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Forecasting in humanitarian operations: a method for anticipating fast-moving aid supplies

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ABSTRACT

Given Indonesia's vulnerability to a diverse range of natural and man-made catastrophes, it is crucial to have a well-executed disaster management system in place. The National Disaster Management Agency (BNPB), as the agency responsible for disaster relief in Indonesia, emphasizes the importance of this matter. This study examines the enhancement of disaster logistics, specifically focusing on the difficulties related to the fast movement of humanitarian aid supplies. The main challenge in disaster logistics is the uncertainty of demand following the occurrence of the disaster, together with the possibility of supply disruptions caused by insufficient inventory in warehouses. This research places significant emphasis on expedited delivery of humanitarian aid supplies, which are crucial for prompt relief operations, especially in situations with limited preparation time. The main aim of the study is to create a safety stock level policy for BNPB's national warehouse, which will be determined by analyzing forecasts of demand and lead times. The research findings for the year 2022 indicate a low percentage of errors in demand predictions. This result emphasizes the efficacy of the safety stock strategy in actively dealing with sudden increases in demand and reducing uncertainty associated with supply schedules.

1. Introduction

Indonesia is a region that possesses an inherent susceptibility to a diverse range of natural and man-made disasters (Siagian et al., 2014). Earthquakes, floods, landslides, volcanic eruptions, storms, tsunamis, land and forest fires, technical and modernization failures, epidemics, and disease outbreaks are all included in this list of risks. To address these difficulties, the Indonesian government has implemented the National Disaster Management Agency (BNPB) at the national level, which is further supported by the Regional Disaster Management Agencies (BPBD) at the regional level. BNPB (2021) reports that the National Disaster Management Agency documented 5,003 national catastrophes in 2020 alone, demonstrating the severity of the issue. The importance of preparedness and disaster management cannot be overstated due to the abrupt and frequently unforeseeable occurrence of catastrophes, as they play a crucial role in reducing the number of casualties.

The process of disaster management is often understood as a multi-stage framework, which includes four key components: mitigation, preparation, reaction, and reconstruction, as outlined by de Smet et al. (2015). The framework for disaster management is defined by a four-stage cycle. The flow of humanitarian logistics is important in this cycle, as it encompasses several activities related to

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logistics and supply chain management. These processes are particularly relevant in the areas of preparedness, response, and reconstruction (Nikbakhsh & Zanjirani, 2011).

Logistics plays a crucial role in the field of disaster management, specifically in the pre-disaster, preparedness, and response stages (Thomas, 2008). The primary goal of efficient disaster logistics is to achieve seven essential objectives: the provision of appropriate humanitarian supplies, in the correct quantity and quality, at the specific locations where they are required, within the designated timeframe, accompanied by accurate reporting, and at a cost-effective rate (Adiguzel, 2019).

In addition, disasters and destructive events necessitate increased logistical efforts in terms of knowledge and costs, as quick action in damaged areas tends to be necessary. Various categories of disasters require unique approaches to management, and logistics consistently plays a crucial role in all humanitarian aid and disaster relief efforts. It is important to highlight that logistics plays a substantial role in the financial aspect of disaster relief, with an estimated contribution of around 80% to the overall expenses associated with disaster management (van Wassenhove, 2006).

Based on the database form BNPB, the needs of fast-moving humanitarian aid supplies have the highest demand immediately after a disaster strikes since it is considered as basic needs. Despite the short lead times, these supplies play a pivotal role in providing immediate relief to affected populations. Ensuring an adequate inventory of these items is essential, as delays in their delivery can result in increased suffering and loss of life. The unpredictability of demand patterns in terms of timing, location, kind, and quantity of humanitarian assistance required is a significant challenge in the field of disaster logistics (Pujawan et al., 2009). Ozbay et al. (2006) have pointed out that there is a possibility of supply disruptions caused by inadequate inventory in the warehouse, which can occur after short waiting periods followed by sudden and significant demands for relief items and services.

The relevance of humanitarian relief supplies in this setting cannot be overemphasized. The absence of a well-organized inventory of critical supplies exposes persons impacted by disasters to significant risks and dangers. According to Whybark (2007), inventories of humanitarian help can be categorized as a subclass of "social" inventories, primarily aimed at benefiting society rather than a specific organization. The presence of this social orientation adds complexity to the task of inventory management, as it involves the complicated interaction of several aspects such as demand, location, supply availability, transportation, and other logistical considerations (Whybark, 2007). Inadequate management practices, such as errors in determining safety stock levels, can lead to stockouts, which in turn result in unfulfilled customer demand. This highlights the significance of proactive planning in inventory management.

In this context, it is important to keep the safety stock level in order to guarantee the uninterrupted supplies of humanitarian aid in unexpected emergency response situations. Safety stock is a crucial metric utilized in the field of inventory control. It denotes the amount of inventory that is required to proactively address anticipated surges in demand or unforeseen requirements. Furthermore, safety stock functions as a protective measure to mitigate the uncertainty associated with supply timelines and lead times for replenishing inventories (Swartz et al., 2015). Therefore, the objective of this study is to develop a safety stock level policy for the national warehouse of BNPB through an analysis of the demand plan and lead time.

Numerous studies have been undertaken to investigate the procurement of humanitarian aid in situations when the level of demand is uncertain, employing a range of methodologies and approaches. Chen et al. (2022) employs stochastic and mathematical models to forecast the need for emergency supplies in the context of flood events. Monzón et al. (2020) also employed these techniques to enhance the effectiveness of humanitarian assistance by optimizing the allocation of distribution sites and the selection of roads. Basu et al. (2019) employed technical innovation and a statistical technique to gather and send resource needs to control centers through the utilization of smartphones. Ozguven and Ozbay et al. (2012) recommended for the implementation of RFID technology and utilized a stochastic model to enable the real-time monitoring of emergency supplies and requests. In a study conducted by Nahleh and Hakami (2013), the concept of Emergency Safety Stock (ESS) was introduced to address and minimize the consequences of unforeseen variations in demand that may arise during times of disasters.

In order to enhance the accuracy of demand projections, this research employs a resampling technique on historical data and integrates safety stock levels and reorder points into the administration of BNPB's national warehouses. The objective of this study is to provide a valuable contribution to the improvement of disaster preparedness and response. It acknowledges the crucial

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role played by humanitarian aid supplies and the growing significance of effectively managing humanitarian assistance inventories in disaster relief operations.

2. Methods

The demand planning procedure is the initial stage in determining what is required, who requires it, when, where, and how to meet the requirement. In disaster management, planning involves the identification of needs, inventory of available resources, accumulation and analysis of data, and production of minimum requirements standards. This planning activity necessitates precision, expertise, and the capacity to accurately assess the condition of the affected community.

This section will explain the methodological steps taken to determine the inventory and safety stock required at the BNPB warehouse. These phases are as follows:

1. Identification of historical data is a series of product type selections that will be analyzed to determine the optimal quantity of safety stock according to predetermined criteria such as:
    a. Goods to be prioritized in the event of a disaster.
    b. Goods for which annual requests are repeated.
2. Applying bootstrap to substitute zero values.
   According to Şahinler and Topuz, D. (2007), bootstrap is a variety of nonparametric resampling in which numerous smaller samples of the same size are taken repeatedly from a single original sample, with replacement. Each value in the sample has the same probability of being chosen, including multiple times, so duplicates are possible. Bootstrap is used to replace missing data with the distribution derived from sampling with B times replication and n-sample size (Efron & Tibshirani, 1994). Because the data sample used as the population is the original data sample, this method can operate without distribution assumptions (Sungkono, J., 2013).
3. Data forecast
   Forecasting has a crucial role, particularly in the areas of planning and decision-making. The categorization of forecasting techniques is based on two approaches: qualitative and quantitative. This study employed the quantitative research approach and relied on historical data provided by BNPB. It is based on the assumption that certain characteristics of past patterns will persist in the future. (Makridakis et al., 1983). Here, the Croston Method used for intermittent data types (data with a lot of zeros) and the Exponential Smoothing Method is used to compare the forecasts with data that have bootstrapped the values in place of the zeros. In the year 2022, the process of forecasting is conducted by utilizing past data.
4. Evaluation of the accuracy of forecasted outcomes
   Our decision of a forecasting method depends in part on whether the calculation's precision results in a small error.
5. Safety stock and reorder point calculation
   In anticipation of customer service levels and replacement lead times, safety stock and reorder point calculations are performed after obtaining the forecasting results.

3. Results and Discussion

3.1 Data Collection

During this phase, a data collection procedure will be conducted to facilitate the study of safety stock calculations. The dataset employed comprises information pertaining to the frequency of humanitarian assistance required after events of disasters in Indonesia. This study specifically concentrates on a limited number of priority items, despite the existence of a wide range of needs.

The dataset utilized comprises monthly data spanning a period of seven years, specifically from January 1, 2015, to September 30, 2021. Notably, the data shows a big presence of zero values. The data was acquired from the inventory system of BNPB. The dataset under consideration comprises a total of 18 items, which have been identified as priority items through consultations with the BNPB team. These determinations have considered the minimum requirements for clothes, food, and shelter. In addition to this, the determination of item priorities is contingent upon the frequency and regularity with which goods are bought (considered as fast-moving humanitarian supplies). The following is the list of 18 priority items that will be discussed in this paper.

Table 1 Priority items

No	Item name	No	Item name
1	Mattress	10	Ready-to-eat meals
2	Blanket	11	Side dishes
3	Evacuation boat	12	Nutritional Supplements
4	Boat machine	13	Sarung
5	Refugee tent	14	Folding mattress
6	Family Kit	15	Family hygiene kit
7	Family tent	16	Infant supplies kit
8	School tent	17	Clothing package
9	Body bag	18	Velbed

3.2 Pre-Processing Data

The purpose of data pre-processing is to ensure that the obtained data is available for processing (Bilalli, 2018). In this phase, the purpose of the data compilation procedure is to generate a forecasting model that can be used to predict the number of demands for humanitarian assistance in the next year. The demand pattern for one of the 18 priority items is shown in the Fig. 1.

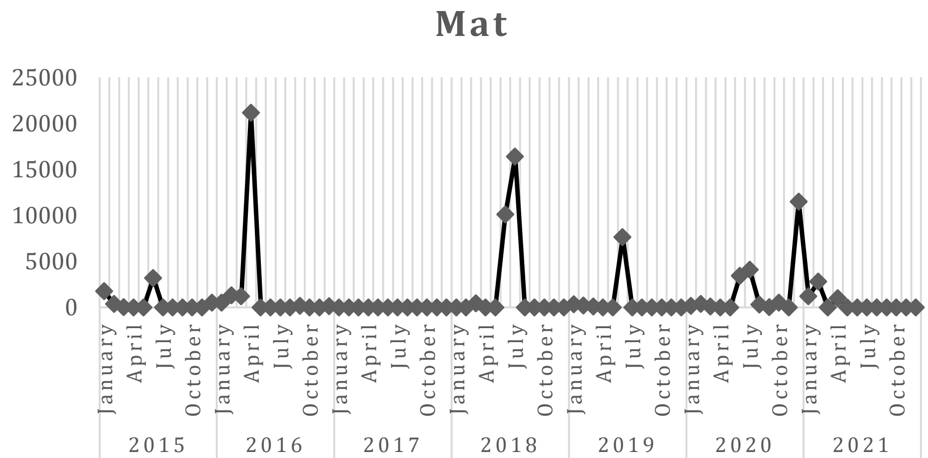

Fig. 1 Demand pattern for Mattress item.

All the data do not represent time series data terms that can be directly analyzed because they lack a trend pattern (upward or downward trend) or seasonality (seasonality) and have a large number of zero values between periods. The zero value for each historical data entry has a high percentage (intermittent data), while the minimum zero value for historical data is 50%. Comparatively, the maximum is equivalent to 95% of all historical data.

Therefore, the next stage is to fill in zero data using bootstrap in Microsoft Excel. The distribution obtained from sampling with B times replication and n samples is utilized for bootstrapping. The bootstrap procedure is executed by initializing the random value of the distribution of the actual request data up to 50 times, which is then averaged to fill in zero data. The example results of replacing the zeros number in comparison to the original historical data for one of the 18 priority items is shown in Fig. 2.

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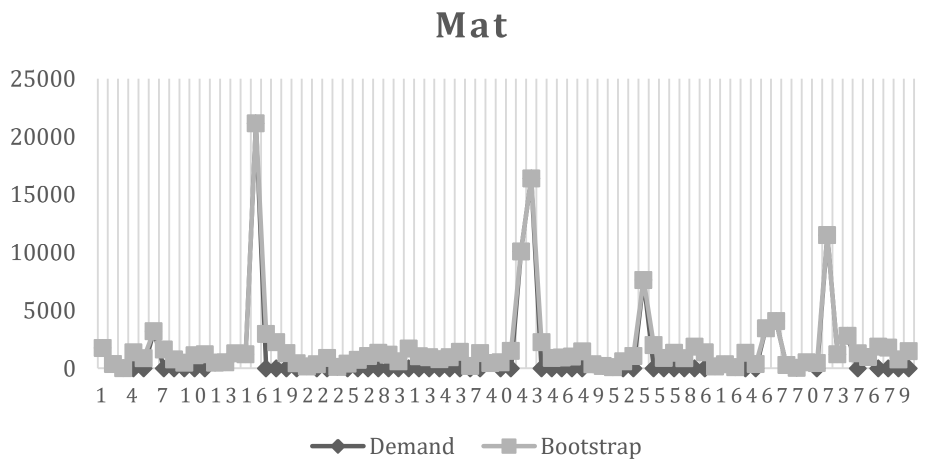

Fig. 2 Demand and bootstrap result of Mattress item.

3.3 Model Design

With intermittent data types, the Croston Method is a technique that can be used to forecast demand. The Croston method proposed by Croston predicts separately for the two time series components. Observed values include the non-zero demand value and the time interval between arrivals of transactions. Then, exponential smoothing is applied separately to each of the two values, and data is only updated in response to a demand (a non-zero demand). The non-zero demand value and forecasted value do not change whenever there is no demand in a period. The Croston method provides the same forecasting value as Exponential Smoothing if demand occurs every period.

After zero values are filled in using bootstrap, the data is separated into training data (training set) and test data (test set). The design of this Croston model employs averaging parameter values (α and β) that will be determined based on an initial assumption in the range 0 to 1. The significance values used for α and β are α=0.3 and β=0.2. Model search is achieved using training data that has been partitioned into real historical demand data and bootstrap data using the Croston approach.

Distribution is carried out by randomly splitting 70% of the training data (training set) and 30% of the test data (testing set). 80 lines of data were collected, with 56 lines serving as training data and 24 lines serving as test data. Actual historical data and bootstrap outcome data are used to segment training data.

3.4 Forecast Accuracy Measures for Training Set

After modeling with training data, the level of accuracy is calculated for each scenario (Croston method with actual historical data and Croston method with bootstrap data) using MAD, MSE, and SMAPE measurements. SMAPE value rests between 0-200%. The better the forecasting results, the lesser the error value (Figure 3).

Depending on the tested technique, each scenario also possesses a distinct level of precision. The graph below represents a comparison of the optimal level of accuracy in the training data for the two scenarios.

3.5 Model Validation

At this stage, tests were conducted on the previously identified models; data testing is performed to determine whether the model is suitable for use in 2022 forecasting calculations. As with training data, estimation for testing data employs smoothing parameter values of =0.3 and =0.2 for estimation.

In addition, it is used to calculate the level of precision using the MAD, MSE, and SMAPE parameters. Fig. 4 is a graph of measurement errors resulting from data testing calculations.

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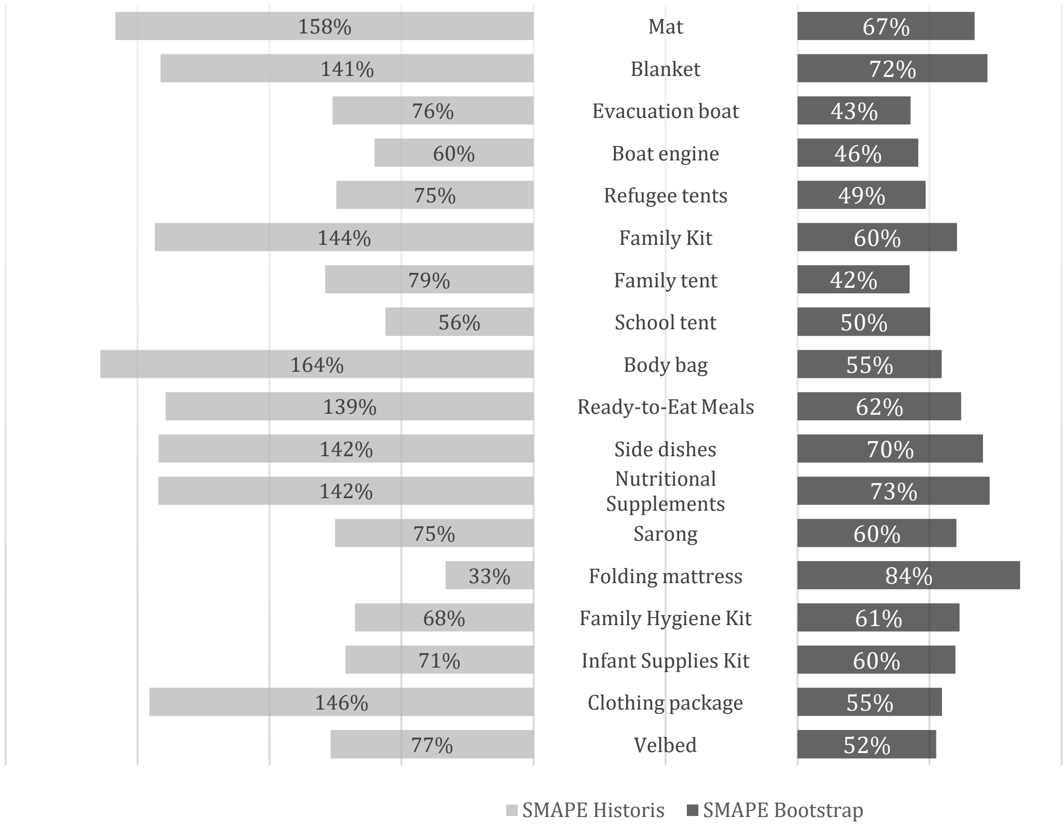

Fig. 3 Forecast accuracy of historis and bootstrap for data training.

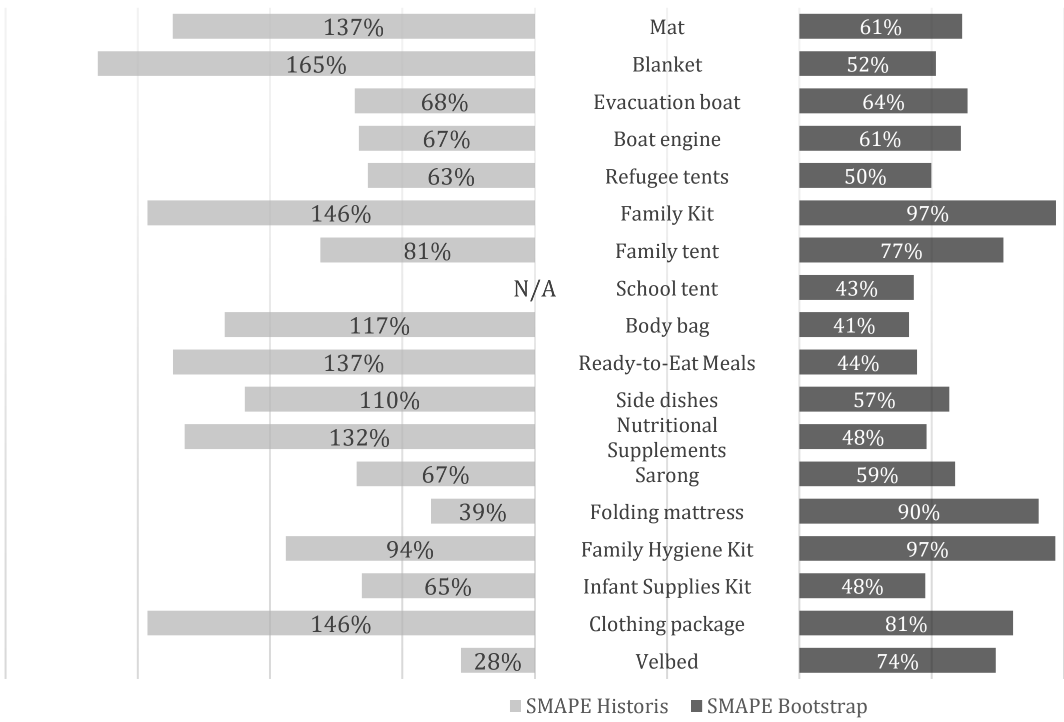

Fig. 4 Forecast accuracy of historis and bootstrap for model validation.

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There are variations in the error values that result from comparing the outcomes of forecasting training data using actual historical data and bootstrap. The results of error calculations performed on bootstrap data have a smaller aggregate value than error calculations performed on actual historical data.

Comparing the results of model testing with those of data testing using actual data and bootstrap reveals that error results also vary, as was the case with calculations by using training data. The following factors influence the error calculation results from the preceding calculation:

1. Data Pattern
   According to what has been stated previously, there are more zero values than non-zero values among the 80 data periods for each item. Additionally, appropriate bootstrap values cannot be generated with minimal demands. This is because the required range of values to initialize the bootstrap value is too narrow, preventing it from receiving a diversity of value variations.
2. Data Distribution
   70% and 30% of training and tests sets were distributed at random, resulting in uncontrolled data groups. If the data from the training set or test set has a non-zero value at the end of the computation period, a small error value may result. According to the Croston method calculations, the demand value is not zero when there is no demand in a period, and the predicted value does not change. This equal value introduces a small quantity of error due to the insignificance of the difference between forecast results and historical data.

3.6 Demand Forecast

Forecasting for the period 2022 is conducted using two models derived from two scenarios: the Croston method model for historical data and the Croston method model for bootstrap data. Both models predict the demand for 18 priority items in 2022, with the actual initial data for 2022 being identical to the actual initial data for 2021. Table 2 is the result of predicting the 18 priority items for the period of 2022.

Table 2 Forecast result for historical data

Item	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mat	4901	4262	3241	2498	2336	2195	1750	1684	1528	1297	1112	3078
Blanket	11043	7145	4579	5650	4185	3413	2351	2428	2134	1767	2513	4636
Evacuation boat	3	16	15	11	7	5	4	3	2	2	2	2
Boat engine	2	2	6	5	4	3	2	2	1	1	2	2
Refugee tents	81	52	37	36	87	64	62	50	37	27	19	22
Family Kit	1072	1011	690	470	615	606	644	566	926	727	802	1129
Family tent	40	27	19	13	10	9	8	7	6	8	8	13
School tent	7	6	4	3	2	5	9	7	5	4	3	3
Body bag	127	111	126	113	120	119	109	575	475	384	324	274
Ready-to-Eat Meals	3956	2954	1921	2308	5777	4456	3654	2502	2686	1975	1666	2256
Side dishes	4071	3361	2186	2570	6036	5696	5213	3567	3095	3048	2967	3494
Nutritional Supplements	4298	3164	2055	2133	5662	6008	5512	3772	4204	3023	2750	3192
Sarong	4369	8040	5413	4297	3033	2119	1592	1091	982	798	666	2431
Folding mattress	234	189	161	217	170	116	111	78	71	53	46	57
Family	215	179	116	151	133	158	208	300	269	278	301	319

Item	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hygiene Kit												
Infant Supplies Kit	1460	972	624	506	432	362	384	382	447	496	463	966
Clothing package	912	967	750	826	764	755	980	1180	1032	1240	1516	1427
Velbed	227	140	146	277	208	584	722	576	404	282	199	142

3.7 Forecast Accuracy Measures

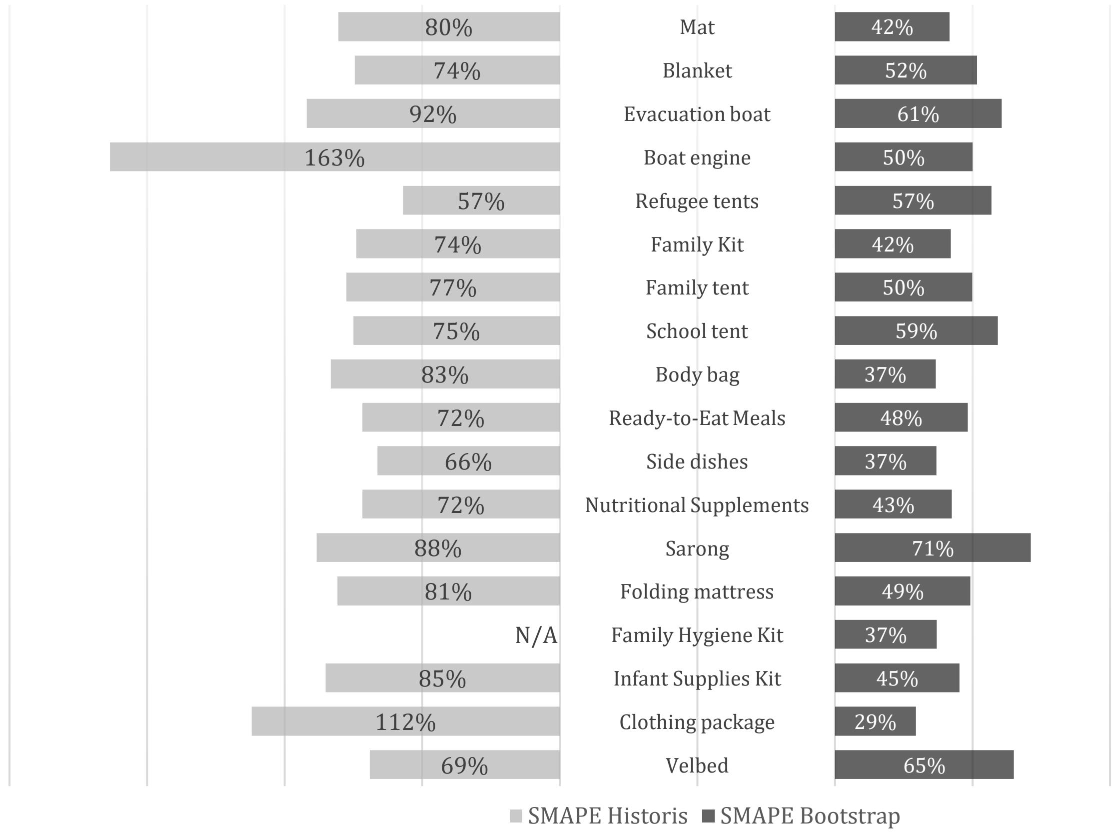

Fig. 5 Forecast accuracy measure for historis and bootstrap data.

Forecasting error is measured by MAD using the same units as the original dataset. MSE reduces the impact of a few large forecast errors while increasing the effect of many minor ones. By comparing the error value and the quantity of real data with the forecasting results, SMAPE illustrates the size of the forecasting error.

The two models above demonstrate that, when using actual historical data for 2021, the Croston approach outperforms the Bootstrap + Croston model in terms of accuracy. In forecasting computations using historical data from 2021, the family hygiene kit has a SMAPE value of 0%, as shown in the comparison chart above. This is because there isn't enough previous data for this item in 2021.

This is a presentation of the forecasting calculations for the 18 priority items for BNPB's disaster preparedness and response. The Croston + Bootstrap method can be used to predict demand for time series data types with lots of zero values (intermittent data). To create more accurate forecasting results that more accurately reflect actual demand, more complete data is preferred.

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3.8 Safety Stock and Reorder Point

After calculating forecasts for 2022, safety stock and reorder points can be calculated for all 19 priority items. Included in the calculation of safety stock and reorder points are CSL (Cycle Service Level) values and lead time information (duration from when an order is placed until it is received). The CSL value utilized is 98%.

The formula used to calculate safety stock is as follows:

$$ss = Fs{-}1(CSL)\ X\ \sigma L = Fs{-}1(CSL)\ X\ \sqrt{L}\sigma D = NORMSINV(CSL)\ X\ \sqrt{L}\ \sigma D$$

$NORMSINV$: a function in Excel that calculates the inverse of the standard normal distribution.
CSL : Cycle Service Level
L : Leadtime
σD : Standard Deviation for Demand

The outcomes of the 2022 safety stock and reorder point estimates are as follows in Table 3.

Table 3 Safety stock and reorder point for 18 items priority

Item	Demand average (D)	σD	Csl	Leadtime	Safety Stock	ROP
Mat	2490	1133,55	0,98	0,17	949	963
Blanket	4320	2549,06	0,98	0,05	1148	1155
Evacuation Boat	6	5,01	0,98	1,40	13	14
Boat Engine	3	1,41	0,98	0,62	3	4
Refugee Tents	48	21,32	0,98	0,36	27	28
Family Kit	771	206,30	0,98	0,05	97	99
Family Tent	14	9,64	0,98	0,10	7	8
School Tent	5	1,89	0,98	1,29	5	6
Body Bag	238	158,36	0,98	0,32	184	187
Ready-To-Eat Meals	3009	1174,41	0,98	0,12	837	850
Side Dishes	3775	1185,71	0,98	0,15	947	967
Nutritional Supplements	3814	1290,53	0,98	0,15	1036	1056
Sarong	2903	2155,66	0,98	0,04	871	875
Folding Mattress	125	64,10	0,98	0,01	16	17
Family Hygiene Kit	219	69,25	0,98	0,01	18	19
Infant Supplies Kit	624	322,21	0,98	0,04	136	137
Clothing Package	1029	249,64	0,98	0,14	190	195
Velbed	326	190,73	0,98	0,05	92	93

4. Conclusion

Planning for demand in 2022 is the first stage in calculating safety stock. The Croston Technique is used to estimate demand for 2022 in this planning process. This approach was selected because demands for disaster events tend to be sporadic. When there is no disaster, there won't be any demand for a certain amount of time (Zero Demand). Consequently, the demand for humanitarian aid does not follow a specific pattern when represented by a graph.

A bootstrap resampling method is used to predict this kind of data to encounter statistical issues, including small data issues, data that deviates from assumptions, and data that has no confidence in its distribution, such as current historical data patterns analyzed, where no need or desire is present for a specific period. The Croston method is used to calculate the demand and needs for 2022, and the findings are obtained with a degree of accuracy that matches the measurement parameters for the forecasting model's accuracy. SMAPE is the parameters that are used to gauge this precision. SMAPE number ranges from 0 to 200%. The accuracy of the findings of the demand estimation increases with decreasing error values. Based on the calculation of the SMAPE forecasting model's parameter accuracy, the results vary from 17% to 150% (between 0% and 200%). This indicates that Croston's method has successfully predicted demand and requirements through 2022.

In order to avoid insufficient stock, the fast-moving goods must be reordered when the inventory reaches the reorder point. An annual reevaluation of safety stock is required because accurate forecasting values are created using historical demand data from the previous year.

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