Demand Forecasting Tool For Inventory Control Smart Systems

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Original scientific article

***Abstract*—With the availability of data and the increasing capabilities of data processing tools, many businesses are leveraging historical sales and demand data to implement smart inventory management systems. Demand forecasting is the process of estimating the consumption of products or services for future time periods. It plays an important role in the field of inventory control and Supply Chain, since it enables production and supply planning and therefore can reduce delivery times and optimize Supply Chain decisions. This paper presents an extensive literature review about demand forecasting methods for time-series data. Based on analysis results and findings, a new demand forecasting tool for inventory control is proposed. First, a forecasting pipeline is designed to allow selecting the most accurate demand forecasting method. The validation of the proposed solution is executed on Stock&Buy case study, a growing online retail platform. For this reason, two new methods are proposed: (1) a hybrid method, Comb-TSB, is proposed for intermittent and lumpy demand patterns. Comb-TSB automatically selects the most accurate model among a set of methods. (2) a clustering-based approach (ClustAvg) is proposed to forecast demand for new products which have very few or no sales history data. The evaluation process showed that the proposed tool achieves good forecasting accuracy by making the most appropriate choice while defining the forecasting method to apply for each product selection.**

***Index Terms*—Demand Forecasting, Intermittent-Demand Forecasting, Time-Series Data, Statistical Forecasting, Machine Learning, Smart Systems.**

I. INTRODUCTION

WITH the availability of data and the increasing capabilities of data processing tools, many businesses are leveraging historical sales and demand data to implement intelligent inventory management systems. Demand forecasting is playing an important role in many areas, particularly in inventory management and supply chain. Indeed, effective inventory management often relies on accurate estimation of the consumption of products or services for future time periods. The results of demand forecasting depend very much on the relevance, quality and accuracy of the forecasts made, which in turn depend on the forecasting model being used [20]. Demand forecasting is often based on time series data, which are the most common type of historical data. There are several methods that can be used for time series forecasting, the first of which appeared in the 50s. Since then, it has become a highly sought-after research topic and other methods have emerged. Statistical methods remain the major part of contribution in demand forecasting research field. Statistical methods have provided highly accurate forecasting results and were very useful in practice. With the emergence of Machine Learning (ML), new methods have been proposed and have generated such a buzz in the forecasting field, which encourage several recent works to implement ML-based demand forecasting for time-series. Many comparative studies have been conducted to discuss the accuracy of the prominent demand forecasting methods (both statistical and ML-based). This paper offers a deep literature review which can support researchers in their work related to demand forecasting, mainly for time-series data. Since this field strongly depends on real-business usecases, this work proposes a new demand forecasting tool for a growing online retail platform, Stock&Buy. In this context, Stock&Buy wants to build a demand-forecasting system allowing effective inventory control. This system shall use robust forecasting techniques to: (a) handle the diversity of products and their underlying demand patterns, but also (b) estimate demands for new products for which there is no historical demand data. Therefore, a forecasting tool is proposed with the following functionalities:

- Weekly and monthly demand forecasting at store level products
- Handle intermittent-demand for slow moving products and predict obsolescence risk
- Demand forecasting for a new product which doesn't have historical demand data

Under Stock&Buy's motivation, the contribution of this project are manifolds:

- Provide an extensive literature review about demand forecasting methods, especially for time-series data
- Design a new forecasting pipeline which introduces a process to optimize the use of data and hence reach a

Manuscript received March 20, 2021; revised May 29, 2021. Date of publication June 24, 2021. Date of current version June 24, 2021.

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Part of this work was presented at the 5th International Conference on Smart and Sustainable Technologies (SplitTech20) 2020.

Digital Object Identifier (DOI): 10.24138/jcomss-2021-0068

higher accuracy while selecting the model to implement. This process will help future researchers on designing new forecasting methods

- Implement and validate the proposed pipeline through Stock&Buy case study. A new demand forecasting tool is proposed containing two new forecasting methods

Note that proposed demand forecating tool have been presented in a previous work with its two new methods [6]. In this extended version, we detail more the entire process and the deployment in real environment after prototyping. We also give an extensive survey which helped us to design the forecasting tool and find the best solution tailored to Stock&Buy request. This survey is a potential source for new researchers in the field of demand forecasting where many methods are presented, in addition to comparative studies, taxonomy and general synthesis.

The remainder of this paper is organized as follows. Section II presents the literature review on demand forecasting approaches with a proposed taxonomy and an extensive comparison. Section III details the solution starting by explaining the forecasting pipeline with the preliminary study that helped to design the tool, followed by the proposed forecasting methods, CombTSB and ClustAvg for Stock&Buy platform. The validation process is explained in section IV including both the standalone prototype and the tool deployment. A final conclusion is given in Section V.

II. Demand Forecasting: A Literature Review

We propose in figure II a taxonomy of different forecasting methods and models that are commonly used in demand forecasting. There are two main forecasting-models families : qualitative forecasting models and quantitative forecasting models. In the latter, three sub-categories can be found: Statistical, ML-based, and hybrid methods. In an inventory context, based on the underlying demand patterns of products, forecasting methods can also be divided into continuous demand methods and intermittent demand methods. The identification of patterns such as intermittency is important in deciding which method is most appropriate for the forecasting problem (continuous demand methods or intermittent demand methods). Demand categorisation schemes discussed in next sections can be very useful in the identification of such patterns and therefore in the selection of the most appropriate forecasting method.

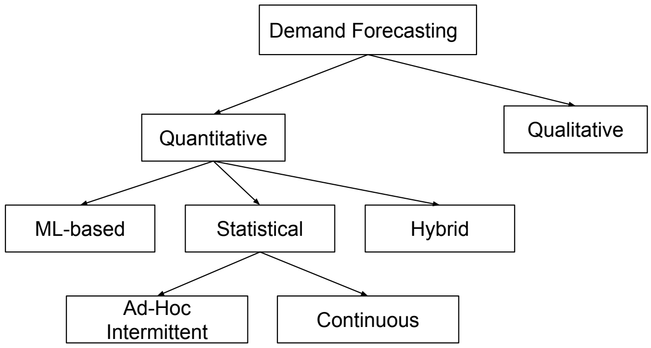

Fig. 1. Taxonomy of demand forecasting methods

A. Qualitative Forecasting Methods

Qualitative forecasting, also known as judgemental forecasting is a common forecasting technique that relies upon expert judgement or consumers' opinions rather than numerical analysis. Qualitative forecasting is useful and often times necessary in the lack of historical data that backs any quantitative forecasting technique. It is also useful in situations where historical values are suspected of having little to no impact on future values. Although it is a common practice, qualitative forecasting methods may lead to biases because it depends heavily on human's opinion which can be influenced by personal or political agendas. Recency also puts an additional challenge to the judgemental forecasting as it is well known that the expert or the forecaster tend to give a bigger importance to recent historical events and the resulting forecasts are therefore close to a near reference point. In what follows, we briefly describe some of the most popular qualitative forecasting techniques that has led to the acceptance of judgemental forecasting as a systematic forecasting approach.

1) Delphi Method: is an interactive forecasting technique that was invented in the 50s. It relies on a panel of experts as the method is built upon the key assumption that forecasts generated by a group of experts are better than the ones generated by individuals. A facilitator is designated to implement and manage the iterative process of Delphi method that involves the following stages [12] : (a) Assemble a group of experts; (b) identify the forecasting challenges and tasks; (c) Return initial forecasts by experts; (d) Provide feedback; and (e) Construct the final forecast.

2) Forecasting by Analogy: is a common practice that relies on the assumption that two similar phenomena should share the same forecasts. Forecasting by analogy can be implemented using quantitative models such as ML clustering techniques, but can also take the form of a qualitative approach just like the one that was proposed in [13]. This approach is very similar to Delphi method by its designation of a facilitator and a group of anonymous experts, the main difference between the two methods resides in the manner of generating forecasts which is achieved by identifying and describing all possible analogies with the target situation and construct forecasts upon these. Authors in [13] found that this method can lead to reliable results especially if experts with a significant experience in forecasting with analogies have multiple analogies with the target situation.

3) Scenario Building: consists of generating forecasts based on building scenarios by considering all possible factors and targets for which forecasts have to be generated. This approach allows to generate a scope of all possible forecasts and is therefore useful in identifying extremities. Often times, at least three scenarios have to be built in order to generate accurate forecasts.

4) New Product Forecasting: is critical for any business as they generate new revenues and drive value. It is usually qualitative and all methods discussed above (Delphi, forecasting by analogy and scenario building) can be used to generate new-product demand or sales forecasts. Quantitative methods can be used for new products forecasting in adjunction to qualitative forecasting methods. We describe hereafter, the most commonly used methods for new-product forecasting:

- Market Research: a very popular approach which involves surveys that customers are asked to fill to determine their purchase intentions.
- Sales Force Composite: consists of aggregating forecasts from each sales manager or any other member of the sales force.
- Jury of Executive Opinion: this approach is very similar to sales-force-composite method but instead of aggregating salespeople forecasts it involves top executives and managers from different areas (finance, marketing, production , etc.) who contribute to the generation of forecasts in a group meeting.

B. Quantitative Forecasting Methods

To make projections about the future, the quantitative forecasting relies on mathematical (statistical) models. Because of the objectivity of quantitative-forecasting models, it is recommended to use them when sufficient amount of historical data is available and are fairly correlated with the future values (i.e. the past patterns may continue into the future). Quantitative forecasting can use either cross-sectional data (i.e. data collected at a single point in time) or time-series data. the latter being the most common type of data used in forecasting. In the context of this work, we are interested in time-series models to which we gave a particular focus during our literature review. In addition to the diversity of data types that can be used, quantitative forecasting comprises several models depending on which predictor variables are used in the model. These models can be described as time-series models, or as explanatory (causal) models. Explanatory forecasting model aims at identifying the underlying factors that influence the target(forecast) variable (e.g. strength of economy, population, etc.). Unlike time-series models, explanatory forecasting models don't take into account demand history (past demand values). Many methods can be used under this category of forecasting the most famous ones are regression analysis, an umbrella term that comprises many methods that all examine the influence of one or more independent variable on a dependent variable.

In the context of this project, we are interested in time-series models which represent most of our clients' data patterns (for Stock&Buy usecase). In what follows, we give a literature survey about different time-series forecasting methods and existing works regarding their applications in demand forecasting. These methods can be grouped under three main subcategories : statistical methods, Machine Learning methods and hybrid methods.

1) Statistical Methods: Statistical methods are the most commonly used methods in time-series forecasting in general and in demand and sales forecasting in particular. They have a long standing history and a strong mathematical basis. Under statistical methods, we distinguish two main sub-categories: (a) Continuous, where there is a continuous time-series pattern for demand history. And (b) Ad-hoc intermittent for slow-moving products where extensive models have been developed, such as Croston methods, SB, TSB[36]. In what follows, we describe some of the most popular statistical time-series forecasting methods including the simplest ones which are usually used as benchmarks.

Simple Forecasting methods are usually used as benchmark to assess and compare more sophisticated models. The most famous ones are the average method, naive method, and drift method. *Exponential Smoothing models* have been widely used for time-series forecasting. The forecasts obtained from this method are weighted averages of past observations. Exponential smoothing has several variants (simple, double and triple Exponential Smoothing model). *ARIMA (Auto Regressive Integrated Moving Average* Model) [7] is the integration of autoregressive and moving average models, the integration is done by differencing the time series. ARIMA is characterised by three iterative phases according to Box-Jenkins methodology, which are: (a) Model identification, (b) Parameter estimation, and (c) Diagnostic checking. Autoregressive models AR(p) are time series models, described by a regression equation, that takes as inputs the p previous observations in order to predict future values. *Theta Model*[4] was among the best-performing methods in the famous forecasting competition M3-competition[21] and is therefore commonly used for time-series forecasting especially in Supply Chain Management and planning due to the accuracy of its points forecasts [27]. *Bootstrapping and Bagging* can be used to improve point forecasts. The idea is to generate new time-series which are similar to the observed series using bootstrapping[1] and then generate forecasts for the observed data by averaging point forecasts from the generated time-series (i.e. bagging). *Vector Autoregressions(VAR) model* is a generalisation of the univariate autoregressive model for forecasting multivariate time-series. It is one of the most common approaches for multivariate time-series forecasting because of its simplicity and flexibility. VAR model describes the evolution of a set of k variables, which are also called endogenous variables, over the same period (1, ..., T) as a linear function of their past values. It assigns an equation for each variable used in the model. Each equation describes the evolution of the variable based on its lagged values, the lagged values of the other model variables, and an error term which represents a white noise process. The most important step in building a VAR model is choosing the number of variables and the number of lags to be included in the model. It is recommended to keep the number of variables small and only include the correlated variables [12].

2) Machine Learning Methods: The first application of Machine-Learning (ML) methods in forecasting goes back to 1964 but did not achieve much follow-up until many years later. Since then, extensive works have been conducted to study ML algorithms application in demand forecasting. The most notable models used for time-series forecasting are: Multi-Layer Perceptron (MLP), Generalized Regression Neural Networks (GRNN), Bayesian Neural Network (BNN),

[1]A metric that uses random sampling with replacement to assign accuracy measures, such as bias or prediction error, to a sample estimates.

Recurrent Neural Network (RNN), Support Vector Regression (SVR), CART regression trees (CART), Radial Basis Functions (RBF), K-Nearest Neighbor regression (KNN), Gaussian Processes regression (GP), and Long Short Term Memory network (LSTM). Very few large-scale comparative studies between these methods have been conducted for the regression or the time series forecasting problems, most of which are empirical studies. In a notable comparative study[2], conducted using M3 time-series competition data which includes 1045 business-type time series, the best two methods turned out to be the MLP and the GP regression followed by BNN and SVR. These results were obtained after testing different preprocessing methods which have been shown to have different impacts on the performance. Another comparative study [25] using a time series made up of 244 time points found that the best model was RBF followed by RNN and MLP while GRNN model is the one with the worst performance. One additional recent comparative study found that MLP is the best forecasting method under the category of Machine Learning models [23]. Empirical studies cannot solely evaluate the accuracy of forecasting methods as it strongly depends on the data being used to conduct the study. Since there is no ”universal” best method in the area of forecasting, each technique has its own advantages and drawbacks. The forecasting problem being addressed, the type of data that is used should all impact the choice of the forecasting technique. However, these empirical studies are very useful in practice and can guide future research directions in this field. Furthermore, most of these studies have found that Neural Networks with their different variants are the best performing ML methods in the area of time-series forecasting.

3) Hybrid Methods: combine features of a set of statistical and/or ML-based forecasting methods to benefit from the advantages of each one. Examples of hybrid methods include SOM-SVR, Stacked generalization, and ANN-ARIMA methods. *SOM-SVR* is a Hybrid Network that first uses Self-Organized Map (SOM) to divide the data set in clusters, then apply Support Vector Regressor (SVR) to ensure a better learning with more accurate prediction results using clustered data. The hybrid SOM-SVR has been applied for many works including electricity price forecasting [9] and financial time series forecasting [38]. *Stacked Generalization* implements a combination of ML-based algorithms to build a better prediction model, which can be generalized to many data sets, and avoid over-fitting of the training dataset. Stacked generalization has been used in many recent works (e.g. A day-ahead household energy consumption forecasting [3], a demand forecasting for an e-commerce website [41], etc.). The combination of *ANN with ARIMA* has demonstrated better forecasts as it handles both linear and non-linear components of a time series [44]. This hybridization has been used for different time-series forecasting problems including electricity price forecasting and stock market forecasting [5]. Kalman Filter Artificial Neural Networks (KF-ANN) is another variant of ANN-ARIMA proposed to improve the accuracy of wind speed forecasting [35].

C. Demand Forecasting Methods: A Comparative Analysis

Many comparative studies have been proposed to assess the accuracy of both ML and statistical methods and to compare their respective performance using different types of time-series data. Most studies among those conducted to compare both categories of methods were based on empirical approach which has been shown to be very useful to identify the methods that work well in practice. As a result, several forecasting competitions were organized in order to empirically compare the accuracy of forecasting methods. In the absence of the universal dominance of a single best method, competitions are the best means of providing objective evidence on the empirical accuracy of forecasting methods a[8]. These competitions have been critical in driving future research directions in forecasting. Makridakis competitions also known as M-Competitions, which are organized by teams led by Spyros Makridakis, have been particularly influential over the years. We summarize in table I the findings of some notable comparative studies, that included a comparison between statistical methods and ML-based methods available in the literature of time-series forecasting and demand forecasting. Statistical methods have been used for many years in forecasting especially in demand-forecasting since they have a solid theoretical background. It has also been shown in different large-scale comparative studies that they are best suited to time-series forecasting problems and that they outperform sophisticated ML methods in spite of their simplicity, linearity assumptions and their supposed biased outliers [23]. However, ML methods do not require any linearity assumptions, are data-driven, and self-adaptive with few prior assumptions. Yet, large-scale comparative studies have shown that pure ML methods perform poorly and don’t outperform statistical methods. The results of such comparative studies may be related to the specific data set being used in the study and although the large-scale empirical studies that were mentioned above, which showed the poor performance of ML methods, use business-type time-series, many other case studies in the field of Supply-Chain demand forecasting have shown that some ML algorithms give more accurate forecasts than the statistical methods[26][8]. To conclude, there is no single universal best method in the field of forecasting [22] and the accuracy of forecasting methods depends on the type of data being used as [18] showed that the particularities of the dataset may affect forecasting accuracy and the conclusions drawn. Besides, the latest M4-Competition has shown empirically that hybrid methods which combine both statistical methods and ML methods give the most accurate forecasting results suggesting that incorporating features of both approaches is the most promising time-series and demand-forecasting approach in the future. Beside, We propose table II to provide some guidelines for choosing and using statistical or ML forecasting approaches considering a set of indicators (computational complexity, preprocessing, interpretability, etc.). The results sum up the findings of some notable comparative studies in the literature of time-series and demand forecasting [23] [22]. Based on our deep synthesis, we have concluded that no single forecasting method performs consistently best across different situations.

TABLE I
COMPARATIVE STUDIES ABOUT THE ACCURACY OF ML AND STATISTICAL FORECASTING METHODS

Study	Description and motivation	Main Findings and Contributions
[21]	- M3-Competition using 24 statistical and ML methods. -3003 yearly, quarterly, monthly and other business-type time-series.	- The software expert system ForecastPro with automatic model selection. - The parameterisation of ES & ARIMA models, and Theta generally outperformed all other methods.
[16].	Neural Network Models for Time Series Forecasts compared to other models used in the M-competition.	Neural Network outperforms statistical methods across monthly and quarterly time series.
[29]	Fuzzy Delphi and back-propagation model (FBPN) for sales forecasting in Printed Circuit Board PCB industry.	FBPN outperforms the three compared statistical forecasting models (using MAPE).
[24]	A Comparison between Neural Networks and statistical forecasting Methods (MA, ARIMA) in an inventory management context of Panasonic Refrigeration Devices Company.	Neural Networks outperform traditional methods.
[26]	- A Comparison between ML Techniques (ANN and SSVM) and statistical methods (moving average, ES, and ES with trend) in long-term supply chain demand forecasting using the data set of the components supplier of the biggest Iranian's car company.	Machine Learning methods are more accurate than statistical methods used to forecast Supply Chain demand.
[8]	- The NN3 competition on time series prediction (extended M3 Competition to Neural Networks). -The study used two subsets of monthly time-series from M3-Competition.	Only one Neural Network outperformed the statistical method damped trend ES using the sMAPE but failed to outperform the statistical method Theta.
[23]	- Empirical study using subset of 1045 monthly time series used in the M3 Competition from the business and economic world characterized by considerable seasonality, some trend and a fair amount of randomness. - Comparaison of ten of the most famous ML methods (RNN,LSTM...) with eight notable statistical methods using MAPE and MASE accuracy measures.	- Statistical methods outperformed all Machine Learning methods across both accuracy measures used and for all forecasting horizons - The computational requirements of ML methods are considerably greater than those of statistical methods.
[22]	- The M4-Competition Extends the previous M-Competitions by: Increasing the number of series, including more ML forecasting methods, and evaluating both point forecasts and prediction intervals. - Used 100,000 yearly, quarterly, monthly, weekly, daily and hourly series of varying sizes and from different fields (economics, finance, industry...etc).	- 12 out of the 17 most accurate methods were combinations of mostly statistical methods. - ML methods performed poorly and only one outperformed naive2 benchmark. - The most accurate method was a hybrid method combined statistical method (ES) and ML method (Recurrent Neural Network) - The second most accurate method was a combination method using seven statistical methods and one ML method with the weights for the averaging being calculated by a ML algorithm that was trained to minimize the forecasting error.

Choosing the appropriate forecasting method shall be based on a thorough analysis of data and its characteristics. This synthesis motivates our choice to design a new forecasting tool and implement the proposed process in Stock&Buy usecase. We detail our contribution in the following sections.

III. Demand Forecasting Tool for Inventory Control: Stock&Buy usecase

The main conclusion from our literature review demonstrates the importance to design the forecasting tool considering the type of dataset to offer better accuracy. For this reason, we present hereafter a new demand forecasting tool for inventory control using time-series dataset. We present the proposed forecasting models based on Stock&Buy case study as a smart system for inventory control. Stock&Buy is an early-stage Norwegian e-commerce platform which provides an online solution for around 4000 small and medium business (SMB) companies selling on multiple channels. Inventory analytic represents one of the main services where Stock&Buy gives deep insights into retailers inventory and order data through demand forecasting to meet the service levels and prevent products from going out of stock or from over ordering variants. For this reason, Stock&Buy wants to offer its customers a genuine inventory analytic experience by providing a robust demand forecasting tool that allows to estimate weekly and monthly demand. The contribution of this work are manifolds: (a) Propose a robust forecasting model which provides accurate demand forecasts and handles the varying demand-patterns of products such as seasonality, trend and intermittency, (b) build a ML-based forecasting model to estimate demand for new products which haven't been sold in the past, and (c) validate the proposed tool by implementing a prototype as a proof of concept before deploying the final solution into Stock&Buy growing platform. The proposed forecasting tool is detailed hereafter by explaining the designing process as follows: (1) The preliminary data analysis which allows exploring different demand patterns that products exhibit in order to appropriately choose the adequate forecasting solution later on, (2) The proposal of a hybrid forecasting model, denoted by CombTSB, which selects the most appropriate method to implement according to the set of pre-processed time-series products, and (3) Clust-Avg, a ML-based forecasting model which estimates demand for new products using clustering algorithm.

A. *Preliminary analysis*

The first phase of building a new demand forecasting tool is to analyze the available demand data that can be used as part of

TABLE II
COMPARISON BETWEEN ML AND STATISTICAL FORECASTING METHODS

	ML methods	Statistical methods
Goodness of fit	Display low fitting error and exhibit over fitting.	Display higher fitting error and better post-sample errors.
Computational Complexity	More computationally expensive.	Less computationally demanding.
Prediction Interval	derive prediction interval is analytically difficult (with non-linear ML algorithms).	Prediction intervals is easily to derive analytically.
Preprocessing	Better forecasting results by seasonal adjustments, detreding and Box-Cox transformation.	Better forecasting results by transforming the time-series.
Time-series length	Critical factor in improving forecasts accuracy.	Not important!
Interpretability	Back box methods : it is difficulty to analyse the role of input variables in the forecasting model.	Information about how forecasts are generated can be easily obtained.
Model parameters selection	Lack a systematic procedure for model construction (experimental selection by trial and error).	Solid theoretical background that makes the selection of the model's parameters easy.

building the solution. As previously introduced in [6], figure 2 showcases the preliminary data analysis process which consists in: (a) Visualizing sales and demand historical data, (b) Studying the main characteristics of demand and sales time-series (e.g. stationarity to determine whether a preprocessing pipeline is required to make the data stationary so that we can use it with the statistical methods based on stationarity assumptions), (c) Studying the cross correlation between demand and other time-dependent variables (e.g product's price for Stock&Buy usecase) to determine if we should also investigate multivariate time-series models that are best suited to cross-correlated time-series, and (d) Categorizing demand for all products sold by each retailer to see if slow-moving products make up a large proportion of the products that are generally sold on the platform, which will require us to investigate intermittent-demand forecasting methods. Note that for Stock&Buy case study, we used at this stage both sales data at the store level which represents daily sales for all product variants of each retailer, and sales data at the product variant level, which represents daily demand and sales data for a particular product variant[2]. After the data analysis phase and with the help of our extensive literature review, we conclude[3] that: (a) price and demand are strongly correlated, (b) many product variants sold by different retailers exhibit intermittent and lumpy demand as defined by the Syntetos-Boylan categorization scheme. This lumpiness and intermittency need to be properly handled by the forecasting solution to obtain accurate forecasts, (c) there is a shortlist of methods which are more suitable for time-series products (mainly MLP, ARIMA,Theta), and (d) There is no best method that can offer accuracy for all type of products. With this conclusion, we came up with a new proposal consisting of a hybrid forecasting tool for time-series products with historical data (while considering intermittent demands), and a ML algorithm for new products forecasting (where no historical data is available). Both proposals, denoted by CombTSB & ClustAvg, are explained in next sections.

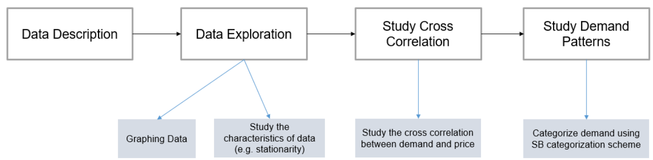

Fig. 2. Preliminary data analysis process [6]

B. New Demand Forecasting Method for Products with Historical Sales Data

We describe hereafter the new proposed hybrid method denoted CombTSB implemented for demand forecasting for times-series products with historical data. CombTSB is based on automatic selection between an ad-hoc intermittent demand forecasting method (TSB method) and a combination method of mostly statistical models which are best suited for forecasting continuous demand (see literature review in section II). The combination method (Comb) uses two statistical forecasting methods (ARIMA and Theta) and one ML-based method, the Feed Forward Neural Network (MLP). To this end, a 4-steps process is executed as illustrated in Figure 3:

- Pre-processing: initially a set of pre-processing operations is excecuted: Detrend time-series, Deseasonalize time-series, Remove outliers, Stabilize the variance of time-series using Box-Cox transformation, and Scale inputs.
- Models training: the models are trained according to the steps using adequate estimation of models' parameters, especially when fitting MLP and ARIMA models which are highly parametric models.
- Post-processing: to obtain the forecasts from each algorithm used in the forecasting model, we rescale the predictions produced by the models and apply the inverse Box-Cox transformation[28], where applicable.
- Model selection: the proposed combination of methods, are evaluated in the last step of the forecasting pipeline. the forecasting error for both models is estimated to select the model with better accuracy.

Figure 4 depicts CombTSB algorithm. Following the forecasting pipeline described in figure 3, the pre-processing, model training, resp. post-processing steps are implemented in lines 1&2, lines 3-5, resp. line 6. The automatic selection between Comb and TSB is based on the Absolute Forecast

[2]We remind that the used data only represent a proportion of the wealth of data available at Stock&Buy and doesn't cover all the retailers selling through the platform. It has been decided to use this subset of data to test and validate the final solution considering the homogeneity of the retail business.

[3]Note that those conclusions are tailored to Stock&Buy case study. For any other datasets, we conduct the same proposed process and use the same findings in our literature review but we may have other results depending on the type of data.

Error (MAE[4]) of each participating method. This selection criteria was used to allow for accurate selection of the forecasting method based on its performance. The combination model (denoted by Comb) fits multiple individual model specifications to allow easy creation of ensemble forecasts. Each model is given a weight that is inversely proportional to the out-sample forecasting error (MAE) in the final ensemble (lines 7.1-7.3). Empirically, this has been shown to give good performance in ensembles and is better than giving more weight to models with better in-sample performance as demonstrated by [23].

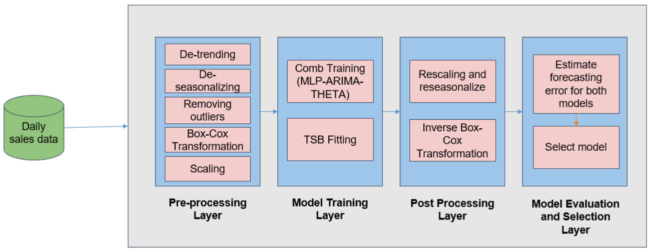

Fig. 3. Overall forecasting pipeline for products with historical sales data

Data: $Z = [z_1, z_2, ..., z_N]^T$: demand time series of a given retailer; h: the forecasting horizon; productVariantID: the ID of the product variant; M = (ARIMA, Theta, MLP) and TSB: the considered models.
Result: $X = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_h]^T$ forecasts vector (h-step ahead forecasts.)
1. subset the data set corresponding to the product variant:
   $Y = subset(Z, productVariantID)$;
2. Preprocess Y. Depending on the fitted model, several resulting preprocessed series are obtained, each one of them corresponds to a specific model // refer to section 5.4;
3. Divide the dataset Y into a pair of training and validation subsets Y_{train} and $Y_{validation}$, respectively as follows:
   $Y_{train} = [y_1, y_2, ..., y_\alpha]^T$
   $Y_{validation.} = [y_{\alpha+1}, y_{\alpha+2}, ..., y_{\alpha+h}]^T$
   such as α is the size of the training set and h is the size of the test set $(\alpha + h = N)$;
4. Train TSB on Y_{train};
5. Train each model Mi (i=1,2,3) on Y_{train} and generate the h-step-ahead forecasts for each one of them ($Y_{Mi} = [y_1', y_2', ..., y_h']_{Mi}^T$);
6. Where applicable, rescale, reseasonalize and apply the inverse Box-Cox transformation to the generated forecasts of each model ;
7. Build the ensemble model as follows:
   7.1 Measure MAE of each fitted model F_i (i=1,2,3) using $Y_{validation}$
   7.2 Calculate the weight w_i of each model F_i such as $w_i = \frac{1}{MAE_i}$
   7.3 Build the ensemble forecasts $X = [\hat{y}_1', \hat{y}_2', ..., \hat{y}_h']^T$ as follows:
   $\hat{y}_t' = \frac{y_t'{}_{arima} \times w_1 + y_t'{}_{Theta} \times w_2 + y_t'{}_{MLP} \times w_3}{\sum_{i=1}^{3} w_i}$;
8. Measure the MAE of TSB model using $Y_{validation}$;
9. Measure the MAE of Comb model using $Y_{validation}$;

if $MAE_{tsb} \leq MAE_{Comb}$ **then**
   10. Return TSB forecasts: $X = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_h]_{tsb}^T$;
else
   11. Return Comb forecasts: $X = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_h]_{Comb}^T$;
end

Fig. 4. CombTSB Pseudo-algorithm.

C. New Demand Forecasting Method for New Products

Forecasting demand for new products before they are introduced into the market is very challenging. In fact, traditional quantitative forecasting methods cannot be used with the absence of historical demand and sales data. Despite these difficulties, sales forecasts for new products are necessary for planning the resources needed to meet actual demand, including inventory, staff and cash flow. We propose hereafter ClusAvg, a new quantitative forecasting technique to estimate demand for new products. ClustAvg is based on the assumption that the new product to be launched has some or most of the characteristics of existing products which is more likely to happen. Therefore, ClusAvg forecasts demand for a new product by projecting from past histories of similar products as inspired by the work of [10] who used clustering to predict market demand for new products. ClusAvg algorithm is depicted in figure 5 [6]. The selected clustering algorithm is K-means due to its simplicity and one of the main tasks of exploratory data mining, and statistical data analysis. Cluster analysis is an iterative method which groups similar elements within a cluster by minimizes the within-class sum of squares (W) for a given number of clusters (i.e elements are similar in their cluster and different to the others). Since K-means algorithm requires the variables to be numerical, categorical variables (e.g. color and size) are first encoded as factors (line 2). Also, as part of the pre-processing pipeline, data are scaled to a common scale before performing K-means clustering (line 1). PCA (Principal Component Analysis) is also used before launching the K-means to decorrelate and reduce the dimensionality of data (line 3). The optimal number of clusters (i.e. k) is determined according to the Hartigan Index [15] (line 4), which is a popular method to determine the optimal value of the parameter k. Then, the clustering algorithm is implemented in lines 5-7. The final demand forecast for the newly-introduced product is equal to the average demand forecast of all the products of the cluster to which the new product belongs (line 9).

Data: $(In)_{ij}$: Inventory data of a given retailer such as $1 \leq i \leq m$ and $1 \leq j \leq n$ where m is the number of product variants and n is the number of inventory variables (including product's characteristics); h: the forecasting horizon; $(P)_j$ the data associated with the new product's characteristics ;
Result: $estimate$: Demand forecast for the new product;
1. Scale $In \cup P$;
2. Encode categorical features;
3. Perform PCA on $In \cup P$;
4. Initialize k according to Hartigan index;
5. Arbitrarily choose k products from $In \cup P$;
6. Repeat:
   6.1 Assign each product to the cluster to which it is the most similar based on Mahalanobis distance;
   6.2 Update the cluster means;
7. Until convergence toward a stable partition;
8. Get C, the cluster to which the new product belongs;
9. Calculate $estimate$ the average demand forecast within C. Demand forecast for each product in the cluster is calculated using the method described in 5.3.2 ;
10. Return $estimate$;

Fig. 5. Clust-Avg Pseudo-algorithm [6].

IV. Stock&Buy Demand Forecasting Tool: Validation Process

To implement the forecasting solution previously described, we proposed a REST API to expose the forecasting method. The choice of this architecture was based on the existing architecture of Stock&Buy platform, which is an Azure cloud native application that incorporates different micro-services, each handling a single business logic. Hence, the best approach to incorporate our solution into the existing ecosystem is web services. The REST API was packaged into a Docker image

[4]MAE measures the average magnitude of the forecasting errors. $MAE = \frac{\sum_{t=1}^{N} |E_t|}{N}$ Where N is the number of observations in the test sample.

and hosted on an Azure Container Registry as illustrated in figure 6. We also proposed a standalone prototype with all the functionalities embedded in the REST API to showcase different use cases of the forecasting API. Next section describes the prototype built as a proof of concept. We explain further the simulation tests conducted to validate the new forecasting methods. Finally, we give some insights about the deployment of the new tool in Stock&Buy smart system.

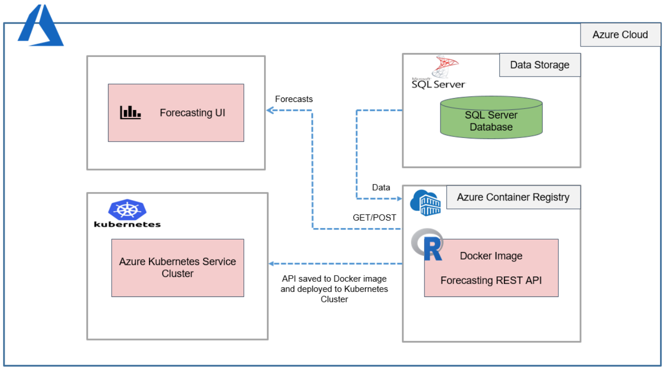

Fig. 6. Forecasting sub-system architecture

A. Proof of Concept: A Standalone Prototype

In addition to the API, we also built a standalone prototype with a web User Interface to handle the presentation logic of the forecasting solution. This web User Interface allows to show how our solution works and uses the forecasting API as back-end. Our interface is divided into: (1) Sales & inventory data visualization (figure 7), (2) Store Forecasting (figure 8), (3) Product forecasting with obsolescence risk (figures 9 and 10), and (4) New product forecasting (figure 11).

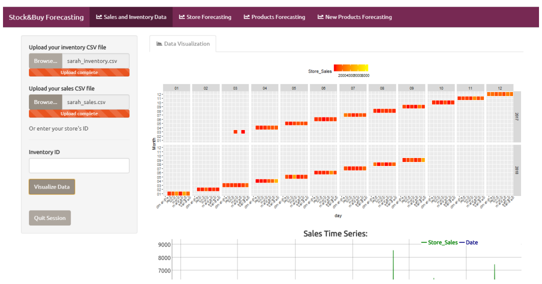

Fig. 7. Prototype: sales visualization

B. Simulation Test and Results

To assess the accuracy of the forecasting models, tests were run on a Windows 10 64 bits machine with Processor Intel(R) Core(TM) i7-354M @ 3.00 GHZ and 8Go Memory. Three major statistical metrics have been selected based on their popularity and interpretability: Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE[5]) and Mean Absolute Scaled Error (MASE[6]). The validation tests use three real retailers data. To ensure the retailers' privacy datasets are anonymously denoted by S-767, S-1088, and S-1224. Data was extracted from a four-years history to assess both 1-step-ahead (i.e. daily forecast), and multiple-horizon-forecast (7-steps for weekly and 30-steps for monthly). The training/test set approach was used to assess the accuracy of the forecasting models. Let n be the size of the demand historical data set and h be the forecasting horizon. Then, the size of the training set is equal to $n - h$ and the remaining data points (h) are used for the test set (i.e. performance evaluation). The validation process for the new proposal is described hereafter, starting by the empirical comparative study which helped us to design the new forecasting tool.

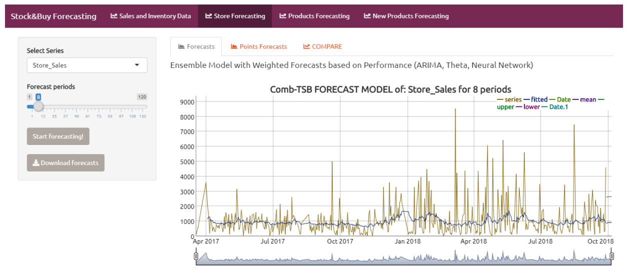

Fig. 8. Prototype: Store forecasting

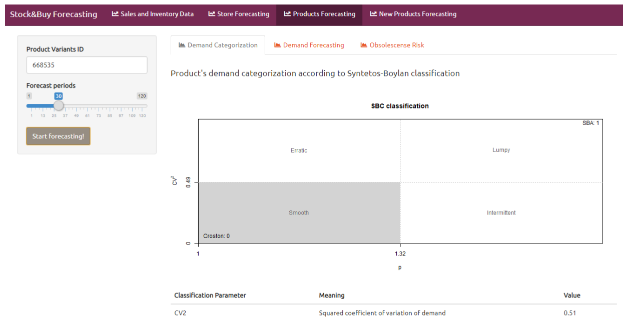

Fig. 9. Prototype: Product forecasting

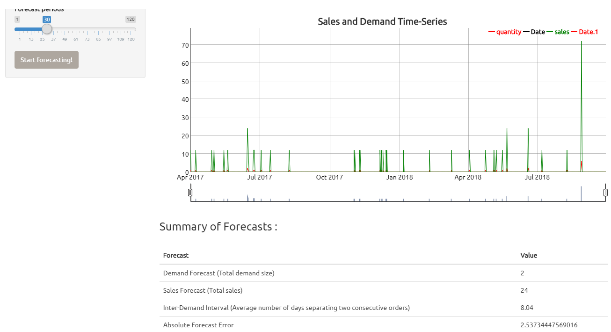

Fig. 10. Prototype: Sales and Demand Time Series

[5] $MAPE = 100 \times \frac{\sum_{t=1}^{N}\left|\frac{E_t}{Y_t}\right|}{N}$; where $E_t = Y_t - F_t$ with Y_t is the actual value and F_t is the forecast for period t.

[6] $MASE = \frac{\sum_{t=1}^{N}|Y_t - F_t|}{\frac{N}{N-1}\sum_{t=2}^{N}|Y_t - Y_{t-1}|}$; where $E_t = Y_t - F_t$ with Y_t is the actual value and F_t is the forecast for period t.

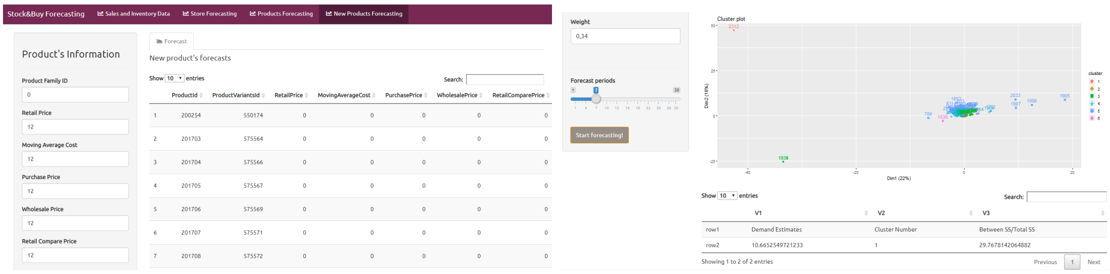

Fig. 11. Prototype: New Product forecasting. Product configuration (left), Visual representation (right)

1) Accuracy of the Studied Models: Analysing and studying different forecasting models was a crucial step that allowed to design the proposed forecasting method. For this, the empirical comparative analysis included seven forecasting methods: three univariate statistical methods (Theta, ARIMA, ETS), one ML method (MLP), one multivariate time-series forecasting method due to cross correlation (VAR) and two ad-hoc methods for intermittent demand forecasting due to intermittency (TSB and SB). Accuracy tests were conducted for all methods, on the three retailers data, before and after pre-processing. Figure. 12 illustrates few graphs among the extensive series of simulation tests that helped us to better understand, and thus design our new proposal. The analysis of the empirical study has conducted to the following conclusion:

- Ad-hoc intermittent demand forecasting methods, in particular TSB, generally perform better than other models included in this study for short-term forecasting (1-step-ahead).
- Statistical methods, in particular ARIMA and Theta, perform better for medium and long-term forecasting.
- MLP neural network rarely outperforms other statistical methods across all forecasting horizons. However, MLP has more accurate 30-step-ahead forecasts and was overall among the best performing methods.
- During the election of the best method, the use of different forecasting metrics can lead to different results (i.e. under the same scenario, one method can give the best performance for the first metric MAE but can be outperformed by another method for the other metrics, MAPE & MASE).

Based on these findings, the forecasting method CombTSB is proposed to combine the best performing methods from this comparative study, which are ARIMA, Theta, MLP and TSB.

2) Validation of the Proposed Forecasting Method CombTSB: The assessment of the accuracy of the proposed forecasting method, CombTSB, was based on different forecasting metrics (MAE, MAPE, MASE) and performed across different forecasting horizons (daily, weekly, monthly). Results show that the proposed forecasting method achieves good forecasting accuracy across all the utilized metrics and forecasting horizons as illustrated in figure 13. In fact, CombTSB selects for every forecasting horizon the best performing method (i.e. TSB for products exhibiting highly intermittent demand or when performing short-term forecasts or Comb otherwise).

C. *Stock&Buy: Deployment Phase*

In order to deploy the R-based forecasting solution and expose it as API endpoints, we used Plumber, which is an R package that allows existing R code to be exposed as a web service through special decorator comments. After exposing the API endpoints, we hosted the API on Azure Cloud using Docker container, which provides lightweight container that can be easily hosted on Azure, following these steps: (a) Package up the API into a Docker image, (b) Store the image on Azure Container Registry, (c) Deploy the image into Azure Container Instance. Just like the API, the SQL Server database which hosts inventory and sales data is deployed on Azure Cloud. It is accessed remotely by the API to retrieve sales and demand data. The primary outcome of the project was to produce APIs, this way our customers can run their own queries and build their own dashboards (figure 14-Right). Currently, a simplified version of the prototype standalone is deployed in Stock&Buy platform (figure 14-Middle). Our customers will also have a tabular view so they can filter their data then export it to Excel for further analysis (figure 14-Left). The source code of most of the algorithms behind the APIs are published into this repository: https://github.com/TOuhrouche/demand_forecasting. For privacy issues and intellectual property owned by Stock&Buy, customer data was trimmed down.

V. Conclusion

The main challenge for the online retail platform Stock&Buy was to design an accurate demand forecasting for thousands of products exhibiting different demand patterns. Another interesting research track was also to predict demand for products which don't have historical sales and demand data. To address these issues, it was important to dive into the State of the Art related to demand forecasting. The survey in this paper proposed an extensive study about many forecasting methods by giving classification, comparison and analysis. It was also important to understand the nature of the data provided to propose a method that handles the underlined patterns. With an extensive literature review, and after a deep data analysis, a forecasting pipeline was suggested to help in designing most accurate solutions for any type of products. Besides, we helped Stock&Buy building a new demand forecasting tool to offer for its thousands of clients. Mainly, CombTSB is the new hybrid forecasting tool for time-series products with historical data, while ClusAvg is the

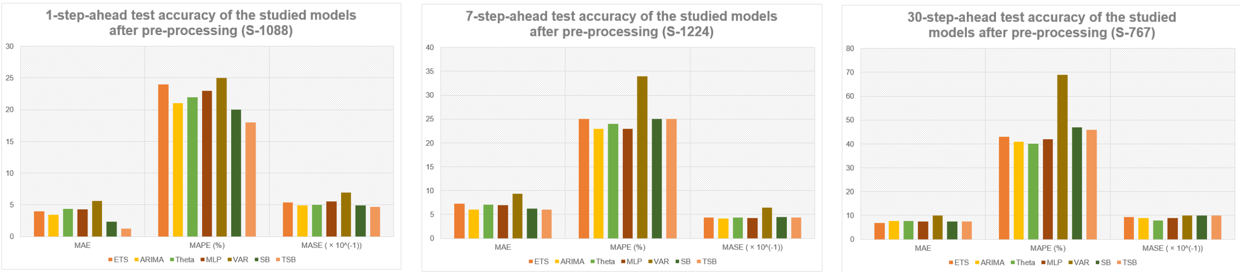

Fig. 12. Accuracy tests after pre-processing: 1-step for S-1088 (left), 7-steps on S-1224 (center), 30-steps on S-767 (right)

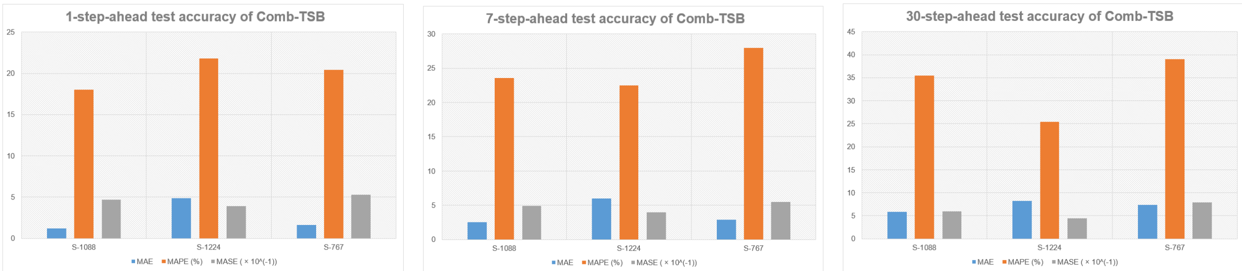

Fig. 13. Comb-TSB accuracy tests.1-step-ahead (left), 7-steps-ahead (center), 30-steps-ahead (right)

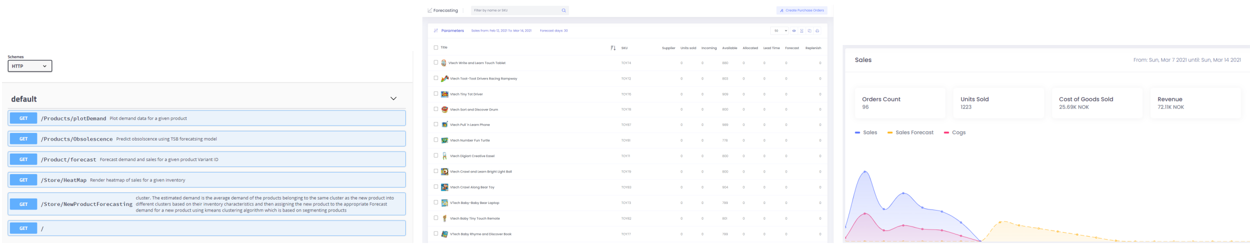

Fig. 14. Stock$Buy forecasting tool: Clients API & interfaces

new forecasting method for new products to be introduced. Both proposals were validated and tested under a standalone prototype with all functionalities using three real retailers data. The deployed tool was presented and algorithms behind the proposed APIs were shared to serve the research community for future investigations. The overall results are very encouraging and can be considerably improved by: (a) Exploring other time-series pre-processing techniques such as Moving Average, Fourier Transform (b) Estimating demand for lost sales in the past and using the resulting estimates to improve the accuracy of demand forecast. (c) Exploring the possibility of using the demand forecasting results as inputs for a price optimization tool that will allows retailers to optimize their pricing strategy.

REFERENCES

[1] Adya, M., & Collopy, F. (1998). How effective are neural networks at forecasting and prediction? A review and evaluation. Journal of Forecasting, vol. 17, no 5-6, p. 481-495.

[2] Ahmed, A., Atiya, A., Gayar, N., El-Shishiny, H. (2010). An Empirical Comparison of Machine Learning Models for Time Series Forecasting. Econometric Reviews, vol. 29, no. 5-6, pp. 594-621. Available: 10.1080/07474938.2010.481556.

[3] Alobaidi, M., Chebana, F., Meguid, M. Robust ensemble learning framework for day-ahead forecasting of household based energy consumption. Applied Energy, vol. 212, pp. 997-1012, 2018. Available: 10.1016/j.apenergy.2017.12.054.

[4] Assimakopoulos & Nikolopoulos, K. (2000). The theta model: a decomposition approach to forecasting. International Journal of Forecasting, vol. 16, no. 4, pp. 521-530. Available: 10.1016/s0169-2070(00)00066-2.

[5] Babu C., Reddy, B. A moving-average filter based hybrid ARIMA–ANN model for forecasting time series data. Applied Soft Computing, vol. 23, pp. 27-38. Available: 10.1016/j.asoc.2014.05.028.

[6] Benhamida F.Z., Kaddouri O., Ouhrouche T., Benaichouche M., Casado Mansilla D., López-de-Ipiña D. (2020). Stock&Buy: A New Demand Forecasting Tool For Inventory Control. Splitech Conference. DOI 10.23919/SpliTech49282.2020.9243824

[7] Box, G. & Jenkins, G. (1970). Time Series Analysis: Forecasting and Control, San Francisco: Holden-Day.

[8] Crone, S., Hibon, M., Nikolopoulos, K. (2011). Advances in forecasting with neural networks? Empirical evidence from the NN3 competition on time series prediction. International Journal of Forecasting, vol. 27, no. 3, pp. 635-660. Available: 10.1016/j.ijforecast.2011.04.001.

[9] Da, L., Dongxiao, N., Yuanyuan L., Guanjuan, C. Combined models for day-ahead electricity price forecasting based on improved gray correlation methodology', Kybernetes, vol. 38, no. 34, pp. 354-361, 2009. Available: 10.1108/03684920910944047.

[10] Daskalova, N., Dragiev, D. (2013). Using Classification Methods to Predict Market Demand for Products with Short Sales History. Doctoral Conference in Mathematics, Informatics and Education.

[11] Eaves, A., Kingsman, B. (2004). Forecasting for the ordering and stockholding of spare parts. Journal of the Operational Research Society, vol. 55, no. 4, pp. 431-437. Available: 10.1057/palgrave.jors.2601697.

[12] Forecasting: Principles and Practice. [Online]. Available: https://otexts.org/fpp2/basic-steps.html.

[13] Green, K. C. & Armstrong, J. S. (2007). Structured analogies for

forecasting. International Journal of Forecasting, vol. 23, no. 3, pp. 365–376.
[14] Gutierrez, R., Solis, A., Mukhopadhyay, S. (2008). Lumpy demand forecasting using neural networks. International Journal of Production Economics, vol. 111, no. 2, pp. 409-420. Available: 10.1016
[15] Hartigan, J.A, Wong, M.A. (1979). K-Means Clustering Algorithm. Journal of the Royal Statistical Society C, 28(1), 100-108.
[16] Hill, T., O'Connor, M., Remus, W. (1996). Neural Network Models for Time Series Forecasts. Management Science, vol. 42, no 7, p. 1082-1092.
[17] Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. Neural Networks, 251–257
[18] Kang, Y., Hyndman, R.J., Smith-Miles, K. (2017). Visualising forecasting algorithm performance using time series instance spaces. International Journal of Forecasting, vol. 33, no. 2, pp. 345–358.
[19] Kourentzes, N. (2013). Intermittent demand forecasts with neural networks. International Journal of Production Economics, 198-206, 2013. Available: 10.1016/j.ijpe.2013.01.009.
[20] Lasek A., Cercone N., Saunders J. (2016) Restaurant Sales and Customer Demand Forecasting: Literature Survey and Categorization of Methods. In: Leon-Garcia A. et al. (eds) Smart City 360°. SmartCity 360 2016, SmartCity 360 2015. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 166. Springer, Cham
[21] Makridakis, S. & Hibon, M. (2000). The M3-Competition: results, conclusions and implications. International Journal of Forecasting, vol. 16, no. 4, pp. 451-476. Available: 10.1016/s0169-2070(00)00057-1.
[22] Makridakis, S. et al. (2018). The M4 Competition: Results, findings, conclusion and way forward. International Journal of Forecasting, https://doi.org/10.1016/j.ijforecast.2018.06.001.
[23] Makridakis, S., Spiliotis E., Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. PLOS ONE, vol. 13, no. 3. Available: 10.1371/journal.pone.0194889.
[24] Mitrea, G., Lee, C., Wu, Z. (2009). A Comparison between Neural Networks and Traditional Forecasting Methods: A Case Study. International Journal of Engineering Business Management, vol. 1, p. 11. Available: 10.5772/6777.
[25] Moreno, J.M., Pol, A.P., Gracia, P.M. Artificial neural networks applied to forecasting time series, p. 8.
[26] Mousavi, S.S., Shahrabi, J., Heydar, M. (2009). Supply Chain Demand Forecasting; A Comparison of Machine Learning Techniques and Traditional Methods. Journal of Applied Sciences, vol. 9, no. 3, pp. 521-527. Available: 10.3923/jas.2009.521.527.
[27] Nikolopoulos, K., Assimakopoulos, V., Bougioukos, N., Litsa, A., Petropoulos, F. (2012). The Theta Model: An Essential Forecasting Tool for Supply Chain Planning. Advances in Automation and Robotics, Vol. 2, pp. 431–437.
[28] Panigrahi, S., Karali, Y., Behera, H.S. (2013). Normalize Time Series and Forecast using Evolutionary Neural Network. International Journal of Engineering Research & Technology, Vol. 2 Issue 9.
[29] P. C. A, Y. W. B. (2006). Abstract Fuzzy Delphi and back-propagation model for sales forecasting in PCB industry.
[30] Prestwich, S., Tarim, S., Rossi, R., Hnich, B. (2014). Forecasting intermittent demand by hyperbolic-exponential smoothing. International Journal of Forecasting, vol. 30, no. 4, pp. 928-933. Available: 10.1016/j.ijforecast.2014.01.006.
[31] Prestwich, S., Tarim, S., Rossi, R., Hnich, B. (2014). Intermittency and Obsolescence: a Croston Method With Linear Decay.
[32] Ripley, B. (2017). RODBC: An ODBC3 driver manager and drivers. R package.
[33] Shale, E., Boylan, J., Johnston, F. (2006). Forecasting for intermittent demand: the estimation of an unbiased average. Journal of the Operational Research Society, vol. 57, no. 5, pp. 588-592. Available: 10.1057/palgrave.jors.2602031./j.ijpe.2007.01.007.
[34] Shearer, C. (2000). The CRISP-DM model: the new blueprint for data mining. Journal of datawarehousing, Vol 5(4):13-22.
[35] Shukur, O., Lee, M. (2015). Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA. Renewable Energy, vol. 76, pp. 637-647. Available: 10.1016/j.renene.2014.11.084.
[36] Solis, A.O., Longo, F., Mukhopadhyay, S., Nicoletti, L., Brasacchio, V. (2014). Approximate and exact corrections of the bias in Croston's method when forecasting lumpy demand: Empirical evaluation. 13th International Conference on Modeling and Applied Simulation, MAS 2014, pp. 205.
[37] Syntetos, A. A. & Boylan, J. E. (2005). The accuracy of intermittent demand estimates. International Journal of Forecasting, vol. 21, pp. 303-314.
[38] Tay, F., Cao, L. (2001). Improved financial time series forecasting by combining Support Vector Machines with self-organizing feature map. Intelligent Data Analysis, vol. 5, no. 4, pp. 339-354. Available: 10.3233/ida-2001-5405.
[39] Teunter, R., Duncan, L. (2009). Forecasting intermittent demand: A comparative study. Journal of the Operational Research Society, vol.60, no.3, pp.321-329.
[40] Teunter, R., Syntetos A., Babai, M.Z. (2011). Intermittent demand: Linking forecasting to inventory obsolescence. European Journal of Operational Research, vol. 214, no. 3, pp. 606-615. Available: 10.1016/j.ejor.2011.05.018.
[41] Tugay, R., Ögüdücü, S.G. (2017). Demand Prediction using Machine Learning Methods and Stacked Generalization.
[42] Willemain, T. R., Smart, C. N., & Schwarz, H. F. (2004). A new approach to forecasting intermittent demand for service parts inventories. International Journal of Forecasting, 20(3), 375-387. doi:10.1016/s0169-2070(03)00013-x
[43] Willemain, T. R., Smart, C. N., Shocker, J. H., De Sautels, P.A. (1994). Forecasting intermittent demand: A comparative evaluation of Croston's method. International Journal of Forecasting, vol.10, no.4, pp.529-538.
[44] Zhang, G. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, vol. 50, pp. 159-175. Available: 10.1016/s0925-2312(01)00702-0.
[45] Zhang, L., Suganthan, P.N. (2016). A survey of randomized algorithms for training neural networks. Information Sciences, 364–365(Supplement C):146–155.

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