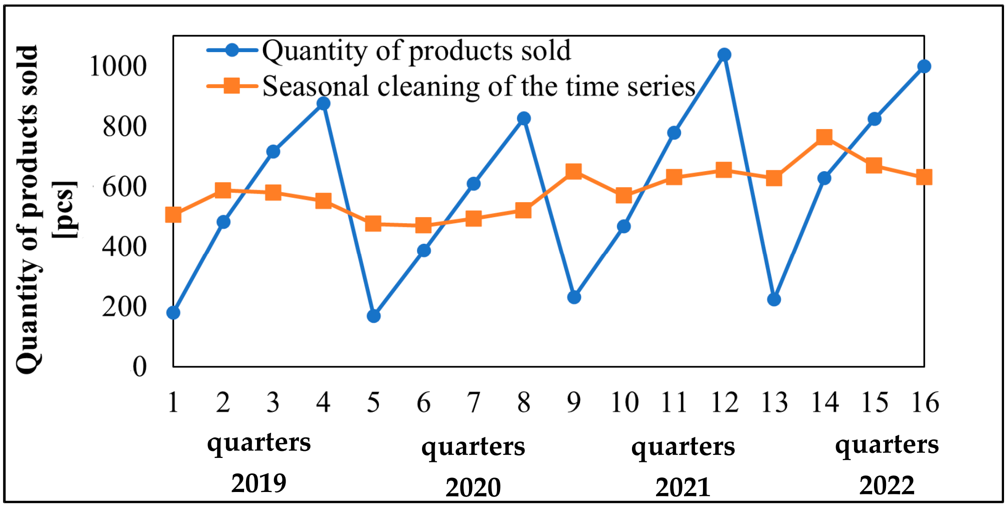

Figure 5. Seasonal adjustment of the quantity of products sales (junction boxes up to 400 A).

Figure 5 illustrates the importance of focusing on sales flexibility in the first quarters of 2019–2022, a key factor in the chase demand strategy. Successful implementation of this strategy also requires changes in the sales process, such as early customer contracting. Due to seasonal variations, the demand for junction boxes up to 400 A fluctuates, underscoring the necessity of ensuring sales flexibility.

Seasonality refers to the regular repetition of an event at consistent intervals, and understanding it correctly allows for early detection of any unusual changes. When dealing with production and economic indicators, it is common to work with monthly or quarterly data. It is crucial to ensure that the available data accurately reflects the quantity of products produced and to assess whether the data exhibits a growing trend over time or fluctuates around a constant level (trend).

Seasonal cleaning demonstrates the elimination of fluctuations in the sale of products. Figure 5 presents the downward trend of sold products in the first quarter of the calendar year. The growing trend of product sales is visible in the second quarter, and the peak of sales of junction boxes up to 400 A products is reached in the fourth quarter.

It is in the first quarters of each year that it is important to ensure exclusivity on the market through the added value of specified products. The sale of specified products must be conditioned by reworking the offer by expanding to third countries, for example countries outside the European Union. It is necessary to increase the market share in the form of price reduction or price increase. In case of price increase, it is necessary to ensure that the product brand becomes strong and customers accept the company's offer.

6. Discussion

This study aims to underscore the importance of linking cleaning data with seasonal influence through the chase demand strategy, as demonstrated in a real-world scenario from the electro-technical industry. This alignment fosters the maintenance of stock levels at an optimal minimum, effectively averting scenarios of overproduction or underproduction. The chase demand strategy, characterized by high demand variability, low storage costs, and production flexibility, is particularly pertinent within industries with dynamic demand patterns, such as the electrical sector specializing in low-voltage plastic cable distribution boxes.

A chase demand strategy is well-suited for enterprises navigating variable demand landscapes, especially those subject to seasonal fluctuations like the market for low-voltage plastic cable distribution boxes. This approach aims to continuously synchronize production capacity with demand.

The integration of seasonal considerations into the chase demand strategy yields several advantages. Chief among them is the reduction of stock levels to a minimum, leading to significant cost savings for the company. However, the successful implementation of a chase demand strategy hinges on effective capacity planning, accounting for fluctuations in production capacity tied to evolving demand dynamics. Challenges may arise due to varying levels of workforce quality resulting from frequent personnel changes.

Adopting a chase demand strategy necessitates the ability to swiftly adjust production output, enabling timely responses to shifts in capacity. This alignment ensures that production capacity aligns closely with demand, mitigating inventory excesses and shortages, thereby optimizing resource utilization and maximizing profitability.

Addressing seasonal influences involves adjusting production capacity in accordance with resource utilization requirements, guided by current and anticipated demand levels. By closely monitoring actual and forecasted demand alongside market fluctuations, companies can fine-tune their capacity management incrementally, ensuring the availability of adequate resources without substantial upfront investments or the risk of stockouts.

The proposed solution entails modest adjustments to production capacities to align with anticipated demand signals and current market potential, thus facilitating the effective management of resources.

7. Conclusions

In conclusion, the meticulous cleansing of seasonal influences from production data is vital for achieving precision in forecasting, effective resource allocation, and strategic decision-making, particularly in the context of manufacturing and production planning. The literature review underscores the critical role of data cleaning, especially in addressing the challenges posed by seasonal variations, by emphasizing the identification and handling of outliers, as well as addressing issues such as missing values and irrelevant data. Machine learning methods, such as the Seasonal Trend Decomposition with Loess (STL) algorithm, prove valuable in optimizing predictions and chase demand strategy, particularly in high-mix, low-volume production environments, where precision in production planning is crucial.

Furthermore, the article emphasizes the crucial link between cleaning data from seasonal influences and the chase demand strategy, as illustrated in a real-world scenario within the electro-technical industry. By showcasing this framework, the study highlights how such an approach aids in maintaining optimal stock levels, thereby mitigating the risks associated with overproduction or underproduction. This contribution is particularly significant in industries characterized by dynamic demand patterns, such as the electrical sector specializing in low-voltage plastic cable distribution boxes.

Moreover, the integration of seasonal considerations into the chase demand strategy presents several advantages, focusing on minimizing stock levels and achieving substantial cost savings for companies operating in the electro-energetics industry. However, the article acknowledges the challenges associated with effectively implementing this strategy, particularly in terms of capacity planning to accommodate fluctuations in production capacity driven by evolving demand dynamics. The proposed solution of making modest adjustments to production capacities to align with anticipated demand signals and current market potential provides a practical framework for effective resource management within the electro-energetics industry. Overall, the article's contribution lies in offering actionable insights into managing dynamic demand patterns and optimizing resource utilization in the electro-technics industry through the integration of seasonal considerations into the chase demand strategy.

Further research efforts could focus on comparing the effectiveness of different demand tracking strategies across various industrial sectors and contexts, with an emphasis on their ability to address seasonal influences and optimize inventory management.

Another direction for research could involve examining long-term trends in demand dynamics across different industrial sectors and their impact on inventory and production management strategies. This approach could help in developing better demand forecasts and improving demand tracking strategies considering seasonal fluctuations.

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