A RECENT REVIEW ARTICLE ON DEMAND FORECASTING

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Abstract-Demand forecast plays a significant role in the decision-making process of a business. The role of forecasting is massive for realistic areas in accounting. Good forecasting helps in proper output preparation, selection of procedures, regression testing and resource management etc. In this review article, we analyze demand forecasting on spare parts, passenger flow, electricity, supply chain demand, and others. Forecasting of intermittent demand is important but it is a challenging problem. It is distinguished by various empty requests, and high non-zero variance values. Croston’s method is commonly used when demand is intermittent. Also, in this review article, we present various demand forecasting approach which involves intermittent demand in spare parts, passenger flow, and others.

Keywords- Intermittent demand, Spare parts, Exponential smoothing, Bootstrapping method, Machine learning technique.

I. INTRODUCTION

Demand forecasting is the method where past sales data are used to create an estimation of the present customer demand outlook. In competitive market conditions proper decision making and planning for future business-related events such as sales, production, staff requirement, etc. is required. Intermittent demand arises when a commodity faces several zero demand cycles. In this review article, we examine the forecasting approach such as Croston, Bootstrapping, SBA, etc., for intermittent demand and applications in different business backgrounds and measurement of accuracy and we discussed demand forecasting approach in various field such as spare parts, electricity demand, passenger flow, supply chain management, etc.,

II. ANALYSIS OF INTERMITTENT DEMAND FORECASTING

Syntetos A.A, et.al.[1]investigated the reasons of the unpredictable performance of the Croston approach and evolved it. Also, Altay.N, et.al. [2]assessed the Croston approach and Holt's winter double exponential smoothing process and developed the Holt approach for reducing the inventory volume. E.S.GardnerJr, et.al.[3]improved an exponential smoothing model designed to forecast demand. Assimkopoulos V et.al. [4] Introduced a new univariate method of forecasting based on the definition of adjusted local time series curvature by means of the coefficient 'Theta'. Syntetos A.A, et.al. [5] Production of stock management of intermittent demand evaluation procedures. Fildes.R,et.al. [6] examine the existing forecasting methods and suggested that OR will continue to make a significant contribution to forecasting by designing models. Teunter R.H, et.al. [7] adopted a new and impartial approach for predicting intermittent demand. Like the Croston method and the SBA method it changes the likelihood of demand in each time. Willemain T.R, et.al. [9] a new bootstrapping technique was developed to predict the distribution of the number of periodic demands over a fixed lead time which was stronger than exponential smoothing and the Croston method.

Kourentzes.N[16] introduced a series of bivariate neural network models to predict intermittent demand. Babai.M.Z et.al.[17] proposed the impact of the forecasting aggregation approach on the stock control empirically assessed through analysis on a large demand dataset. Spithourakis G.P, et.al. [18] explored the application of the aggregation-disaggregation forecasting method to fast-moving supply data for intermittent demand. Ward Romeijndres, et.al. [19] suggested a method which considers the type of component repaired, in addition to the demand for spare parts. This two-step forecasting approach checks separately the number of parts needed per repair and the amount of repairs expected for each kind of product. Altay,N, et.al. [20] introduced the impacts on forecasting and stock management of intermittent demand products of three different association types. Bahman Rustami, et.al. [21] reviewed the effectiveness of the non-overlapping temporal aggregation method to forecast results when non-aggregate data observe a first-order moving average or a first-order univariate autoregressive cycle.

Nemati Amirkolaii, K, et.al. [22] argued that existing methods of forecasting to account for intermittent demand trends were not accurate. Consequently, methods of data-driven AI-based forecasting could provide more accurate results. Boylan J.E, et.al.[23] analyzed the statistical performance of the non-overlapping and overlapping approaches and shows that overlapping approach suits when demand history short, also greater for longer lead times. Fotios Petropoulos, et.al.[24] discussed the creative method of aggregating intermittent demand data temporarily to reduce supply volatility. Syntetos A.A, et.al. [25] discussed the impact of forecasting on inventory control output in various demand series. Babai M.Z, et.al.[26] examined the performance of Croston's and TSB method for intermittent demand. Tim J.Van Kampen, et.al.[27] discussed classifications of stockholding units that are commonly used in production and operations management. Chongshou Li, et.al. [28] introduced a new greedy aggregation decomposition method for intermittent demand forecasting. Paul W.Murray, et.al.[29] introduced a framework for establishing consumer segments based on noisy past transaction data, generating segment level forecasts and then implementing consumer forecasts. Tabar B.R, et.al. [30] assumed a double-tier supply chain and we analytically evaluated the efficiency and bullwhip effect of the temporal aggregation method as non-aggregate series follow an autoregressive moving average order process(1,1).

Hasni M, et.al.[31] examined the performance of the two bootstrapping approaches and parametric approach. Babai M.Z, et.al.[32] introduced a new technique for intermittent demand which is modified SBA method and studied numerically through an extensive simulation experiment. Sungil Kim, et.al. [33] introduced a new prediction accuracy test called absolute percentage error mean arctangent and analytical properties of MAAPE are discussed. Hasni M, et.al. [34] introduced two modified forms of bootstrapping assuming demand occurs within the first cycle of increasing bucket lead time. Lolli.F, et.al. [35] proposed a single layer neural networks for intermittent demand by back propagation and extreme learning machines along with other forecasting methods.

Clint L.P Pennings, et.al.[36] proposed advanced forecasting approach that takes advantage of the time elapsed to handle intermittent spare parts demand. Wenhan Fu, et.al. [37] buildup UNISON data-driven inquiry framework combining machine learning methodology and temporal estimation method to measure the demands of intermittent components of electronics. Nikolopoulos K, et.al. [38] significant concern has been given to both the modeling of fast-moving time series and the development of causal models. Fotios Petropoulos, et.al. [39] concentrated on statistical methods for model selection and examine the performance of judgmental model selection. Gamze Ogcu Kaya, et.al. [40] specialized approaches with a method selection for each intermittent demand-type are considered and simplifies the intermittent demand forecasting.
III. FORECASTING SPARE PARTS DEMAND

Jose Roberto do Rego, et.al.[41] a case study on inventory control of spare parts was suggested and few approaches were explored by simulation of field data. Sha Zhu, et.al. [42] analyzed statistical methodology using extreme value theory to reveal the tail of the distribution of lead time demand assumed two tiers of operation: the estimated processing period and the duration operation point. AhmadiMobarakhe, et.al.[43] focused on different forecasting approaches, their versions, and AI models designed to implement the right approach version for unpredictable demands. FengGuo, et.al.[44] introduced a double-level composite forecasting methodology focused on appropriate repairable spare parts data and an analysis of the factors impacting the market for repairable spare parts. E.VanWingerden, et.al. [45] examined few forecasting methods to calculates reorder points for spare parts with the infrequent demands of three companies. Maria RosienKiewicz, et.al. [46] introduces a new demand forecasting approach for mining companies dedicated to hybrid spare parts. PetrosBoutselis, et.al. [47] Bayesian networks used to predict the need for spare parts from equipment failures in changing service logistics environments. Sarah Van der Auweraer, et.al. [48] suggests a method of forecasting spare part demand by using data as to the maintenance operations and discussed that maintenance information to produce forecasts. Topen E, et.al. [49] gives an outline of operational spare parts planning in-service control towers. They distinguish traditional examination bearings.

IV. PASSENGER DEMAND FORECASTING

TsungHsien Tsai, et.al. [50] presented two new computational models for predicting short-term rail passenger traffic. Erma Suryani, et.al.[51] Suggested an strategy for the development of an air passenger demand forecasting model and the assessment of certain policy scenarios relevant to the expansion of runway and passenger terminal capability to satisfy expected demand.. Shu Zhi Zhao, et.al. [52] introduced a non-linear model for forecasting passenger movement patterns in a transit network and analyzing its operational characteristics. Seongdo Kim, et.al. [53] developed a forecasting model of short-term air passenger demand using big data.

Nilabhra Banerjee, et.al. [54] gives a short and acute overview of the specific work carried out on demand forecasts in the scheduled passenger transport sector. Jintao Ke, et.al. [55] presented a new deep learning method named the fusion convolution long short-term memory network and the method applied to the short-term forecasting of passenger demand. Jeremy Roos, et.al. [56] introduced a complex Bayesian network process for predicting short-term movements of passengers on the Paris regional rail system. Yang Li, et.al. [57] Suggested a new multi-scale radial base function network to predict unusual traffic flow variations in the subway. Yirong Zhou, et.al. [58] introduced a forecast model for multistep citywide passenger demand prediction based on spatiotemporal attention mechanism, named ST-Attn. sequence to sequence modeling was adopted by the general encoder-decoder framework.

V. ELECTRICITY DEMAND FORECASTING

Tawfiq Al-saba, et.al. [59] described the application of artificial neural networks to long-term load forecasting and the energy requirements of an electricity usage forecast by ANN model. Saima Hassan, et.al.[60] analyzed the proficiency of various aggregation algorithms to forecasts the electricity demand. Jatin Bedi, et.al. [61] introduced a deep learning-based framework to forecast electricity demand. Dimitrios Angelopoulos, et.al. [62] disaggregating time series on various comprehensive forecasting criteria and gives long-term electricity demand forecasts in Greece. Tanveer Ahmad, et.al. [63] concentrated to forecast the short and medium-term electricity load of water source heat pump. Kumar Biswajit Deb Nath, et.al. [64] proposed a systematic and judgmental survey of forecasting methods which are analyzed for forecasting accuracy.

SoonhoHwangbo, et.al.[65] proposed an innovative sustainable prediction concept under the hybrid EMD-DL concept and proposed a self-sustaining hydrogen-based, distributed renewable energy network. Ping Jiang, et.al. [66] proposed composite forecasting definition and applies to the show of predicted success capacity. Sean Williams, et.al.[67] introduced the simple method to energy forecasting operators for decentralized energy management and provide a series of simple data transformations to effective representation of demand time.
series. Jason Runge, et.al. [68]the use of ANN models for multi-stage forward forecasting of supply fans in institutional buildings was discussed. Lulu Wen, et.al.[69] a deep learning algorithm was developed for predicting the load demand of residential buildings. Peter Nusrup, et.al. [70] gives short-term energy demand forecasts by temporary hierarchies with the autocorrelation strategy in four pricing areas in Sweden.

VI. DEMAND FORECASTING IN SUPPLY CHAIN MANAGEMENT

Xiang Yue, et.al. [71]discussed the importance of exchanging demand predictions and, in certain conditions, evaluated supply chain efficiency with and without the relevant networks. Liu Hong, et.al. [72] established the simulation models and investigates demand forecasting technology in supply chain by bullwhip effect. Real Carbonneau, et.al. [73] examine the applicability of developed techniques of machine learning. Liljana Ferbar, et.al. [74] suggested the theory of wavelet and analyzed it. SanjitaJaipuria, et.al. [75] presented a new approach of demand forecasting by integrated Discrete Wavelet Transforms(DWT) analysis. Kathleen S. Hartzel, et.al.[76] discussed factors affecting demand forecast quality improvement across Sales Reporting Level.

AdityaJha,et.al.[77] the consequences of transmitting demand prediction data on a supply chain for drug production in the pharmaceutical industry have been studied. Juan Pedroselvulved-Rojas, et.al. [78] proposed an alternative approach for estimating the finest forecast model without estimating all of the forecast models or complementing it. Wang Guanghui, et.al. [79] implements the support vector regression(SVR) method to supply chain demand forecasting. Liljana FerbarTrater, [80] presented an optimized forecasting method by selecting the suitable initial and smoothing parameters and achieves the best result than other forecasting methods. Babai, et.al. [81] examine an ARMA(0,1,1) demand process supply chain created by a supplier and a retailer. Marco A. Villegas, et.al.[82] presented a new model selection approach using a support vector machine. Jiao Wang, et.al.[83] gives the association among uneven demand signal and predictive accuracy. M.M.Ali, et.al. [84] gives demand inference techniques for supply chains in which information cannot be shared by considering simple smooth downstream moving strategy.

Niles perera. H, et.al. [85] gives the first systematic literature survey of critical forecasting. Warren Lian T, et.al.[86] proposed a new approach for examining the correlations between prediction losses and production costs in the supply chain. Erica Pastore, et.al.[87] studied a two-tier single item output network with a definite demand distribution that is controlled by the established AR(1) method but with undefined parameters. BurcuBalcik, et.al. [88] gives survey and focus on humanitarian inventory planning and management. KoussailaHamiche, et.al.[89] proposed a new robust and easy approach for demand forecasting in managing the supply chain. Chih-Hsuan Wang, et.al. [90] mentioned problems in demand forecasting and supply chain management of financial prediction by developing time series models and vector autoregression process. Galina Merkuryeva, et.al. [91] examined the new methods and major problems in demand forecasting for the pharmaceutical industry.

VII. OTHER TECHNIQUES IN DEMAND FORECASTING

Kourentzes N, et.al. [92] presented a heuristic to determine the appropriate reservoirs, while the modeler did not want an arbitrary cut-off point that should or should not be included in the mixture. M.Kalshschmidt, [93] reports on best practices in demand forecasting and deals with the principle of best practices from three different perspectives. Liljana Ferber, [94] developed Holt's winter’s method for noisy demand forecast and achieved a reduction in forecast error. SuganthiL., et.al.[95] attempts mad to study the different predictive models for energy demand. Kaminivinkatesh, et.al.[96] proposed the forecast of cash demand for groups of ATMs with cluster demand patterns to develop ATM's cash demand forecasts.

Clint L.P Pennings, et.al. [97] presented an optimized hierarchical forecasting approach to forecast the products demand at separate yet hierarchically connected rates of aggregation. Anna Lena Beutel, et.al.[98] proposed an integrated framework to forecast and coordinate the procurement of defense supplies in conditions where demand relies on many external factors. Binzhang, et.al.[99] discussed the advantage of the fast shipping method because a retailer would use the original inventory information to adjust the order quantity in a multi-
product situation with two cycles. Jorge E. Pesantez, et.al.[100] presented a group of forecasting water demand models using data collected by installed user-level smart meters.

VIII. CONCLUSION

In this review article, we collected more recent research articles based on demand forecasting and conclude that the above-mentioned various research outputs and its developments which are vital for day to day life to forecast demand arising in various industry.

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