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Framework for predictive sales and demand planning in customer-oriented manufacturing systems using data enrichment and machine learning

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Abstract

Companies with Make-to-Order (MTO) manufacturing have always faced the conflict of meeting a large volume of individual customer orders on time while remaining as flexible as possible. Unlike Make-to-Stock (MTS) manufacturing, planning the production requirements for MTO is a challenging task since incoming orders may vary in time and quantity, while also being subject to a number of variables. In some cases, the delivery time allocated by the customer can be less than the required Order Lead Time to fulfil the order. Manufacturers can respond to this with either with approached from production management or from data science. This paper presents a framework to leverage the benefit of both domains. We conduct a literature review and present the results of an expert workshop. We propose criteria for a suitable data enrichment and the application of Machine Learning (ML) methods in sales and demand forecasting. In conclusion, the proposed framework helps to equip manufacturing companies with a structured strategy for data management and to utilize the benefit of ML for sales and demand forecasting.

Keywords: Sales forecast; demand forecast; production planning; production control; predictive analytics; machine learning; make-to-order; make-to-forecast

1. Introduction

In order to be able to reliably fulfil the highest possible number of customer orders, manufacturing companies must efficiently handle their production program. At the same time, it is necessary to maintain a high degree of flexibility with regard to new orders or changed operating conditions. Two approaches are prevalent to achieve these objectives.

- Manufacturers use data-driven approaches from sales forecasting to predict upcoming levels of customer orders.
- They use approaches from production management to decouple the production program from individual orders.

First, knowledge of future sales that is gained through forecasting facilitates the planning of plant operations, from procurement to production planning to logistics and warehousing. Second, manufacturing companies achieve a decoupling of sales orders by individualizing products at a later stage in the order fulfilment process. In this context, *Order Lead Time* (OLT) refers to the total time required to fulfil an order [1]. A *Customer Order Decoupling Point* (CODP) represents the phase in the value stream from which a customer-specific customization of the product takes place [2]. The later the CODP is situated in the value stream, the higher the flexibility of the organization with regard to fluctuations in customer demand [3]. A reliable sales forecast enables manufacturing companies to be independent of the CODP, since they can initiate the production even before receiving orders [4].

This paper presents a framework for predictive sales and demand planning for customer-oriented manufacturing. This approach is particularly developed for scenarios where the time

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to meet the customer's demand is shorter than the OLT. In this paper, we will particularly examine the first approach in more detail. Therefore, this paper summarises the current state of the literature in the context of forecasting in customer-specific manufacturing. We present a framework to enable small and medium-sized enterprises in particular to increase flexibility in processing customer orders to hold the customer-desired delivery dates. With the help of a number of companies, we have identified requirements that must be met in order to use it.

2. Fundamentals

2.1. Sales- and demand forecasting in order manufacturing

Sales and demand (SD) forecasting in order manufacturing involves predicting the future sales for a company's products and materials. *Sales* represent the quantity of all goods sold by a company and are therefore calculated after the actual sale has taken place. *Demand* includes all resources necessary for the production of goods and services. Demand is often subdivided into primary (finished products), secondary (assemblies, raw and individual parts, materials) and tertiary demand (auxiliaries and operating materials) [5, 6]. It can be planned demand-based or consumption-controlled. To deal with it in a proper way, knowledge of the product quantities required in the future, which are subject to typical demand characteristics, referred to as *demand profiles*.

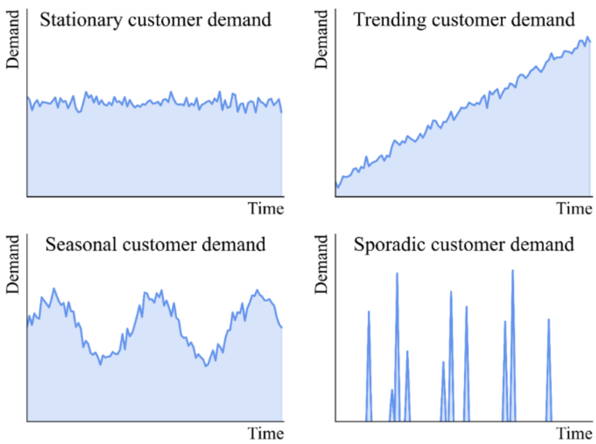

Fig. 1. Visualisation of characteristic demand profiles.

Fig. 1 shows four types of demand profiles. The stationary profile remains steady, while the trending profile approximates a linear nature. Seasonal demand shows recurring patterns, whereas sporadic demand is characterised by a high number of zero values and irregular demand [7]. Instead of pure versions, hybrid forms of demand profiles are more common in practice.

The information on past demand enables an empirically based forecast of future demand using quantitative methods [8] which can be either *univariate* or *multivariate* [9, 10]. Univariate forecasts are based on the assumption that future SD quantities can be determined on the basis of one characteristic, usually the time-based quantities of past SD.

Multivariate forecasting methods imply that the quantity of SD to be forecast can be represented as a function of several independent variables and the demand can be described causally. For example, Winters' *second-order exponential smoothing*, an extension of Holt's method with a seasonal factor, is well suited for applications with seasonal demand profiles [11]. The procedures are primarily suitable for stock-based production and can only be used to a very limited extent in contract manufacturing, which processes individualised orders according to specific customer requirements.

In addition to quantitative methods, qualitative forecasting methods are used, which are based on subjective factors, e.g. expert assessments. These methods are used when no representative data from the past is available and are in principle suitable for use in contract manufacturing [7]. The aim is to map the implicit knowledge of specialised personnel, such as planners, managers or salespeople, on current developments and system states. The methods are often less costly than qualitative methods in comparable applications, but are also more prone to error [12]. Since qualitative methods are particularly suitable for longer-term predictions of entrepreneurial trends, they are often used for strategic SD planning and rarely for operational [12].

2.2. Strategies for customer-specific order manufacturing

Order manufacturing is a strategy in which products are produced only after a specific customer order was received. The approach differs from traditional Make-to-Stock (MTS) manufacturing. In MTS products are manufactured ahead of time and kept in stock for future sales. Well known order-oriented strategies in manufacturing are Make-to-Order (MTO), Assemble-to-Order (ATO) and Engineer-to-Order (ETO). [13].

The strategies have a different position of their respective CODP. While MTO and ETO can utilize forecasting only to limited extent for operational planning due to the high customer dependencies, quantitative forecasts in particular can be used for ATO and MTS. To expand forecasting applications in SD planning, the *Make-to-Forecast* (MTF) strategy is postulated [14]. Especially for MTO, but also for ATO and ETO systems, MTF can enable greater independence from the CODP and translate forecast customer behaviour into specific production orders. In Figure 2, the CODP shift is represented by an MTF area, which represents a reduction in order processing times with a simultaneous increase in customisation [15].

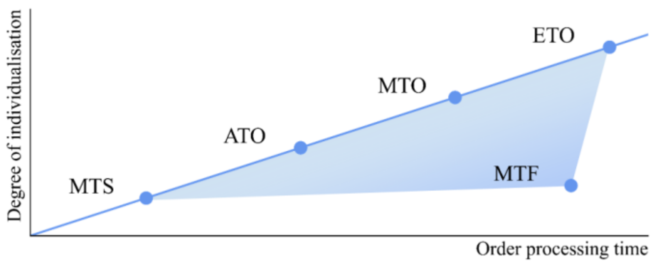

Fig. 2. Schematic visualization of manufacturing strategies with regard to individualisation and order processing time [15].

MTF originates from operations research and represents a current research approach, which has so far mainly been considered in the work of Akinc and Meredith [14–16]. They outline potential for higher delivery speeds by individualised products, customer decoupling through a floating the CODP [15, 17]. Other hybrid systems with a floating CODP are represented under the term Virtual-Built-to-Order (VBTO) or Built-to-Forecast (BTF), which use simulation and control structures to create a moving CODP from the perspective of production [18]. Although the idea dates back to the 1990s and 2000s [16, 18, 19], there are hardly any examples of practical applications for strategies like MTF so far, despite extremely promising potentials and a potentially very broad target group [17, 20].

2.3. Machine learning for sales and demand predictions

To enable better forecasting in order manufacturing, the often good historical sales data should be enriched with additional qualitative and quantitative data. Since the volume and inherent complexity of the resulting data generally make manual evaluation uneconomical, the use of ML methods for efficient evaluation and use of the implicitly available knowledge is sought [21]. In the project, the use of regression methods is aimed at predicting SD quantities, which, analogous to the univariate and multivariate approaches of the quantitative methods, use a dependent or several independent variables for modelling and predict future values of this variable [22]. Depending on the input data, a distinction is also made between univariate and multivariate methods for forecasting time series [23], whereby ML also enables the combination of qualitative and quantitative input data, for example through one-hot encoding [24]. A promising approach to time series forecasting is represented by neural networks or deep learning methods, with which significant successes have been achieved in various application areas in the past decades [25]. The decisive factor for these successes and the cross-domain spread is the ability of these ML methods to recognise complex, non-linear patterns in data and to map unstructured relationships without using a-priori hypotheses [26]. One promising modelling method is *Long Short-Term Memory Networks* (LSTM), which have an internal memory through feedback neurons arranged in layers and are typically used to discover time-related information [27]. At the same time, practical applications already show that SD forecasting with ML actually works in certain domains. The focus is often on retail. This is because a large part of the logistics costs incurred for warehousing etc. are directly dependent on sales planning. At the same time, there are product-specific requirements, for example, the products could be perishable, especially in the food sector [28, 29]. It becomes clear that ML is more applicable in large scenarios than classical forecasting approaches, but they do not outperform them in accuracy in all use cases. Similarly, Güven and Şimşir [30] and Ren *et al.* [31] in the fashion industry focus more on the inventory planning problem than on perishability. Here, too, different algorithms are used and compared, including support vector machines and neural networks.

2.4. Data enrichment

In the comparison of the different cases, the use of quantitative data is particularly apparent. This usage of additional data is called data enrichment. It provides a more comprehensive understanding of the market and the consumer behaviour. It allows the user to understand the influence of various other variables on the corresponding sales and to include them in the forecast [32]. The most common data sources are shown in Table 1.

Table 1. Common sources for Data Enrichment in SD Forecasting

Data Source	*Data Type*
Historical sales figures [6, 33]	Quantitative
Sales figures of similar products [34]	Quantitative
Assessment of in-house experts [35]	Qualitative
Advertising, marketing and online usage [36, 37]	Quantitative/ Qualitative
Customer surveys [35]	Quantitative/ Qualitative
Environmental Conditions (weather, seasonality, indices of economic situation) [38, 39]	Quantitative/ Qualitative

Data enrichment and the selection of appropriate sources will become crucial in the course of the PrABCast research project in order to use machine learning methods in SMEs in a target-oriented way in SD forecasting.

3. Framework

3.1. Concept

The PrABCast research project aims to enable SMEs with contract manufacturing to produce more accurate SD forecasts. To this end, qualitative and quantitative data from different sources and suitable ML methods as explained in the literature review are to be used to create better forecasts depending on the production strategy, the variety of variants and the customer profiles. The improvement for the company lies not only in shortening the order lead time, but also in optimising the degree of individualisation of the products. In order to implement these SD forecasts in contract manufacturing, practical research was carried out in the project from the very beginning. Within the framework of a qualitative initial study in the form of expert surveys, it was ascertained how situations are currently solved in the actual state at the companies of the project-accompanying committee, in which the OLT of customer orders is longer than the DT. It emerged clearly from all SMEs that they do not initially work on the method or procedure of forecasting itself, but try to shorten the OLT with the help of production management measures. The reasons for this vary. They can be divided into three categories:

- Competence,
- Speed of implementation
- Acceptance.

Firstly, companies often implement changes in work system design or in production management as part of the continuous improvement process. Therefore, they rate their *competence* in this area higher than in understanding and adapting forecasting methods and algorithms. Secondly, the impact of changes on the shop floor can be measured manually, which allows for faster experimentation. As a result, SMEs see a higher implementation speed of measures on the shop floor itself. Finally, the issue of acceptance plays a major role in critical decisions. This is closely related to the area of Explainable AI. Adjustments in production are often understood by SME decision makers because they have a technical background. However, changes to traditional forecasting methods are more critically scrutinised, because the origins of the forecast results are not understood. The acceptance of the decisions based on them is smaller.

To this end, a first draft of a framework was developed with which SMEs can work on their on-time delivery rate in a structured way.

If the OLT is longer than the DT, the first step is to improve the production system to shorten the OLT. This can be done using Operational Excellence or Lean methods. Using group technology ideas to shift the CODP is also a possibility. If the OLT is still longer than the DT, the forecast needs to be optimised. This is the main focus of the PrABCast research project According to the current state of the literature, data enrichment and the use of machine learning methods can be promising approaches. We aim to provide SMEs with the right recommendations for action based on their prerequisites in terms of data, staff competence and organisation. To this end, we define requirements and analyse numerous use cases with the users to determine which combination of measures is best in which situation. The concept presented in Fig. 3 is always followed.

3.2. Requirements in Order Manufacturing environment

This draft concept needs to be detailed within the framework of the research project in order to make it applicable in SMEs. This concept was therefore initially discussed within the framework of a survey and a user workshop. Since the focus is on the practicability of the application in SME, the requirements that are placed on such a concept were initially elicited. Since experts from the corresponding sales departments, managers, data scientists and providers of corresponding software solutions were in the group, a comprehensive picture emerged. Due to the great practical relevance and the relevance of expert knowledge in SD planning in SME, a socio-technical approach according to Strohm and Eberhard [40] on the basis of Emery [41] is appropriate. This is supplemented by the inevitable data-analytical perspective in Industrial Data Science topics. In essence, the requirements can be divided into four categories: Data, Technology, Human, Organisation.

3.2.1. Data

In relation to data, two areas of requirements were discussed: *Data availability* and *data quality*. *Data availability* is crucial from two points of view. Since data enrichment is core to the concept and necessary for sufficient training of corresponding ML methods, it must be available or made available. At the same time, this point companies lack digitalisation, especially in the production area. Good *data quality* is indispensable for forecast quality. For this purpose, it is a requirement to specify an appropriate data quality level for the respective data types and processes of the respective company in order to ensure the success of the forecasts.

3.2.2. Technology

Technically, special requirements apply in the heterogeneous system landscape in Germany's SME. This affects the three areas of *software, hardware* and *security*. On the software side, integration is crucial. On the one hand, there must be a software option to apply any forecasting procedures at all, as many companies rely on standard solutions from manufacturers with limited functions. Furthermore, it must be possible to integrate the forecasting results into downstream systems so that previously automated processes continue to function in a lean manner. The same applies to the hardware. Many order manufacturers fear the high computing power that the corresponding models require, as the results must be available quickly. The hardware plays a role in ensuring that this requirement for fast availability is met. A technical infrastructure with servers or cloud-based must be created that meets this requirement. Security plays a decisive role in this. SD planning data in particular is sensitive. If this data or forecasts get to competitors, the entire position in the market is at risk. Data security must therefore be ensured on the hardware and software side.

3.2.3. Human

The human factor results directly from the application of ML in an industrial environment, as people bear responsibility in the decision-making process here. There is a requirement for *acceptance* of the concept as well as for *competence development*. Acceptance is important insofar as decisions that determine the success of a company are made on the basis of sales forecasts. Depending on the company, different people are responsible for these decisions. In detailing the concept and its introduction, it is important to take into account that these people accept and support the decision that is made for them by a process from the field of artificial intelligence. Even deciders

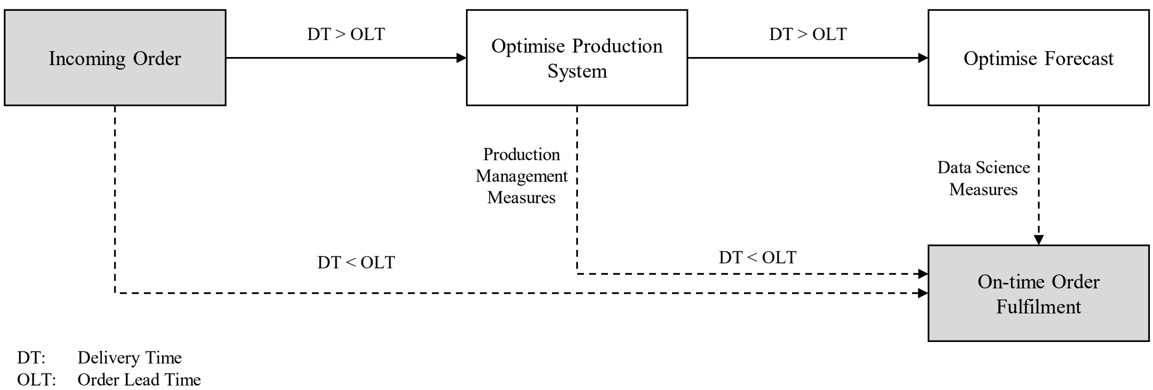

Fig 3. Step-based concept in PrABCast research project

in Management positions need to carry the results. Competence development also plays a significant role in this. The employees concerned must be enabled to comprehend the decisions and understand them up to a certain point. It must be taken into account that people with an affinity for data (analysis) do not always work in corresponding roles.

3.2.4. Organisation

In addition, there are organizational requirements for such a concept. *Individuality, limitation, strategy and management support* are decisive requirements. It must first be taken into account that there are always exceptional cases in order manufacturing. The workshop showed that none of the manufacturers pursues one single production strategy, but mostly offers all versions for different products from ETO to MTS. In addition, in some product areas, a few customers account for a large proportion of sales. This is just one case that must be taken into account when analysing the historical requirement profiles and must always be considered on a company-specific basis. As a result, individual solutions are often necessary. Accordingly, when developing the concept, it is necessary to look as closely as possible at which input variables and data sources are relevant for a company and are included in the model. In addition, a precise limitation of the product portfolio to be considered is necessary when the concept is first introduced. Due to the large company-internal differences for the sale of different products, one model does not work for the entire portfolio, a useful area must be selected during the introduction. This leads directly to the strategy. The target variable to be optimized for is decisive for the selection of the best model. This is also individual. Sales and requirements planning are followed by other areas of production planning and control. Different methods and procedures are chosen according to different objectives. In order to deal with these production logistics goals, a company needs different forecasting horizons in different aggregations. The product is also relevant for doing this. Management support results from the human factors. The workshop participants agreed that the introduction of digitization solutions and industrial data science only works if the management is fully committed with the project.

4. Conclusion and Outlook

The extensive literature research shows that for the goal in Order Manufacturing - the greatest possible flexibility in production itself with simultaneous fulfilment of all customer orders in the appropriate time – a corresponding forecast as well as the customer decoupling point are decisive. In other areas, there are numerous other data sources that also show potential for Order Manufacturing in addition to the data already used. Furthermore, the initial surveys and workshops show that a structured approach such as the one shown in Fig. 3 for combining known approaches to optimising the production system with optimising the forecast is appealing to the companies. By adapting available ML methods to a specific use case and enriching them with additional qualitative and quantitative data sources, it can be concluded that ML that reliable SD forecasts can also be generated in Order Manufacturing. However, it is important to take into account the requirements when developing the concept and in the context of the exemplary analyses. Special framework conditions apply here due to the objective of enabling the application in SME. At the same time, the literature offers useful tools in numerous areas that are mentioned in the requirements. Models for evaluating data quality should be mentioned here, as well as classic methods for combining different data sources on one hand or Group Technology approaches for shifting the CODP on the other hand. The volatile field in ML is also promising, which always offers new developments that fit for many individual cases - also in the area of SD forecasting. At one user company, we have already carried out an individual project to introduce levelling using group technology and, in parallel, improved the forecast by changing the method from linear regression to Holt-Winters, in this case without data enrichment. Both have a positive effect on delivery reliability and compliance with DT. This, and the companies major participation in the elaboration of requirements and the framework, is a promising start to the PrABCast project, in which we want to draw conclusions about the general applicability via further individual use cases and the analysis in the respective procedure.

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References

[1] C.-J. Liao and C.-H. Shyu, “An Analytical Determination of Lead Time with Normal Demand,” *Int Jrnl of Op & Prod Mnagemnt*, vol. 11, no. 9, pp. 72–78, 1991, doi: 10.1108/EUM0000000001287.

[2] J. Olhager, “The role of the customer order decoupling point in production and supply chain management,” *Computers in Industry*, vol. 61, no. 9, pp. 863–868, 2010, doi: 10.1016/j.compind.2010.07.011.

[3] M. Rudberg and J. Wikner, “Mass customization in terms of the customer order decoupling point,” *Production Planning & Control*, vol. 15, no. 4, pp. 445–458, 2004, doi: 10.1080/0953728042000238764.

[4] T. Heuer, J. T. Maier, M. Schmidt, and P. Nyhuis, *Fulfillment of Heterogeneous Customer Delivery Times through Decoupling the Production and Accelerating Production Orders*: Hannover : publish-Ing, 2022.

[5] W. Dangelmaier and H.-J. Warnecke, *Fertigungslenkung: Planung und Steuerung des Ablaufs der diskreten Fertigung*. Berlin, Heidelberg: Springer Verlag, 1997.

[6] G. Schuh and V. Stich, Eds., *Produktionsplanung und -steuerung 1: Grundlagen der PPS,* 4th ed. Berlin: Springer, 2012.

[7] G. Schuh, C. Schmidt, and F. Bauhoff, “Produktionsprogrammplanung,” in *Produktionsmanagement*, G. Schuh and C. Schmidt, Eds., 2nd ed., Berlin: Springer Vieweg, 2014, pp. 63–107.

[8] F. Herrmann and M. Manitz, “Ein hierarchisches Planungskonzept zur operativen Produktionsplanung und -steuerung,” in *Produktionsplanung und -steuerung: Forschungsansätze,*

Methoden und deren Anwendung, T. Claus, F. Herrmann, and M. Manitz, Eds., Berlin, Heidelberg: Springer Verlag, 2015, pp. 7–22.

[9] P. Aboagye-Safro, Q. Mai, F. M. Sanfilippo, D. B. Preen, L. M. Stewart, and D. M. Fatovich, "A comparison of multivariate and univariate time series approaches to modelling and forecasting emergency department demand in Western Australia," *Journal of Biomedical Informatics*, vol. 57, pp. 62–73, 2015.

[10] M. Motamedi, N. Li, D. G. Down, and N. M. Heddle, "Demand Forecasting from Platelet Usage: From Univariate Time Series to Multivariate Models," *CS Machine Learning (arXiv)*, 2021.

[11] A. A. Shahin, "Using Multiple Seasonal Holt-Winters Exponential Smooting to Predict Cloud Resource Provisioning," *International Journal of Advanced Computer Science and Applications*, vol. 7, no. 1, pp. 91–96, 2016.

[12] K. Alicke, *Planung und Betrieb von Logistiknetzwerken: Unternehmensübergreifendes Supply Chain Management,* 2nd ed. Berlin, Heidelberg: Springer, 2005.

[13] O. Willner, D. Powell, A. Duchi, and P. Schönsleben, "Globally Distributed Engineering Processes: Making the Distinction between Engineer-to-order and Make-to-order," *Procedia CIRP*, vol. 17, pp. 663–668, 2014, doi: 10.1016/j.procir.2014.02.054.

[14] J. Meredith and U. Akinc, "Characterizing and structuring a new make-to-forecast production strategy," *Journal of Operations Management*, vol. 25, no. 3, pp. 623–642, 2007.

[15] U. Akinc and J. R. Meredith, "Make-to-Forecast: Customization with Fast Delivery," *International Journal of Operations & Production Management*, vol. 35, no. 5, pp. 728–750, 2015.

[16] A. S. Raturi, J. R. Meredith, D. M. McClutcheon, and J. D. Camm, "Coping with the build-to-forecast environment," *Journal of Operations Management*, vol. 9, no. 2, pp. 230–249, 1990.

[17] K. Peeters and H. van Ooijen, "Hybrid make-to-stock and make-to-order systems: A taxonomic review," *International Journal of Production Research*, vol. 58, no. 15, pp. 4659–4688, 2020.

[18] P. G. Brabazon and B. L. MacCarthy, "Virtual-Build-to-Order as a Mass Customization Order Fulfilment Model," *Concurrent Engineering Research and Applications*, vol. 12, no. 2, 2004.

[19] D. M. McClutcheon, A. S. Raturi, and J. R. Meredith, "The Customization-Responsiveness Squeeze," *Sloan Management Review*, vol. 35, no. 2, pp. 89–99, 1994.

[20] M. Rabbani, M. Monshi, N. Manavizadeh, and M. S. Jalali, "Designing an advanced available-to-promise mechanism compatible with the make-to-forecast production system integrating inventory allocation and job shop scheduling with due dates and weigthed earliness/tardiness cost," *International Journal of Industrial Engineering Computations*, vol. 7, pp. 451–462, 2016.

[21] M. Eickelmann, M. Wiegand, B. Konrad, and J. Deuse, "Die Bedeutung von Data-Mining im Kontext von Industrie 4.0," *Zeitschrift für Wirtschaftlichen Fabrikbetrieb*, vol. 110, no. 11, pp. 738–743, 2015.

[22] K. Backhaus, B. Erichson, W. Plinke, and R. Weiber, *Multivariante Analysemethoden: Eine anwendungsorientierte Einführung*. Berlin, Heidelberg: Springer Gabler, 2016.

[23] S. Rong and Z. Bao-Wen, "The research of regression model in machine learning field," *MATEC Web Conf.*, vol. 176, p. 1033, 2018, doi: 10.1051/matecconf/201817601033.

[24] P. Cerda and G. Varoquaux, "Encoding high-cardinality string categorical variables," *IEEE Transactions on Knowledge and Data Engineering*, vol. 2020, pp. 1–17.

[25] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "Statistical and Machine Learning forecasting methods: Concerns and ways forward," *PloS one*, vol. 13, no. 3, 1-26, 2018.

[26] S. Smyl, "A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting," *International Journal of Forecasting*, vol. 36, no. 1, pp. 75–85, 2020, doi: 10.1016/j.ijforecast.2019.03.017.

[27] A. Sherstinsky, "Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network," *Physica D: Nonlinear Phenomena*, vol. 404, p. 132306, 2020, doi: 10.1016/j.physd.2019.132306.

[28] V. Semenov, V. Chernokulsky, and N. Shevskaya, *Research of artificial intelligence in the retail management problems*, 2017.

[29] J. Huber and H. Stuckenschmidt, "Daily retail demand forecasting using machine learning with emphasis on calendric special days," *International Journal of Forecasting*, vol. 36, no. 4, pp. 1420–1438, 2020, doi: 10.1016/j.ijforecast.2020.02.005.

[30] İ. Güven and F. Şimşir, "Demand forecasting with color parameter in retail apparel industry using artificial neural networks (ANN) and support vector machines (SVM) methods," *Computers & Industrial Engineering*, vol. 147, p. 106678, 2020, doi: 10.1016/j.cie.2020.106678.

[31] S. Ren, H.-L. Chan, and T. Siqin, "Demand forecasting in retail operations for fashionable products: methods, practices, and real case study," *Ann Oper Res*, vol. 291, 1-2, pp. 761–777, 2020, doi: 10.1007/s10479-019-03148-8.

[32] Q.-Q. He, C. Wu, and Y.-W. Si, "LSTM with particle Swam optimization for sales forecasting," *Electronic Commerce Research and Applications*, vol. 51, p. 101118, 2022, doi: 10.1016/j.elerap.2022.101118.

[33] E. Tarallo, G. K. Akabane, C. I. Shimabukuro, J. Mello, and D. Amancio, "Machine Learning in Predicting Demand for Fast-Moving Consumer Goods: An Exploratory Research," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 737–742, 2019, doi: 10.1016/j.ifacol.2019.11.203.

[34] S. Ma, S. Kolassa, and R. Fildes, "Retail forecasting: research and practice," 2018.

[35] J. K. Ord, R. Fildes, and N. Kourentzes, *Principles of business forecasting,* 2nd ed. New York, NY: Wessex Press Inc, 2017.

[36] J. R. Saura, P. Palos-Sánchez, and L. M. Cerdá Suárez, "Understanding the Digital Marketing Environment with KPIs and Web Analytics," *Future Internet*, vol. 9, no. 4, p. 76, 2017, doi: 10.3390/fi9040076.

[37] G. Assmus, J. U. Farley, and D. R. Lehmann, "How Advertising Affects Sales: Meta-Analysis of Econometric Results," *Journal of Marketing Research*, vol. 21, no. 1, p. 65, 1984, doi: 10.2307/3151793.

[38] P. Weichel and J. Herrmann, "Wie Controller von Big Data profitieren können," *Control Manag Rev*, vol. 60, S1, pp. 7–15, 2016, doi: 10.1007/s12176-016-0012-0.

[39] T. Huang and J. A. van Mieghem, "Clickstream Data and Inventory Management: Model and Empirical Analysis," *Prod Oper Manag*, vol. 23, no. 3, pp. 333–347, 2014, doi: 10.1111/poms.12046.

[40] O. Strohm and U. Eberhard, "Unternehmen umfassend bewerten," in *Arbeitssituationsanalyse*, C. Meyn, G. Peter, U. Dechmann, A. Georg, and O. Katenkamp, Eds., Wiesbaden: VS Verlag für Sozialwissenschaften, 2011, pp. 322–338.

[41] F. E. Emery, "Analytical Model for Socio-Technical Systems: Address to the International Conference on Sociotechnical Systems," in *The emergence of a new paradigm of work*, F. Emery, Ed., Canberra: Australian National University, 1978.