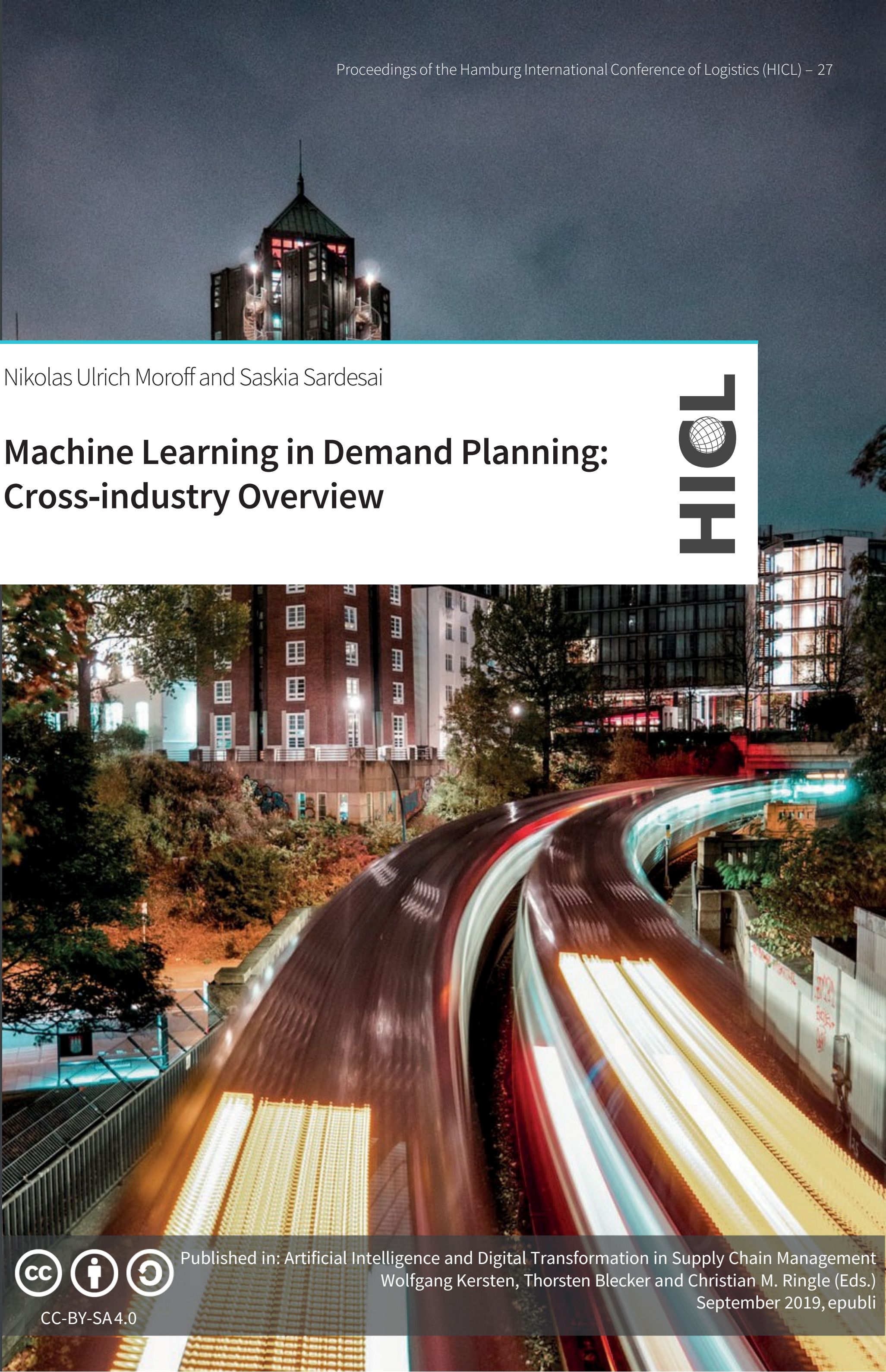
Proceedings of the Hamburg International Conference of Logistics (HICL) – 27

Nikolas Ulrich Moroff and Saskia Sardesai

Machine Learning in Demand Planning: Cross-industry Overview

HICL



Published in: Artificial Intelligence and Digital Transformation in Supply Chain Management
Wolfgang Kersten, Thorsten Blecker and Christian M. Ringle (Eds.)
September 2019, epubli

Machine Learning in Demand Planning: Cross-industry Overview

Nikolas Ulrich Moroff[1] and Saskia Sardesai[1]

1 – Fraunhofer Institute for Material Flow and Logistics IML

Purpose: This paper aims to give an overview about the current state of research in the field of machine learning methods in demand planning. A cross-industry analysis for current machine learning approaches within the field of demand planning provides a decision-making support for the manufacturing industry.

Methodology: Based on a literature research, the applied machine learning methods in the field of demand planning are identified. The literature research focuses on machine learning applications across industries wherein demand planning plays a major role.

Findings: This comparative analysis of machine learning approaches provides/creates a decision support for the selection of algorithms and linked databases. Furthermore, the paper shows the industrial applicability of the presented methods in different use cases from various industries and formulates research needs to enable an integration of machine learning algorithms into the manufacturing industry.

Originality: The article provides a systematic and cross-industry overview of the use of machine learning methods in demand planning. It shows the link between established planning processes and new technologies to identify future areas of research

Keywords: Machine Learning, Demand Planning, Artificial Intelligence, Digitalization

First received: 14.May.2019 **Revised:** 29.May.2019 **Accepted:** 20.Jun.2019

1 Introduction

In recent years, digitalization has become more and more important, and hence it has a high significance for the manufacturing and planning processes of industrial companies. According to a study by the VDI, up to 25% of companies intend to deal with the topic of artificial intelligence (AI) and machine learning (ML), which is one of the main tasks of digitalization in the following years (Verein Deutscher Ingenieure e.V., 2018). Artificial intelligence describes a field of research that becomes increasingly relevant in the digitalization process for the automation of planning processes. Machine learning is a sub-area of artificial intelligence and describes a method for the implementation of self-learning systems. The study shows, that these topics already have a high priority in the economy today and their importance for future economic success is very present. Table 1 supports the estimated potential of the new technologies (Reder, 2018).

Table 1: Studies for AI and ML (Verein Deutscher Ingenieure e.V., 2018)

Study	**Date**	**Extrapolation (increase by)**	**Market**	**Until Year**
Accenture	July 2017	gross value added (12 trillion Euros)	12 industrial countries (incl. Germany)	2035
McKinsey	April 2018	gross domestic product (16 billion Euros)	Germany	2030
PwC	June 2018	gross domestic product (430 billion Euros)	Germany	2030
BMWi, iit Berlin	July 2018	gross value added (31,8 billion Euros)	Industry Germany	2023

The process of digitalization and its analysis began in the 1990s with the increasing creation of data records, digital transactions and networked systems (Zuboff, 2010; Bryanjolfsson and Mcafee, 2014). Especially in logistics and supply chain management, a high amount of transaction data is generated and collected, displaying the high potential for the use of this information (e.g. for forecast improvement) (Röniger, 2018).

Along with the increasing computing power, it is now possible to analyze the generated data sets of a company and render them usefully (Papenfort, Frank and Strughold, 2015). Methods and algorithms have to be developed for the usage of the data sets that can analyse large amounts of information in order to recognize patterns and rules that can be used as decision support for future processes and planning (Haasis, et al., 2015). One of these methods for analysing large amounts of datasets is machine learning, an algorithm that evolves using feedback information and historical data (Michie, 1968). Especially demand forecasting in the area of supply chain planning (e.g. in manufacturing industry) is an important application area for machine learning methods, as many different factors affect the sales market and conventional statistical methods reach their limits (Deutschländer, 2003).

2 State of the Art

2.1 Demand Planning

Demand planning describes the process of determining future material requirements according to quantity and time and represents a major task within the area of Supply Chain Management (SCM) (Tempelmeier, 2018). The SCM task model from Kuhn and Hellingrath describes the interfaces between the individual SCM tasks and the planning horizon of each individual module (Hellingrath and Kuhn, 2013). Originally, the SCM task model was designed to structure requirements for SCM software, to define all areas and respective interfaces in detail (Koch, 2012). Within the SCM task model, demand planning covers the interface between tactical and strategic planning. It serves as an input for further underlying planning processes (e.g. procurement, production and distribution planning). A large number of planning parameters are therefore dependent on the results of demand planning. Consequently, it is essential for the profitability of a company to achieve a high forecast quality and to minimize uncertainties (Ashayeri and Lemmes, 2006). There are several different forecasting methods, which form the basis for the strategic and operative planning of a company (Hammer, 1998). Current forecasting methods, though, analyze the past in order to draw conclusions about future events. It is assumed, that events always have the same implications and follow the same pattern. This approach is known as the time stability hypothesis. Based on this assumption, there are deviations between the forecast result and reality, which are evaluated as forecast errors (Hansmann, 2013; Stickel, Groffmann and Rau, 2013). Methodically, the forecasting procedures can be divided into two categories: quantitative and qualitative. The characteristics of the different methods are briefly summarized in Table 2.

In summary, it can be said that demand planning is based on the forecast results of the procedures briefly outlined before. The forecast thus determines the demand of goods for a fixed period (e.g. monthly). However, in order to achieve a high forecasting quality, an exponentially increasing computing effort and sufficient database is necessary, so that a structured and case-dependent selection of the forecasting method is essential (Feindt and Kerzel, 2014; Kühnapfel, 2014).

Due to the advancing development of information technologies, classical forecasting methods are slowly being replaced by more complex methods. The trend is tending towards the use of e.g. machine learning or neural networks to enhance the forecast with further internal and external data (Mertens and Rässler, 2012). Machine learning can combine quantitative and qualitative methods so that it is possible to integrate both, historical data and expert knowledge (semantic data) in the decision-making process (Shalev-Shwartz and Ben-David, 2014). Furthermore, it is possible to integrate additional internal sources (e. g. intranet, social media) of information that provide extra knowledge for the planning process. The following section of the article gives a brief overview of the challenges in forecasting demand in the manufacturing industry.

Table 2: Properties of forecast methods (Hansmann, 2013; Stickel, Groffmann and Rau, 2013)

Quantitative forecasting methods	**Qualitative forecasting methods**
Mathematical model which is applied to a company's historical data	Use of expert knowledge to generate recommendations for action
One-dimensional or multidimensional	Often no database available/required
Linear and non-linear models	

2.2 Challenges in the demand planning of manufacturing companies

Demand planning in the manufacturing industry is affected by a high degree of forecasting uncertainty. This is due to the many different factors which can influence the demand of a company and to the length of the forecasting horizon. These uncertainty factors can be divided into the following types: aleatoric and epistemic uncertainties (Helton, et al., 2010). Aleatoric uncertainties describe the stochastic influences on the forecast quality. In addition to statistical uncertainties, there are further factors (epistemic uncertainties) influencing the forecast quality, which are briefly described in the following list (Grömling, 2005; Egri, et al., 2008).

- Data revision: Data in the model is incorrect, resulting in a wrong basis for the forecast model.
- Unpredictable events: Statistical methods do not consider new events and hence do not forecast the resulting effect.
- Human factor: Humans tend to override the output and adhere to familiar principles (status-quo preservation).

To overcome some of the issues mentioned above, Habla analyzed machine learning methods in demand planning of a manufacturing company in order to improve the forecast quality. The author concluded that many areas in the modelling and application of the algorithm were still insufficiently illuminated. For example, the integration of trends and seasonal effects is not mentioned in his study and he also argues that data mining methods can be used to generate different aggregation levels to enable a robust forecast (Habla, et al., 2007). The main reasons lie in the high complexity of the data structure and the changing customer behavior. Because of the ever shorter product life cycles, thus, it is not possible to collect enough historical data over a long period of time or for a specific product phase (start-up, peak or phase-out phase) to make statistically sound statements regarding the demand forecast (Johnson, 2018; Mayr and Moser, 2018). The type of product is also decisive here: Innovative products have a significantly shorter product life cycle than standard products, hence their sales behavior can be predicted much less accurately (Lee, 2002). Even in case a good data basis is available, there are further challenges in the analysis and interpretation of the data. It is crucial to filter the essential data and ignore unimportant data. This can only be done in relation to the use case to be examined, since the importance of a data set highly depends on the target size and data structure (Alansari, et al., 2018). In 2017, Scheidler developed a process model to extract knowledge from the database of a supply chain in order to create a usable data basis. The process model focuses on the definition of the desired target quantity, the selection and cleansing as well as the preparation of the data stock and the application of a data mining procedure (Scheidler, 2017). Each of these tasks involves its own challenges. The following list presents the greatest challenges specifically for the use of machine learning methods in demand planning in the manufacturing industry. For the handling of the mentioned challenges artificial intelligence methods are increasingly applied.

- Creation of a database
- Data acquisition/recording; Data preparation; Data analysis
- Creation of data model as basis of the algorithm
- Consideration of influencing parameters (environmental factors, regional factors,
- Political factors) depending on the branch
- Definition of the Output Parameter (Modelling)
- Changing products and shortened product life cycles

The following section of the paper gives a brief overview of current machine learning methods and provides an initial overview of the most common methods used in demand planning.

2.3 Machine Learning Methods in Demand Planning

Machine Learning is a field of research that deals with the modelling and implementation of learning phenomena and is part of artificial intelligence

(Engemann & Sudmann, 2018). The first research work in this field began in the 1950s, but only through technological advancements and the use of graphics processing units (GPUs) is it possible to handle data sets quickly and cost-effectively since 2015 (Wesseler, 2018). To implement machine learning methods, no static programming rules are used, instead the program extracts regularities from sample data in order to subsequently develop a model. After a learning period, the model is then applied to new data sets.

The main difference between traditional programs and machine learning algorithms is the feedback loop within the model. This allows the model to get a feedback on the quality of the output parameter and then adjust its own decision rules in order to improve the result. A self-learning system is created through the feedback loop as the machine learning algorithms continue to improve along with the duration of use and the amount of data (Gottschlich, et al., 2018; Wittpahl, 2019). Due to these characteristics machine learning methods are suitable for the following problems (Géron, 2017):

- Complex problems without an existing good solution
- Problems with changing environmental influences
- Large amounts of data as a basis
- Complex lists with existing solutions

In summary, machine learning algorithms can handle large amounts of data and flexibly react to changing conditions and environmental influences. According to Géron, there are three different strategies for implementing a machine learning algorithms:

- With and without human supervision
- Incremental learning and non-incremental learning system
- Pattern recognition

In demand forecasting, supervised learning algorithms are preferably used, as they can handle large amounts of data very efficiently and precisely. The algorithm's approach here is to identify patterns based on training data and to derive rules that can then be transferred to new data sets (Marsland, 2011; Mello and Ponti, 2018). Example algorithms are Logistic Regression or Random Forest, but also artificial neural networks (ANN) which are explained more in detail in the following section, as they play an important role in the context of artificial intelligence and machine learning. The ANN is a replica of the organic neuronal structure of humans. It is a mathematical-statistical method, which processes information on the basis of the human neuronal nerve structure and is very well suited for prognosis procedures and prediction models. Structurally, ANN do not represent a classically programmed algorithm, but a structure that can be flexibly adapted to data or system changes (Crone and Preßmar, 2006). The data points of the artificial neural network are linked and trained to react to unknown situations. The knowledge of the neural network lies in the weighted connection between the individual data points, which influence the transmission of the data and the result of the output function. A key capability of the ANN is its generalization capability. Therewith, good results can also be obtained for data sets whose behavior has not previously been trained. Especially in connection with prognosis problems, neural networks have the advantage of being able to model linear, non-linear or all interrelationships between data sets, which allows a very large scope for design (Hornik, Stinchcombe and White, 1989; Zell, 2000; Haykin, 2009). After the presentation of the individual implementation strategies and the ANN, the best known algorithms of machine learning will be discussed briefly. It is not our intention to present a complete list of all machine learning algorithms, as there is no clear definition or demarcation between the algorithms. The number of machine learning algorithms varies between 1,000 and 10,000 (Engemann and Sudmann, 2018). The best known machine learning algorithms can be subordinated into the tasks of classification, regression and clustering (Géron, 2017). In the following, these tasks are shortly explained.

2.3.1 Classification

Classification procedures are used to classify objects or data points according to their properties. Based on the underlying set of data, the classes are calculated. New data points are sorted into the calculated grid based on their attributes (e.g. K-Means-Algorithm). It is important to note that the classification problem is discrete, hence the assignment is always unambiguous (Marsland, 2011). After the assortment of the data point, the classes are recalculated on the basis of the new dataset to achieve a continuous improvement of the classification result. These methods are often used in the field of pattern recognition or artificial intelligence (Wittpahl, 2019).

2.3.2 Regression

Regression analysis is already used in many areas for forecasting demand because it predicts the trends of the future on the basis of historical values and a statistical model. For this purpose, the dependency between two variables (dependent and independent) is examined in order to define their relationship to each other. This can be a simple regression (an independent variable) or a multiple regression (several independent variables). For this reason, they are particularly useful in forecasting and scenario analysis because they can consider several different data sources (internal data, weather data, regional data, etc.) (Stoetzer, 2017; Welc and Esquerdo, 2018). For further development of regression analysis, it is linked to a machine learning architecture, to use new and actual data sets to constantly regenerate and optimize the model that has been developed on the basis of the historical data.

2.3.3 Clustering

Clustering procedures are used to group and classify data points according to their properties. For this purpose, it is essential that the similarity between data points is described in a measurable manner as to enable comparative analysis. Clustering algorithms work through two procedures one after the other. First, the similarity measure between the new data point and the existing data basis is determined. This is followed by a division of similar data into groups thus creating cluster. At this point, a distinction is made between hard and soft clustering algorithms, i.e. the unique assignment of a data point to a cluster. If it is a soft clustering algorithm, data points can also belong to several clusters. If a data point is always uniquely assigned to a cluster, it is a hard clustering algorithm (Ester and Sander, 2013; Backhaus, et al., 2016). This method is also often used to prepare data sets. For example, to summarize customers based on their specific properties so that they can be handled equally in the demand forecast (Murray, Agard and Barajas, 2015). In addition to the different methods and learning strategies of machine learning approaches, the data analyst has to consider the phases of learning, which segregate into a training phase and an application phase. During the training phase, the algorithm develops the knowledge from example data in order to use it in the application phase or, depending on the algorithm and learning strategy, to extend it afterwards (Neef, 2017). In the next section of the article, the requirements of demand planning processes in the classical manufacturing industry are first presented, followed by demand planning processes in other industries using machine learning.

3 Cross-industry application of ML in Demand Planning

3.1 Methodology comparative cross-industry analysis

In order to gain new findings for the implementation of machine learning methods, the methodology of a cross-industry comparative analysis is used. The findings are processed in a CRISP (Cross-industry standard process) model for standardized collection and clustering of the results (Wirth and Hipp, 2000).

Different industries are analyzed with regard to one problem in order to transfer solution approaches between the industries. Cross-industry innovations and analyses are increasingly implemented in product development to prevent conventional thinking (Schulthess, 2013). The aim of this analysis is to identify commonalities between different industries in order to transfer already established machine learning approaches to demand planning in the manufacturing industry. As the concept and the basic schema in demand planning is similar throughout the industries this allows a possible transfer to demand planning in SCM. Each industry has a certain demand variable to plan follow-up processes, e.g.:

- Energy: Energy consumption
- Finances: Market and shares development (Arroyo, Espinola and Maté, 2011)
- Agriculture: Crop development

In this paper, machine learning approaches in the sectors of energy, finance and agriculture are examined, since the financial and energy sectors in particular, are pioneers in digitalization according to a survey conducted by the Institute of the German Economy in Cologne (Demary, et al., 2016). The reason to choose these three industries are the different influencing factors which have a direct influence on supply chain processes. The energy industry is strongly influenced by climatic conditions, which impact the supply, and direct contact with the end consumer who has a high influence on the development of demand. In agriculture, regional and environmental factors are decisive for the expected crop yield. In contrast, in the financial sector these are usually global factors (e.g. market dependencies, political influences) that affect market development and performance on the financial market. The following Table lists the primary influencing factors and dependencies of the individual industries.

Table 3: Influencing variables in different industries

Industry	**Influence variables/dependencies**	**Source**
Energy	Climatic conditions Direct contact with the end consumer	(Lüdeke-Freund and Opel, 2014)
Finances	Market dependencies Political influences	(Onischka and Orbach, 2008)
Agriculture	Environmental/ regional influences	(Döring, et al., 2011)

3.2 Machine Learning Methods Forecasting Energy

The energy sector is highly dependent on current climatic conditions and has direct contact with end consumers (households and industry). For this reason, consumption data are the main input for machine learning algorithms and thus provide a large and detailed data basis. To prepare the data basis, the following steps are performed in order as named: specification (variable declaration and selection of secondary data sources (e.g. weather data or socio-economic data sets)), inspection (quality analysis) and preprocessing (filtering and data curation). These steps are necessary to provide a suitable input for the machine learning algorithm (Al-Alawi and Islam, 1996). Table 4 presents three research papers concerning predicting power demand using machine learning techniques.

Table 4: Machine Learning in Forecasting Electricity consumption

Database	**Machine Learning Algorithm**	**Results**	**Source**
Electricity consumption: 70,128 data points in the period 01.01.2008-31.12.2015 and weather data	ANN; Random forest Algorithm; Support Vector Machine Algorithm	Average percentage error 3.10% 96.3% of peak loads are covered	(Gajowniczek and Ząbkowski, 2017)
Electricity consumption Years: 1980-2000 (training data); 2001-2008 (test data)	ANN	Average percentage error 0.64	(Küçükdeniz, 2010)
Electricity consumption Years: 2006-2007 (training data); 2008 (test data); Influencing variables: Time; Seasons	Support Vector Regression	Average percentage error 0.41-0.53 depending on combination of influencing variables	(Setiawan, Koprinska and Agelidis, 2009)

These three papers were selected because they use different approaches and data bases, and all provide good results. In contrast to Küçükdeniz, Gajowniczek and Ząbkowsk focus on a short time horizon, which allows to evaluate the advantages of the different algorithms in relation to the considered application case. The last paper analyzes different time windows, but focuses only on support vector machines, therefore a comparison of the three publications gives a good overview of the state of the art in this industry.

The first column describes the used database, afterwards the used machine learning algorithm is described. The results column displays the quality of the results and the calculated error size. The results of the research work show that artificial neural networks and supervised machine learning methods provide the qualitatively best prognosis results. In addition, the quality of the results increases with the number of training data of the primary data set (see Küçükdeniz) or with the consideration of further secondary data sets (see Setiawan).

3.3 Machine Learning Methods Forecasting Finance

Intelligent forecasting methods are already widely used and established within the financial sector. Krollner has prepared a compilation of the techniques (time horizon, algorithm) and data bases (data evaluation, data selection, input parameters) used in this area in 2010 (Krollner, Vanstone and Finnie, 2010). The following figures are based on his literature research and are intended to give a brief overview of the use of machine learning methods in forecasting financial time series. As shown in Figure 1, the artificial neural networks (ANN) based algorithm is most widely used in the financial sector followed by evolutionary and optimization techniques. In addition several multiple and hybrid applications are employed. The trend moves towards the use of existing methods of artificial neural networks, which are upgraded with innovative training algorithms or combined with new technologies to hybrid systems. This development leads to the integration of machine learning methods to improve the training algorithms (Krollner, Vanstone and Finnie, 2010).

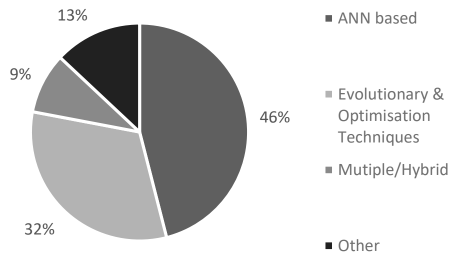


Figure 1: Machine Learning Methods for Forecasting in Finance sector (Krollner, Vanstone and Finnie, 2010)

Figure 2 displays secondary data used to improve the forecast quality in the financial sector. As the second graph shows, a wide variety of secondary data is referred to. The data can be separated into three categories: Firstly, finance-specific data such as the trading volume and exchange rate, secondly specific comparative rates such as oil price, gold price and thirdly, macro-economic data as the unemployment rate.

Before the respective data can be used, they must be processed. Krollner does not deal with the topic of data preparation, so that further research is necessary to give a detailed overview about concepts of data preparation.

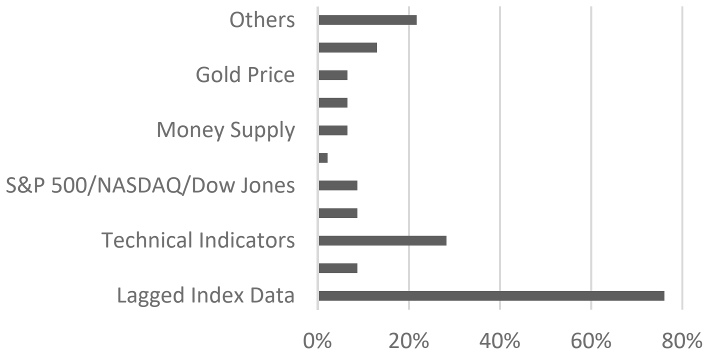


Figure 2: Percentage of used secondary data bases (Krollner, Vanstone and Finnie, 2010)

Tsang (Tsang, Yung and Li, 2004) has developed a method to process data sets specifically for the financial sector and to prepare them for use in machine learning algorithms. In his research work, the author described strategies and procedures for solving data problems, which are briefly listed below:

- Too few data: Generation of missing data's (Data mining based methods)
- Too many data: Classification and discretization
- Noise in the data: Regression-based data smoothing
- Season/Trend: Log difference
- Differently scaled data sets: Line scaling method

These approaches are already used in conventional historical data analysis and can be adopted to prepare the database for the machine learning algorithm.

3.4 Machine Learning Methods Forecasting Agriculture

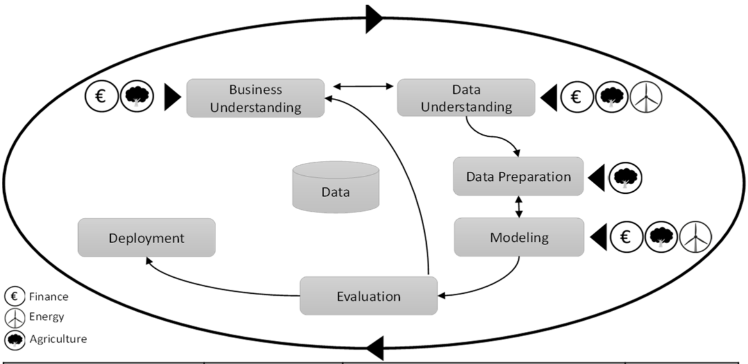
Table 5: Used Machine Learning methods in Forecasting Agriculture (Liakos, et al., 2018)

Machine Learning Method	**Quantity (of 46)**
Bayesian Model	2
Ensemble Learnings	2
ANN	22
Regression and Clustering	4
Instance based models	1
Decision trees	1
Support Vector Machines	14

In contrast to the financial or energy sector, qualitative forecasting areas are also considered (e.g. animal welfare or harvest quality). It is important to note that the algorithms used in the qualitative approach differ to the once used for quantitative forecasting. Ensemble Learning or Decision trees are the most commonly used methods, which can be subsumed in the area of regression for supervised learning. In the study of Liakos, the machine learning methods are analyzed according to their frequency of use, a qualitative analysis of the results is not considered. In addition, no information is provided on established methods for data preparation. Having analyzed the demand forecasts in agriculture, energy and finance, the following section applies the findings to the requirements of demand planning in the manufacturing industry.

4 Solution approaches and strategies for demand planning in manufacturing industry

The analysis of the different industrial sectors has shown that certain problems and challenges are common (e.g. data basis or algorithm selection). Due to the relatively low degree of digitalization in the manufacturing industry, it is useful to learn from more advanced industries and to use the experience gained (Demary, et al., 2016). Based on the available knowledge in those sectors, recommendations for action can be formulated for the application of machine learning methods for demand planning in the field of supply chain management in the manufacturing industry.



Challenges for using ML-Methods in demand planning	CRISP-Model	Possible Solution Approaches	Industry sector
Creation of a data base	Data Understanding/Data Preparation	▪ Historical data ▪ Preparation of the data base (use existing models and algorithm)	Energy, Finance
Definition of influencing parameters	Business Understanding/Data Understanding	▪ Use secondary sources ▪ Specific and general sources of information ▪ Take environmental and regional influences into account	Finance, Agriculture
Shortened product life cycles	Data Preparation	▪ Use data from similar products	Agriculture
Algorithm Selection	Modeling	▪ High effectiveness ANN and support vector machines	Energy, Finance
Definition of the Output-Parameter	Modeling	▪ Decision qualitative or quantitative statement influences the selection of algorithms	Agriculture

Figure 3: CRISP-Model solution approaches and strategies for using ML

Figure 3 summarizes the findings from the comparative analysis of other industries using the CRISP-Model (Cross-industry standard process) and provides recommenda-tions for the structured use of machine learning methods in the manufacturing industry. The challenges identified previously in chapter 2.2 are compared to the possible solutions from the three industrial sectors. The following section explains the approaches and findings of the analysis more in detail.

The data basis is essential for the success of machine learning methods and must be prepared for each application. Historical data sets are used in the energy industry to overcome this difficulty. In order to improve data quality, they can still be processed in order to eliminate missing data or data noise.

Afterwards a model must be designed for a specific target variable. This model takes into account both the data basis and the influencing factors that affect the target variable to be calculated. It is recommended to use secondary data (general or industry-specific) in addition to the primary data to enable a better integration of fluctuations (agriculture and finance sector). Publicly accessible data are of advantage, as they are available in a standardized form and with sufficient data quality, so that the process steps of data acquisition and data preparation can be reduced. In addition, during the selection of the algorithm, the use case must be taken into account, since the different algorithms depend on the type of the forecast value (qualitative or quantitative).

In the area of data exploitation in particular, successful approaches have already been developed in the financial sector, but the literature research also shows that challenges due to product behavior (shorter product life cycles) or in modelling can be solved by approaches from agriculture.

5 Conclusion

In this article, the authors have shown that machine learning methods are already used in several industries. This promises a high potential for the manufacturing industry. Requirements for the application in demand planning have been formulated and prepared in a structured way. It has been shown that many areas have not been sufficiently analyzed and described (e.g. Modelling, influencing factors (internal and external) and data preparation). This is especially valid for the modelling of the ML approach and the underlying data basis. There will be a need for future research in the area of demand planning in the context of the manufacturing industry. This includes the specification of necessary and influencing data sets. This would allow the creation of an initial model for successful demand planning. It is of utmost importance to focus further research in the field of the design of the data model to guarantee optimal input for the ML algorithms. Only if the required set of data is defined and available, the true value of machine learning can be evaluated.

References

Al-Alawi, S. M. and Islam, S. M., 1996. Principles of electricity demand forecasting. I. Methodologies. Power Engineering Journal, 10(3), pp. 139–143.

Alansari, Z., Anuar, N. B., Kamsin, A., Soomro, S., Belgaum, M. R., Miraz, M. H. and Alshaer, J., 2018. Challenges of internet of things and big data integration. International Conference for Emerging Technologies in Computing, pp. 47–55.

Arroyo, J., Espinola, R. and Maté, C., 2011. Different approaches to forecast interval time series: a comparison in finance. Computational Economics, 37(2), pp. 169–191.

Ashayeri, J. and Lemmes, L., 2006. Economic value added of supply chain demand planning: A system dynamics simulation. Robotics and Computer-Integrated Manufacturing, 22(5-6), pp. 550–556.

Backhaus, K., Erichson, B., Plinke, W. and Weiber, R., 2016. Multivariate Analysemethoden: Springer.

Bryanjolfsson, E. and Mcafee, A., 2014. The second machine age: Work, progress, and prosperity in a time of brilliant technologies.

Crone, S. F. and Preßmar, D. B., 2006. An extended evaluation framework for neural network publications in sales forecasting. Artificial Intelligence and Applications, pp. 179–186.

Demary, V., Engels, B., Röhl, K.-H. and Rusche, C., 2016. Digitalisierung und Mittelstand: Eine Metastudie: IW-Analysen.

Deutschländer, T., 2003. Über Möglichkeiten und Grenzen der statistischen Langfristprognose.

Döring, S., Döring, J., Borg, H. and Böttcher, F., 2011. Vergleich von Trockenheitsindizes zur Nutzung in der Landwirtschaft unter den klimatischen Bedingungen Mitteldeutschlands. Hercynia-Ökologie und Umwelt in Mitteleuropa, 44(2), pp. 145–168.

Egri, P., Csáji, B. C., Kemény, Z., Monostori, L. and Váncza, J., 2008. Komplexität der Bedarfsprognosen und ihre Wirkungen in kooperativen Logistiknetzwerken. pp. 455–469.

Engemann, C. and Sudmann, A., 2018. Machine Learning-Medien, Infrastrukturen und Technologien der Künstlichen Intelligenz: transcript Verlag.

Ester, M. and Sander, J., 2013. Knowledge discovery in databases: Techniken und Anwendungen: Springer-Verlag.

Feindt, M. and Kerzel, U., 2014. Prognosen bewerten: Statistische Grundlagen und praktische Tipps: Springer-Verlag.

Gajowniczek, K. and Ząbkowski, T., 2017. Two-stage electricity demand modeling using machine learning algorithms. Energies, 10(10), p. 1547–1547.

Géron, A., 2017. Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems: O'Reilly Media, Inc.

Gottschlich, J., Solar-Lezama, A., Tatbul, N., Carbin, M., Rinard, M., Barzilay, R., Amarasinghe, S., Tenenbaum, J. B. and Mattson, T., 2018. The three pillars of machine programming. Proceedings of the 2nd ACM SIGPLAN International Workshop on Machine Learning and Programming Languages, pp. 69–80.

Grömling, M., 2005. Konjunkturprognosen: Verfahren, Erfolgskontrolle und Prognosefehler.

Haasis, H.-D., Kopfer, H., Kotzab, H., Dethloff, J. and Schönberger, J., 2015. Logistics management. Products, actors, technology -- proceedings of the German Academic Association for Business Research, Bremen, 2013.

Habla, C., Driebel, R., Monch, L., Ponsignon, T. and Ehm, H., 2007. A short-term forecast method for demand quantities in semiconductor manufacturing. 2007 IEEE International Conference on Automation Science and Engineering, pp. 94–99.

Hammer, R. M., 1998. Unternehmensplanung: Lehrbuch der Planung und strategischen Unternehmensführung: Oldenbourg.

Hansmann, K.-W., 2013. Kurzlehrbuch Prognoseverfahren: Springer-Verlag.

Haykin, S. S., 2009. Neural networks and learning machines: Pearson education Upper Saddle River.

Hellingrath, B. and Kuhn, A., 2013. Supply chain management: Optimierte Zusammenarbeit in der Wertschöpfungskette: Springer-Verlag.

Helton, J. C., Johnson, J. D., Oberkampf, W. L. and Sallaberry, C. J., 2010. Representation of analysis results involving aleatory and epistemic uncertainty. International Journal of General Systems, 39(6), pp. 605–646.

Hornik, K., Stinchcombe, M. and White, H., 1989. Multilayer feedforward networks are universal approximators. Neural networks, 2(5), pp. 359–366.

Johnson, M. D., 2018. Kundenorientierung und Markthandlung: Walter de Gruyter GmbH & Co KG.

Koch, S., 2012. Logistik: Eine Einführung in Ökonomie und Nachhaltigkeit: Springer-Verlag.

Krollner, B., Vanstone, B. J. and Finnie, G. R., 2010. Financial time series forecasting with machine learning techniques: a survey. 2010. ESANN.

Küçükdeniz, T., 2010. Long term electricity demand forcesting: An alternative approach with support vector machines. Istanbul university of engineering sciences, pp. 45–53.

Kühnapfel, J. B., 2014. Vertriebsprognosen: Methoden für die Praxis: Springer-Verlag.

Lee, H. L., 2002. Aligning supply chain strategies with product uncertainties. California management review, 44(3), pp. 105–119.

Liakos, K., Busato, P., Moshou, D., Pearson, S. and Bochtis, D., 2018. Machine learning in agriculture: A review. Sensors, 18(8), p. 2674–2674.

Lüdeke-Freund, F. and Opel, O., 2014. Energie. Nachhaltigkeitswissenschaften: Springer, pp. 429–453.

Marsland, S., 2011. Machine learning: an algorithmic perspective: Chapman and Hall/CRC.

Mayr, S. and Moser, M., 2018. Produktvorlaufkosten im Blick haben. Controlling & Management Review, 62(5), pp. 42–47.

Mello, R. F. de and Ponti, M. A., 2018. Machine Learning: A Practical Approach on the Statistical Learning Theory: Springer.

Mertens, P. and Rässler, S., 2012. Prognoserechnung-Einführung und Überblick. 2012. Prognoserechnung: Springer, pp. 3–10.

Michie, D., 1968. "Memo" Functions and Machine Learning. Nature, 216(5136), pp. 19–22.

Murray, P. W., Agard, B. and Barajas, M. A., 2015. Forecasting supply chain demand by clustering customers. IFAC-PapersOnLine, 48(3), pp. 1834–1839.

Neef, A., 2017. Wie Künstliche Intelligenz die Wertschöpfung transformiert. Z-punkt The foresight company.

Onischka, M. and Orbach, T., 2008. Klima und Finanzmarkt. So investiert die Welt: Springer, pp. 77–96.

Papenfort, J., Frank, U. and Strughold, S., 2015. Integration von IT in die Automatisierungstechnik. Informatik-Spektrum, pp. 199–210.

Reder, B., 2018. Studie Machine Learning/Deep Learning.

Röniger, O., 2018. Self-Service Analytics Unlimited. Controlling & Management Review, 62(2), pp. 14–23.

Scheidler, A. A., 2017. Methode zur Erschließung von Wissen aus Datenmustern in Supply-Chain-Datenbanken: Cuvillier Verlag.

Schulthess, M., 2013. Ein Blick in fremde Branchen lohnt sich. Marketing Review St. Gallen, 30(1), pp. 98–107.

Setiawan, A., Koprinska, I. and Agelidis, V. G., 2009. Very short-term electricity load demand forecasting using support vector regression. 2009 International Joint Conference on Neural Networks, pp. 2888–2894.

Shalev-Shwartz, S. and Ben-David, S., 2014. Understanding machine learning: From theory to algorithms: Cambridge university press.

Stickel, E., Groffmann, H.-D. and Rau, K.-H., 2013. Gabler: Wirtschaftsinformatik Lexikon: Springer-Verlag.

Stoetzer, M.-W., 2017. Regressionsanalyse in der empirischen Wirtschafts-und Sozialforschung Band 1: Eine nichtmathematische Einführung mit SPSS und Stata: Springer-Verlag.

Tempelmeier, H., 2018. Begriff der Logistik, logistische Systeme und Prozesse: Springer.

Tsang, E., Yung, P. and Li, J., 2004. EDDIE-Automation, a decision support tool for financial forecasting. Decision Support Systems, 37(4), pp. 559–565.

Verein Deutscher Ingenieure e.V., 2018. Künstliche Intelligenz. VDI-Statusreport, 2018, p. 5–5.

Welc, J. and Esquerdo, P. J., 2018. Applied regression analysis for business: Springer.

Wesseler, B., 2018. Nichts verallgemeinern. iX Developer 2018-Machine Learning: Verstehen, verwenden, verifizieren, p. 38–38.

Wirth, R. and Hipp, J., 2000. CRISP-DM: Towards a standard process model for data mining. 2000. Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining, pp. 29–39.

Wittpahl, V., 2019. Künstliche Intelligenz: Springer.

Zell, A., 2000. Simulation Neuronaler Netze.

Zuboff, S., 2010. Creating value in the age of distributed capitalism. McKinsey Quarterly.