Methodology for inventory management with sporadic demand in the conditions of custom production of a small and medium-sized enterprise

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Keywords: demand forecasting, sporadic demand, Croston's method, bootstrap method, custom production.
Abstract: The article deals with the very actual topic of inventory management with sporadic demand in small and medium-sized enterprises. The research aims to propose an easy-to-apply procedure for predicting dependent demand or consumption based on the analysis of the inventory assortment. The proposed methodology is particularly suitable for small and medium-sized enterprises and therefore does not require any special software products. The requirement is that it must be sufficiently reliable in terms of prediction accuracy. The methodology can be applied using commonly available spreadsheets. The solution is based on dividing the inventory assortment into nine groups based on the results of ABC/XYZ analyses. The sample consists of 60 inventory items with fluctuating demand predominating. Six forecasting methods were tested on this sample (naive forecasting, shorter and longer moving averages, linear regression with and without seasonal indices, and Croston's method). The solution was then supplemented with a bootstrap simulation. The reliability of each method's forecast was evaluated using the metrics of mean absolute error, mean absolute percentage error, and demand planning accuracy. Based on the empirical results, recommendations were formulated for selecting a suitable forecasting method for each inventory group.

1   Introduction

Inventory management is a key area of logistics that directly impacts production efficiency, customer service levels and the company's economic performance. One of the key challenges in inventory management is demand forecasting, i.e., the ability to estimate the future consumption of a specific material item as accurately as possible. Demand forecasting is particularly challenging in a custom manufacturing environment, where there are irregularities and fluctuations due to the execution of individual projects, technical specifics, and often seasonal effects. Traditional forecasting methods that rely on stable or trend time series fail in these conditions. In such an environment, it is essential to use approaches that reflect both consumption shortfalls, strong fluctuations and low frequency of product demand.

Many approaches for predicting sporadic demand can be found in the literature. Small and medium-sized enterprises face sporadic demand relatively often, as their production is usually tailored to customer needs and is custom-made or small-batch. Methods for predicting sporadic demand can be classified into traditional analytical predictive algorithms, simulation models, and, more recently, predictive methods based on machine learning and artificial intelligence. Small and medium-sized enterprises often find it challenging to navigate these methods, as they lack data analysis experts, and purchasing expensive software products is usually beyond their financial means. Therefore, our research aimed to examine easy analytical prediction tools that can be applied using commonly used spreadsheets and propose a practical procedure for predicting dependent demand or consumption in small and medium-sized enterprises with custom manufacturing. Our methodology is based on a combination of several traditional methods. The initial step is to classify inventory using ABC and XYZ analyses and propose a suitable prediction procedure based on analytical prediction methods for each combination. These easy prediction methods are supplemented in the next step by bootstrap simulation, which allows for a better understanding of the behaviour of demand for individual inventory items. Bootstrap simulation is then used to estimate the uncertainty surrounding predictions made using one of the analytical methods. The proposal of an application-easy methodology using common software tools represents a gap in the literature, which this article attempts to fill. The methodology has been verified using real business data.

2   Literature review

Sporadic demand, also referred to as intermittent demand, is a specific type of demand characterized by irregular fluctuations in the quantity and frequency of products demanded. The low frequency of occurrence of demand can lead to gaps in data collection, which reduces the effectiveness of traditional forecasting methods. Such a characteristic

Acta Logistica, Volume 13, Issue 1, Pages 174-185, 2026 ISSN 1339-5629

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complicates forecasting future demand and makes effective inventory planning more difficult [1]. In practice, this type of demand is found, for example, in spare parts, especially in the repair or maintenance of complex equipment, and in project production.

Forecasting and managing sporadic demand is a challenge in inventory management, as commonly used forecasting techniques such as exponential smoothing or linear regression cannot respond reliably enough to randomness and discontinuity in demand trends [2]. For these reasons, several specialized methods have been developed, among which Croston′s method stands out, which separately smooths the magnitude of demand (consumption) and the intervals between occurrences [3]. Simulation approaches such as the Bootstrap method significantly contribute to sporadic demand management. Simulation enables modelling of different demand scenarios based on historical data without knowing the specific probability distribution [4]. According to [5], simulation methods play a crucial role in accelerating the analysis of inventory movements, which is essential to decision making in sporadic demand conditions.

When managing inventory under sporadic demand conditions, it is essential to concentrate efforts and resources on the most important items, regardless of their frequency of occurrence, while reducing the overall costs associated with storing less important products. Applying traditional ABC analysis combined with XYZ analysis may be recommended in such conditions. ABC analysis allows the company to concentrate resources on critical category A items, while simpler supply strategies can be implemented for category C items that have less impact on the company's performance [6]. XYZ classification categorizes inventory items based on demand variability. The integration of ABC and XYZ analyses can improve inventory management efficiency in an environment with sporadic demand [7,8].

The complexity of inventory management in sporadic demand environments stems from the high level of uncertainty that is not only in predicting future demand but also in supply chain management. As stated by [9], traditional inventory planning models cannot respond effectively to sudden changes in demand volumes and require the introduction of modern analytical tools. Demand forecasting methods can be classified into several categories depending on their complexity and focus, ranging from simple naive approaches to sophisticated machine learning algorithms. Different methods have different applications and uses. For example, simple techniques such as moving average or exponential smoothing are suitable for environments with low demand variability. At the same time, Croston's method or neural networks are effective in the case of irregular or intermittent demand [2].

The simplest demand prediction methods include the naive method, which assumes that future demand will be identical or similar to the last observed value, see formula (1). Predictions using the naive method are fast and intuitive, but in many cases, they are unreliable [10].

$$F_{t+1} = D_t \tag{1}$$

Where F_{t+1} is the demand forecast for the next period, D_t is the demand in the last observed period.

Moving averages are another widespread method of demand forecasting used to smooth short-term fluctuations and provide better identification of trends over time [11]. This method calculates the average of the demand values over a specified number of periods, see relation (2).

$$F_{t+1} = \frac{\sum_{i=1}^{n} D_{t-i}}{n} \tag{2}$$

Where F_{t+1} is the demand forecast for the following period, D_{t-i} is the actual demand in period $t-i$, and n is the number of periods included in the calculation.

Moving averages show reliable results, especially when demand is stable, but they are not sensitive enough to sudden changes in trends or fluctuations in market behaviour [9,12].

Another common tool for demand forecasting is regression analysis, which allows for the identification and quantification of the influence of individual factors on demand and the creation of predictions based on them. The regression model can be expressed by relation (3).

$$D_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{3}$$

Where D_t is the demand at time t, β_0 is the coefficient (initial value, excluding the effect of independent variables), $\beta_1, \beta_2,...,\beta_n$ are the regression coefficients (the impact of independent variables on demand), $X_1, X_2,..., X_n$ are the independent variables and ε is the model error, which represents the deviations from the predicted behaviour. The advantage of regression analysis in demand forecasting is the possibility of including various factors such as seasonal or specific influences affecting demand [13]. Using stepwise regression can help track changes in demand as a function of various factors; this approach allows for more robust models that can better capture the complexity of sporadic demand [14].

Linear trend analysis is an application of linear regression that focuses on modelling and predicting long-term changes in demand. The variable under study is time. This method assumes that demand follows a linear increase or decrease over

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time, which makes it a useful tool, especially in environments with clearly defined trends. It can be expressed by relation (4).

$$F_{t+1} = aX_t + b \tag{4}$$

Where F_{t+1} is the demand forecast for period $t+1$, a is the trend coefficient which gives the average rate of change in demand X_t, b is the coefficient which expresses the initial value of demand independent of time, and t expresses the time variable.

Linear trend analysis is best suited for prediction in environments with regular changes, such as manufacturing processes or for commodities with stable market conditions that can be tracked based on historical data [15]. The advantage of this method is its simplicity and ease of implementation, but [11] points out its limitations when forecasting in environments with irregular fluctuations or seasonal effects. Therefore, combining this approach with more advanced methods, such as seasonal decomposition, is often recommended, which can account for specific demand effects.

Seasonal indices make it possible to capture periodic fluctuations in demand and thus increase forecasting accuracy. The seasonal index expresses the relative deviation of demand in a given period compared to the values predicted by the regression model, therefore complementing the underlying linear trend with a seasonal component that occurs at regular intervals [9]. The seasonal indices are determined according to relation (5).

$$SI_i = \frac{Y_t}{aX_t + b} \tag{5}$$

Where SI_i is the seasonal index for period i, Y_t is the actual value of demand in period t, and $(aX_t + b)$ is the demand value predicted by the linear trend function according to relation (4). From the individual seasonal indices, the average seasonal indices can be determined (6).

$$SI_{average} = \frac{1}{n}\sum_{t=1}^{n} SI_i \tag{6}$$

Where $SI_{average}$ is the average seasonal index for a given season (e.g., month), n is the number of years in the sample, and SI_i is the individual seasonal indices calculated for a given period (e.g., month) in each year.

The seasonally adjusted prediction model can then be expressed by equation (7).

$$\widehat{Y_t^{sez}} = (aX_t + b).SI_{average} \tag{7}$$

Where $\widehat{Y_t^{sez}}$ represents the seasonally adjusted predicted demand.

Widely used demand forecasting methods include exponential smoothing, which provides a balanced approach to tracking current trends while preserving the influence of historical data. The method emphasizes the most recent observations, while gradually reducing the weight of older data [1]. Exponential smoothing is the preferred tool for environments with gradual changes in demand, with its main advantage being its simplicity of implementation and low computational power requirements. The method is particularly suitable for dynamic environments where seasonal or long-term trends are not obvious [16]. The forecast calculation can be expressed by relation (8).

$$F_{t+1} = \alpha D_t + (1 - \alpha)F_t \tag{8}$$

Where F_{t+1} is the demand forecast for the next period, D_t is the actual demand in the current period, F_t is the forecast from the previous period, and α is the smoothing constant, where $0 < \alpha < 1$. The value of the smoothing constant α determines how important the current observation is for the forecast. A higher value of α places more importance on current data and is appropriate for environments with rapid changes in demand. A lower value is more appropriate for more stable demand cases that better reflect longer-term trends [17].

The Croston's method is a specific technique used to forecast intermittent demand, which is characterized by its irregularity and low frequency of occurrence. This method was first introduced by Croston in 1972, and its main contribution lies in splitting the forecast into two components: an estimate of the magnitude of demand and an estimate of the interval between orders. This approach allows for a more efficient and accurate forecast where traditional methods often fail [14].

The method assumes that demand size and inter-order intervals are statistically independent and can be modelled separately using exponential smoothing. This assumption minimizes the risk of forecast bias, a common problem with methods based on univariate approaches [2]. The overall demand forecast is defined by relation (9).

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$$F_{t+1} = \frac{Q_t}{P_t} \tag{9}$$

Where F_{t+1} is the demand forecast for the next period, Q_t is the estimate of the demand size according to relation (10), and P_t is the estimate of the interval between orders, see relation (11).

$$Q_t = Q_{t-1} + \alpha(D_t - Q_{t-1}) \tag{10}$$

Where D_t is the actual demand in the current period, α is a smoothing constant ($0 < \alpha < 1$).

$$P_t = P_{t-1} + \beta(T_t - P_{t-1}) \tag{11}$$

Where T_t is the interval between the current and the last order, β is the smoothing constant ($0 < \beta < 1$).

The balancing constants α and β determine the degree of adaptation of the model to current changes in demand. Higher values lead to faster response to changes, while lower values provide more stable demand forecasts [18]. Croston's method is better able to predict periods with zero demand and periods with more pronounced fluctuations. Compared to simple exponential smoothing, it considers the temporal distribution between demand occurrences, allowing predictions to be better tailored to specific types of demand [3,19].

Although Croston's method significantly improves over traditional prediction approaches, it has limitations. It cannot account for seasonal and trend influences [19]. It assumes the independence of the two components, but in the real world, demand size and order spacing can be interdependent [2]. The classical Croston's method tends to overestimate demand, especially when demand occurrence data is sporadic, leading to its refinement in the Syntetos-Boylan Approximation method [20].

The Bootstrap method is mainly used in the field of time series analysis and demand forecasting to quantify the uncertainty of the prediction. Instead of a single point prediction, it allows the generation of a full range of possible future scenarios, thus providing a basis for estimating confidence intervals and variance of the predicted variable. This allows a much better assessment of the risk associated with a decision, such as inventory levels or material purchases. In practice, this approach has proven particularly useful in environments with high demand variability or insufficient length of historical data [21].

The principle of bootstrapping is that many alternative sets (called replications) are generated from the original sample using random sampling with returns the same size as the original sample [22]. For each set, the observed variable – the mean, median or regression coefficient – is then calculated. The result is an empirical distribution of the estimated statistic, from which an appropriate confidence interval can be derived or the entire interval trend can be simulated. This feature is particularly useful when setting service levels or safety stocks in logistics systems [4]. Bootstrap can be integrated into the structures of predictive models, such as exponential smoothing, ARIMA models, or irregular methods such as Croston [23]. Croston's method can be improved by using the bootstrap to remove some inherent shortcomings, such as bias in the results [19]. By running the bootstrap on the prediction results from Croston's method, more robust estimates and intervals can be obtained, which helps firms to better adapt to fluctuations in demand and minimize the average inventory cost [24].

The above review of approaches used for demand forecasting shows that there is no one-size-fits-all tool to cover the diverse range of situations that may arise in practice. We intend to partially fill this research gap and propose a methodology for dependent demand or consumption forecasting that is sufficiently reliable on the one hand and relatively simple in application on the other hand, so that it can be easily applied in the SME environment.

3   Methodology

The methodological approach adopted in this paper is based on quantitative time series analysis to propose an optimal demand forecasting method for items with irregular consumption occurrence. For the analysis, data from an industrial company was chosen, which contained 22,753 inventory items for 27 months from 2019 to 2023. The source data was in the form of rows in a text file (more than 11 million rows), so it was not possible to analyse it directly in Microsoft Excel. Preprocessing required data cleansing, which included removing redundant elements such as headers and blank rows and filling in missing information for selected transactions based on their context.

After data cleansing and preprocessing, transformation functions were used in Power BI to calculate the total demand value of individual items based on system data. This data was then exported to Microsoft Excel, where an ABC analysis was performed to classify the items according to their importance to the total inventory value. Group A comprises approximately 80% of the total inventory value, Group B comprises approximately 15%, and Group C represents the remaining 5%. This approach allowed the identification of key items to focus attention on in inventory management and the design of strategies to optimize inventory management.

Acta Logistica, Volume 13, Issue 1, Pages 174-185, 2026   ISSN 1339-5629

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After the ABC analysis was performed, XYZ analysis was applied to further understand the items' consumption characteristics, which allows for the classification of items based on the stability and predictability of demand. This approach is important for optimizing inventory management as it distinguishes items with regular demand from those with irregular fluctuations. XYZ analysis examines the demand variability over time based on the standard deviation or coefficient of variation. Items in category X are characterized by only moderate volatility in demand, items in group Y already have moderate fluctuations in demand and items in category Z have highly irregular and difficult to predict demand. In contrast to the ABC analysis, different values of the coefficient of variation can be found in the literature for classifying stock items into XYZ groups. The relative variability values range from 10-50% for category X, 11-100% for group Y and above 20% or even above 100% for group Z. Lower values of the coefficient of variation are reported, e.g., by source [25]. In contrast, higher variability values are reported, e.g., by source [26]. Because using lower values of the relative variability would result in a high proportion of inventory items being in category Z, we used the thresholds given in [26] to classify the inventory items. Due to the limited space in the paper, we always present selected results for the first 20 items from each category according to the ABC analysis.

Combining ABC analysis, which evaluates inventory items based on their value importance, and XYZ analysis, which assesses demand variability, results in a comprehensive inventory classification that enables more efficient management of inventory items. The resulting matrix (Table 1) links the two approaches and provides a detailed view of the importance of inventory and the optimal inventory management strategy. Table 1 shows that most items exhibit more intense demand fluctuations.

Table 1 Distribution of inventory items according to ABC and XYZ classifications in the research sample

	X	Y	Z	Sum
A	7	11	2	**20**
B	0	8	12	**20**
C	3	2	15	**20**
Sum	**10**	**21**	**29**	**60**

After the ABC and XYZ analyses were performed, the methods described in the previous section of the paper, i.e. naive method, moving averages, linear regression, supplemented with seasonal indices, Croston's method and Bootstrap method, were applied to the demand data.

The prediction accuracy was evaluated using the indicators Absolute percentage error (APE), Mean absolute percentage error (MAPE), Demand planning accuracy (DPA) and Mean absolute error (MAE).

Absolute Percentage Error (APE) measures the relative deviation between the actual and predicted values and provides an overview of the model error rate in percentage. According to [27], APE is one of the most used indicators for evaluating the accuracy of regression models. A higher value of APE indicates a greater deviation of prediction from reality, which means lower model accuracy. The value of APE is calculated according to formula (12).

$$APE_t = \left| \frac{D_t - F_t}{D_t} \right| \times 100 \tag{12}$$

The mean absolute percentage error (MAPE) expresses the average percentage error of the prediction across all periods, giving an overall view of the model's accuracy. As reported by [28], MAPE is a widely used consumption and demand forecasting metric. It is defined by formula (13). A lower MAPE value means a higher accuracy of the model. Values below 10% are generally considered very accurate, while values above 50% indicate high model error [28].

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} APE_t \tag{13}$$

Demand planning accuracy is an indicator that expresses prediction accuracy as a complement to MAPE. It can be expressed by relation (14).

$$DPA = 1 - MAPE \tag{14}$$

A DPA value close to one indicates high prediction accuracy, while lower values indicate more significant prediction errors [29].

The mean absolute error (MAE) expresses the average deviation of the predicted values from the actual demand values, see relation (15), while ignoring the direction of the error (positive or negative difference). The advantage of this metric is its simple interpretation in natural units of the variable under analysis, which allows an easy assessment of the magnitude of the forecast errors. MAE is also robust to problems that can arise with relative metrics, such as very low demand values or outliers where MAPE may be unreliable [30]. When comparing prediction models, a lower MAE value is an indicator of higher prediction accuracy.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|D_t - F_t| \tag{15}$$

4   Results of demand forecasts by each method

The demand forecasting methods presented in Chapter 2 were applied to historical monthly time series of individual inventory items. For each item, 27 historical months were used to calculate forecasts for the next 4 months. The results were then compared with actual demand values obtained from company data and evaluated using MAPE, DPA, and MAE metrics. This approach allowed a quantitative assessment of the accuracy of the forecast using standardized metrics. The results are summarised in Table 2. If NA is indicated in the table, the metric could not be calculated due to division by zero (a common problem in sporadic demand where some periods show zero demand). All calculations were performed in MS Excel.

Table 2 shows that the naive forecasting method can roughly estimate future demand for stable items or very few important items. It fails in an environment with high demand variability (Y, Z).

Moving averages were applied in two variants - 10 and then 20 periods. The mean absolute percentage error (MAPE) for the variant with 10 periods is 201%, and for the variant with 20 periods, 253%, which speaks in favour of using shorter moving averages. However, for items with higher demand fluctuations (Y, Z), moving averages are practically useless as a forecasting method, as demand forecasting accuracy is extremely low (see MAPE values in Table 2). On the other hand, for category X items, the moving average method is quite applicable, with shorter moving averages showing better predictive ability. This phenomenon can be explained by the fact that a shorter averaging horizon allows for a faster response to changes in the time series and better reflects actual developments in the data, which is typical for variable demand.

Regression analysis or linear trend analysis is one of the most commonly used statistical approaches for modelling time series trends. The regression coefficients a, b for relationship (4) were determined based on all available data using the LINREGRESE function in MS Excel. The results show that the accuracy of linear regression varies considerably depending on the stability and consistency of the historical series. A minimum MAPE of 12% was achieved for one item in the AX category. In general, the predictive ability of the linear trend analysis for category X items can be described as good. However, its application is limited in environments with greater dynamism and irregularity, as illustrated by the results for categories Y and Z.

Given the identified limitations, the logical extension of the linear model is to include seasonal indices to account for recurring cyclical fluctuations in demand. This approach is based on the assumption that, in addition to the trend component of demand, there may also be a seasonal component which needs to be captured by appropriate adjustment indices. From a methodological point of view, it is therefore a two-stage model, where a baseline forecast is first calculated using a regression equation and then adjusted by seasonal indices for the relevant month. The seasonal indices were calculated for all 27 historical periods according to relation (5). Subsequently, these values for each item were averaged across months to obtain representative average seasonal indices. Figure 1 shows the average seasonal indices for the entire stock range. It can be seen from the figure that the seasonal component in the stock mix is not very significant. The final prediction values were then obtained as the product of the original regression prediction and the corresponding seasonal index for that month. It can be seen from Table 2 that there was an improvement over the baseline linear model for some stock items. Still, for other items, there was a deterioration in predictive ability. This is because for some items, the fluctuations in demand are not due to seasonality but to the randomness of demand. In this case, using seasonal indices does not make logical sense. If the seasonal indices oscillate around the value of 1, the seasonal component is not significantly present in the data set, and its application is not beneficial. Only in cases where the seasonal indices are more pronounced does their inclusion in the forecast make sense.

To apply Croston's method, it was necessary to estimate the optimal values of the parameters α and β. The calculation was performed in MS Excel, with smoothing parameters optimized for each item using a custom grid-search macro. This macro systematically tested different combinations of α and β parameter values in the range 0.1-0.6 (up to 1 in rare cases) in steps of 0.025 and recorded the error metrics MAE and DPA values for each combination. The optimal combination was chosen based on minimizing the MAE metric. A higher parameter range (up to 1.0) was used because items with significantly negative DPA values needed to achieve higher reactivity - i.e., more sensitive model responses to sudden changes. In these cases, a high α value of up to 0.975 proved useful, allowing the model to quickly adapt the forecast to new inputs.

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Table 2 Accuracy of demand forecasting by method

Category		Item	Naive forecasting method			10-period moving averages			20-period moving averages			Linear regression			Linear regr. + seasonal indices			Croston method		
ABC	XYZ	No.	MAPE	DPA	MAE	MAPE	DPA	MAE	MAPE	DPA	MAE	MAPE	DPA	MAE	MAPE	DPA	MAE	MAPE	DPA	MAE
A	X	53591776	28%	72%	609759	15%	85%	372511	18%	82%	438924	12%	88%	314134	22%	78%	495359	11%	89%	235293
A	X	51381042	17%	83%	141837	17%	83%	143161	12%	88%	105628	15%	85%	123222	18%	82%	145485	7%	93%	55040
A	Z	51381043	458%	-358%	135829	387%	-287%	114197	329%	-229%	103538	290%	-190%	96617	197%	-97%	97023	19%	81%	19791
A	Y	53591770	56%	44%	151578	114%	-14%	360487	95%	5%	283023	73%	27%	204136	88%	12%	223607	23%	77%	63147
A	Y	53591674	82%	18%	585620	25%	75%	260782	23%	77%	241015	27%	73%	231311	13%	87%	107220	21%	79%	151761
A	Y	53591787	40%	60%	209972	32%	68%	138382	34%	66%	151239	24%	76%	127332	32%	68%	158828	18%	82%	85403
A	Y	3451913-PRO	40%	60%	94821	49%	51%	97343	123%	-23%	258006	20%	80%	47296	8%	92%	17133	14%	86%	37111
A	Y	3451913-2	1073%	-973%	265751	4714%	-4614%	316717	6381%	-6281%	350746	2096%	-1996%	225127	1848%	-1748%	227195	28%	72%	21866
A	Y	51381102	40%	60%	95132	19%	81%	53701	36%	64%	78283	17%	83%	46923	21%	79%	58335	15%	85%	37184
A	Y	53593036	90%	10%	266742	111%	-11%	240012	117%	-17%	260533	101%	-1%	227091	86%	14%	270209	33%	67%	83819
A	X	54320072	44%	56%	105955	41%	59%	86951	79%	21%	178502	33%	67%	78311	30%	70%	82908	20%	80%	45849
A	Y	54289817	26%	74%	107911	21%	79%	85078	17%	83%	71653	14%	86%	66469	26%	74%	120944	9%	91%	35701
A	X	53591781	18%	82%	72346	13%	87%	59984	17%	83%	69110	13%	87%	61474	13%	87%	60252	8%	92%	32747
A	Z	50A03754	86%	14%	26369	149%	-49%	46096	128%	-28%	39040	119%	-19%	36041	27%	73%	13076	34%	66%	10656
A	Y	2501222	37%	63%	29018	22%	78%	15099	164%	-64%	138198	61%	39%	56273	42%	58%	33996	14%	86%	10969
A	X	54280051	49%	51%	186067	40%	60%	151619	42%	58%	145040	38%	62%	145158	38%	62%	128595	23%	77%	87735
A	Y	53593038	38%	62%	202311	30%	70%	158117	21%	79%	131763	33%	67%	157660	75%	25%	326473	14%	86%	75029
A	X	51382071	58%	42%	173461	30%	70%	77518	39%	61%	96513	25%	75%	72504	42%	58%	116264	17%	83%	51758
A	X	53130352	24%	76%	98056	15%	85%	56274	12%	88%	48413	17%	83%	64794	17%	83%	67586	8%	92%	31240
A	Y	51381022	31%	69%	123634	32%	68%	102266	39%	61%	121564	31%	69%	99000	27%	73%	92923	11%	89%	40693
B	Z	50A02398	NA	NA	658	NA	NA	2770	NA	NA	6116	NA	NA	1862	NA	NA	1652	NA	NA	1546
B	Z	54053050	36%	64%	3026	37%	63%	2528	21%	79%	1604	40%	60%	2891	34%	66%	3233	15%	85%	1190
B	Z	50507158	NA	NA	4687	NA	NA	4991	NA	NA	5655	NA	NA	4589	NA	NA	6752	NA	NA	3238
B	Y	50A20221	153%	-53%	9010	75%	25%	4729	62%	38%	4693	68%	32%	4541	50%	50%	4138	41%	59%	2849
B	Y	S048194	49%	51%	1678	173%	-73%	3428	177%	-77%	3220	140%	-40%	2705	173%	-73%	3177	25%	75%	763
B	Z	54280955	NA	NA	7807	NA	NA	11015	NA	NA	10666	NA	NA	11341	NA	NA	7687	NA	NA	9882
B	Z	50A61091R	NA	NA	6602	NA	NA	6666	NA	NA	3799	NA	NA	6445	NA	NA	8188	NA	NA	4123
B	Y	50T11364	56%	44%	5833	38%	62%	4313	36%	64%	4280	32%	68%	3418	50%	50%	5779	19%	81%	1926
B	Y	52731016	141%	-41%	2639	545%	-445%	5178	548%	-448%	4838	331%	-231%	3489	277%	-177%	3198	79%	21%	1315
B	Y	2500507	65%	35%	2986	38%	62%	2231	29%	71%	1837	27%	73%	1838	25%	75%	1841	22%	78%	1099
B	Z	2405829-2	NA	NA	7374	NA	NA	4424	NA	NA	5553	NA	NA	5943	NA	NA	5099	NA	NA	6137
B	Z	2500638	40%	60%	3761	42%	58%	4808	43%	57%	5142	30%	70%	3351	57%	43%	6642	25%	75%	3001
B	Y	54056452	108%	-8%	2920	290%	-190%	3885	299%	-199%	3774	130%	-30%	2660	191%	-91%	2993	63%	37%	1307
B	Z	54296077	NA	NA	3581	NA	NA	3697	NA	NA	3628	NA	NA	2763	NA	NA	2560	NA	NA	2572
B	Z	53110111	112%	-12%	22643	60%	40%	16894	69%	31%	19066	35%	65%	10666	59%	41%	20196	22%	78%	6933
B	Y	2500226	32%	68%	1943	31%	69%	1970	22%	78%	1337	28%	72%	1765	62%	38%	2909	21%	79%	1245
B	Z	50370945	29%	71%	1436	30%	70%	1431	101%	-1%	3287	32%	68%	1712	47%	53%	2251	32%	68%	2060
B	Z	53592441	NA	NA	17801	NA	NA	11051	NA	NA	10722	NA	NA	10451	NA	NA	7465	NA	NA	9973
B	Z	52731132	NA	NA	0	NA	NA	0	NA	NA	10074	NA	NA	674	NA	NA	41	NA	NA	8016
B	Y	54050494	41%	59%	2200	188%	-88%	3559	291%	-191%	3636	142%	-42%	3278	139%	-39%	2842	25%	75%	1374
C	Z	50A64226R	NA	NA	0	NA	NA	1727	NA	NA	1252	NA	NA	1437	NA	NA	786	NA	NA	645
C	Z	MATRIX OP5	NA	NA	6243	NA	NA	4792	NA	NA	4853	NA	NA	4701	NA	NA	19692	NA	NA	4288
C	Z	2501671	NA	NA	633	NA	NA	964	NA	NA	1048	NA	NA	918	NA	NA	1036	NA	NA	752
C	Z	50384720	48%	52%	365	58%	42%	527	53%	47%	547	60%	40%	528	104%	-4%	783	22%	78%	233
C	Y	50359863	NA	NA	360	NA	NA	348	NA	NA	534	NA	NA	271	NA	NA	341	NA	NA	254
C	Z	50A30072R	60%	40%	411	93%	7%	426	129%	-29%	569	76%	24%	352	35%	65%	229	17%	83%	171
C	Z	50A36029	NA	NA	567	NA	NA	368	NA	NA	577	NA	NA	459	NA	NA	309	NA	NA	502
C	Z	50369774R	NA	NA	292	NA	NA	486	NA	NA	533	NA	NA	540	NA	NA	813	NA	NA	552
C	Z	5K00A352	NA	NA	3575	NA	NA	2223	NA	NA	2458	NA	NA	2262	NA	NA	2353	NA	NA	1986
C	Z	53455313	NA	NA	709	NA	NA	683	NA	NA	548	NA	NA	490	NA	NA	556	NA	NA	360
C	Z	50A47394	NA	NA	636	NA	NA	764	NA	NA	1130	NA	NA	866	NA	NA	903	NA	NA	702
C	Y	53412045	88%	12%	1285	37%	63%	868	27%	73%	776	31%	69%	749	69%	31%	1163	33%	67%	505
C	Z	50T36971	56%	44%	1070	46%	54%	690	39%	61%	762	61%	39%	774	55%	45%	1082	21%	79%	452
C	X	57351941	23%	77%	230	17%	83%	166	17%	83%	162	14%	86%	144	13%	87%	118	9%	91%	87
C	Z	56340082	NA	NA	0	NA	NA	400	NA	NA	802	NA	NA	111	NA	NA	84	NA	NA	589
C	X	53410977	50%	50%	474	35%	65%	311	27%	73%	250	37%	63%	320	42%	58%	391	15%	85%	144
C	X	50A19826	82%	18%	351	119%	-19%	392	135%	-35%	456	90%	10%	317	115%	-15%	409	36%	64%	150
C	Z	50366174	NA	NA	651	NA	NA	919	NA	NA	1067	NA	NA	810	NA	NA	435	NA	NA	921
C	Z	50339631	NA	NA	798	NA	NA	682	NA	NA	726	NA	NA	637	NA	NA	558	NA	NA	583
C	Z	50A72702R	NA	NA	1084	NA	NA	1850	NA	NA	1300	NA	NA	1947	NA	NA	269	NA	NA	295

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In contrast, Croston's method behaved similarly to classical exponential smoothing for items whose time series was continuous, and the β parameter had minimal effect on the accuracy of the results in these cases. For example, the item 53591776 (AX) in Table 2 exhibited very stable behaviour, with optimal values of α and β of 0.575 and 0.1, respectively, and a resulting MAPE error of 11%. Compared to the previous methods, in this case, Croston's method offered approximately comparable accuracy, with the advantage of higher robustness to possible zero values in the demand time series. In contrast, for the item 51381043 (AZ), which is characterized by high volatility, Croston's method produced a prediction that is practically applicable and does not exhibit negative DPA. The increased reactivity of the model drives this result - using values of α = 0.975 and β = 0.1 managed to compress the MAE to 19.791, compared to 96.617 for the simple linear regression.
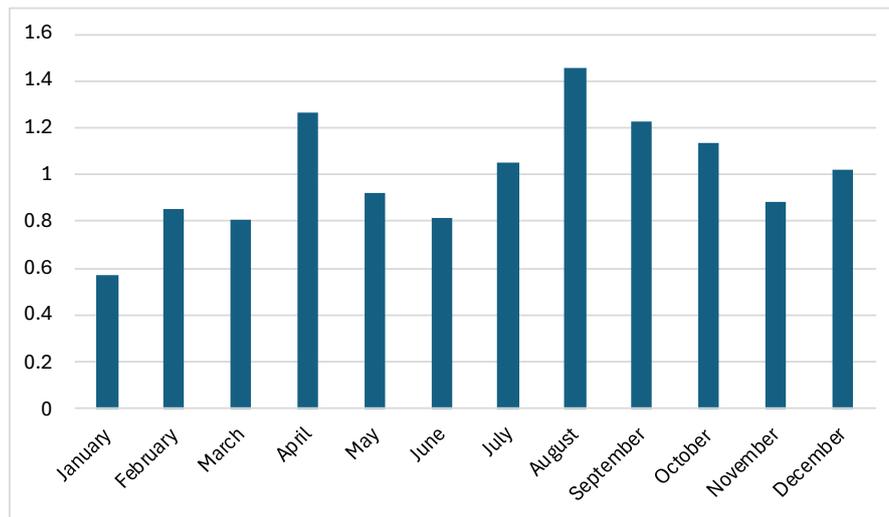
Figure 1 Average seasonal indices

Croston's method proved highly suitable for handling discontinuous and irregular time series, especially for items falling into the AY, BZ and CZ categories, where traditional prediction models – such as linear regression or moving averages – failed or provided irrelevant results. An important contribution of this method is its ability to ignore nulls while smoothing the magnitude and frequency of demand separately. This significantly improves prediction accuracy, where conventional methods fail to respond adequately to the fluctuations or irregularly recurring nature of demand.

It should be added, however, that despite the generally positive results, there were a few exceptions where Croston's method did not provide a significant improvement. This was mainly the case for items whose nature was closer to continuous or periodic consumption - in these cases, the model de facto converged to the results of classical exponential smoothing, while the parameter β did not have a significant impact on the result here. In these situations, it was found that other methods (e.g. linear regression with indices) could offer similar or even higher accuracy with less computational effort.

The bootstrap method, the principle of which was explained in Chapter 2, provides an alternative approach to quantifying demand uncertainty through repeated random sampling of historical values. Although it does not directly predict future values, it allows for estimating the likely range of future demand and identifying variability across items.

The process of generating the simulations was implemented in MS Excel through a function (16).

$$=INDEX(\$B\$2:\$B\$28;RANDBETWEEN(1;COUNT2(\$B\$2:\$B\$28))) \tag{16}$$

This formula combines the INDEX, RANDBETWEEN, and COUNT2 functions. The COUNT2 function determines the number of non-empty cells in the input series (in this case, the demand observations). RANDBETWEEN randomly generates an integer between 1 and that number, and INDEX returns a value at the corresponding position. This procedure creates a new simulated sample that respects the original empirical distribution. The mean and quantiles (5th and 95th percentiles) were then calculated from each simulation generated, producing a confidence interval representing the likely range of future demand. For example, for 53591776 (AX), the average simulated demand ranged between 1.7 and 1.8 million. CZK with a relatively narrow range from 788,473 CZK (5% quantile) to 2,526,740 CZK (95% quantile), indicating relatively stable and predictable behaviour, see Figure 2. The use of this approach, therefore, provides important context for future supply decisions, especially when building insurance stocks or planning a purchasing strategy.
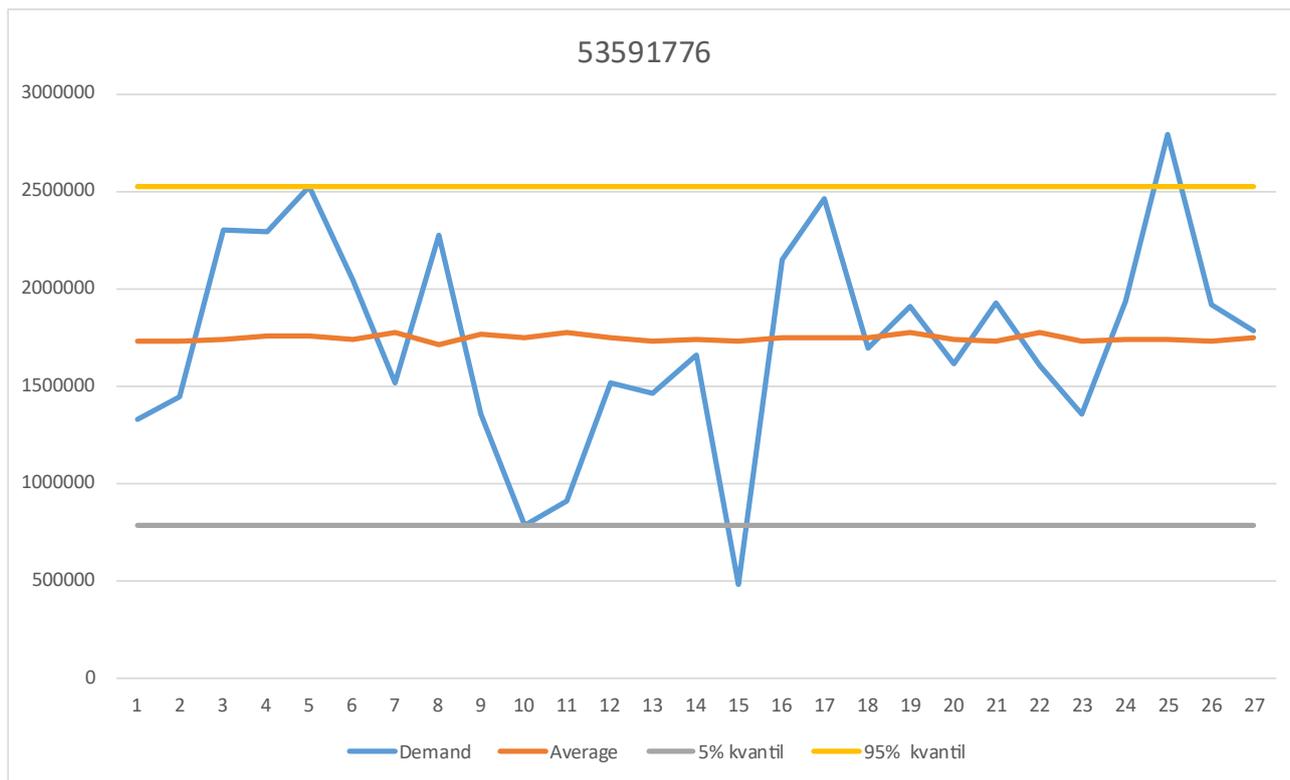
Figure 2 Simulated stock item demand 53591776

5   Results and discussion

Based on the analyses, the following procedure can be recommended for demand (consumption) forecasting. The first step is an ABC analysis, which divides the stock assortment into three basic groups according to the selected indicator. Group A should be given the greatest attention in inventory management, and the most accurate prediction of stock levels should be sought. On the other hand, for groups B and C, it may be acceptable to use simpler prediction methods. The second step is to carry out an XYZ analysis to identify fluctuations in demand or consumption. For items in categories Y and Z, looking for the causes of fluctuations is necessary. Therefore, it may be recommended to calculate seasonal indices, which can be used to determine whether seasonality or other causes or randomness are behind the fluctuations in demand.

Based on the ABC/XYZ classifications, a specific prediction method can be recommended for each group of items, considering the stability of demand, its variability and the item's importance. For the AX group of items characterized by high stability and often trend behaviour, linear regression or moving average with a shorter period (10) may be recommended. Croston's method for this group has frequently provided results comparable to simpler methods. It can therefore be regarded as unnecessarily demanding for this group of stocks. Alternatively, a simple exponential smoothing may be recommended instead of Croston's method, as there are virtually no periods of zero demand in the time series for the AX group.

Group AY included items with regular but more volatile demand. If seasonality is the cause of the fluctuations, a linear regression supplemented with seasonal indices may be well recommended. If the causes of volatility differ, Croston's method proved to be the only reliable method in specific cases, with an extremely high reactivity setting (α approaching 1.0), because demand, although not intermittent, was highly volatile and difficult to predict.

The analysis showed that Croston's method, which was initially designed typically for series with sporadic demand (group Z), proved to be successful in optimizing the parameters α and β (0.1-1.0) for other groups as well. In the BY group, Croston's method often showed more reliable prediction results than moving averages or linear regression. This result is particularly accurate for time series with occasional demand shortfalls. In this group, Croston's method performed best when the parameter α was set in the range 0.1-0.6, when it was able to smooth the slightly discontinuous series effectively.

Croston's method was often the only applicable method in the AZ and BZ groups, where outages were frequent and predictability was very difficult. For items in category C with low demand values, the naive method can be considered in terms of application difficulty or simplicity. The recommendations are summarised in Table 3.

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Table 3 Recommendations for individual methods for demand forecasting

	X	Y	Z
A	Linear regression Moving averages (10) Exponential smoothing	Linear regression plus seasonal indices Croston's method	Croston's method
B	Linear regression Moving averages (10) Exponential smoothing	Croston's method	Croston's method
C	Naive forecasting Croston's method	Naive forecasting Croston's method	Naive forecasting Croston's method

For key inventory items (Group A), we also recommend supplementing traditional forecasting algorithms with a bootstrap method for estimating uncertainty and setting service levels, allowing the company to manage its insurance inventory better and prepare for fluctuations in demand.

Based on the research results, it was recommended that the company implement a predictive inventory management system and integrate it into the Power BI environment, with a potential connection to an existing ERP system. This system would automate planning and, at the same time, reduce decision risk in purchasing and production. In conclusion, it must be emphasized that the selection of a prediction method cannot be done in a completely universal way – for each item, an appropriate model should be individually selected, taking into account not only the type of time series, but also its turnover, importance in the supply chain and impact on the company's operational activities. This approach can ensure that the prediction is simple in application and practical in day-to-day decision-making.

6   Conclusions

The main contributions of the article can be divided into two areas. The first area is research and practical application. As part of the research, an easy-to-apply methodology was proposed for predicting individual inventory items based on their importance and fluctuations in demand or consumption. This methodology was verified using real data from a custom manufacturing company. The second benefit is educational. The proposed methodology can be used to teach inventory management in subjects such as logistics or operations research.

The research proposed a methodological procedure for forecasting and inventory management for specific assortment items concerning their variability, significance and demand occurrence over time. The solution included both data preparation and classification of items using ABC/XYZ methods, as well as the application and evaluation of six prediction methods based on real data from the company.

The chosen approach allowed a detailed assessment of the behaviour of individual items. It also provided a practical tool to approach the selection of a prediction method systematically. It was found that the accuracy of the different methods varies significantly depending on the type of time series. Within the ABC/XYZ classifications, groups of items were identified for which a particular method repeatedly performed well (e.g. Croston's method for categories Y or Z and linear regression and moving average for category X). The results confirm that no method is universally applicable. For successful prediction, knowledge of item behaviour must be combined with an appropriate analytical technique. To understand the demand behaviour of inventory items, we recommend using a bootstrap simulation, which is relatively easy to apply. Bootstrap simulation provides essential information about demand uncertainty and allows the creation of predictive scenarios. The article offers practical instructions on how to perform such a simulation in MS Excel.

Three metrics – MAE, MAPE and DPA – were used to evaluate the methods, with the outputs compiled into clear tables and graphs. Particular attention was paid to Croston's method, for which the α and β parameters were optimized by grid search.

The results are limited by the nature of the data and the corporate environment of custom manufacturing with irregular demand. The analysis was also affected by the computational constraints of optimizing the parameters of Croston's method and performing bootstrap simulations in MS Excel and VBA, where a trade-off between computational finesse and time was required. Another limitation was the incompleteness of the input data.

The main contribution of the research was the development of a repeatable and adaptable demand forecasting procedure that considers the series' variability and the items' importance. The proposed system allows both the selection of the correct forecasting model and the quantification of risk and uncertainty, which is essential for decision-making in inventory planning. Last but not least, the research provides a basis for the possible integration of predictive logic into the business environment, either in the form of Power BI tools or as a basic output for an ERP system.

From a practical point of view, it can be recommended that each company should base its inventory management not only on historical data, but also on the nature and importance of individual items. Combining ABC/XYZ classifications with testing methods based on their performance under given conditions has proven to be a workable framework that can serve as a model for other manufacturing companies with similar demand characteristics.

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