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Application of Artificial Intelligence to optimize forecasting capability in procurement

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Abstract

The aim of this paper is to show to what extent Artificial Intelligence can be used to optimize forecasting capability in procurement as well as to compare AI with traditional statistic methods. At the same time this article presents the status quo of the research project ANIMATE. The project applies Artificial Intelligence to forecast customer orders in medium-sized companies.

Precise forecasts are essential for companies. For planning, decision making and controlling. Forecasts are applied, e.g. in the areas of supply chain, production or purchasing. Medium-sized companies have major challenges in using suitable methods to improve their forecasting ability.

Companies often use proven methods such as classical statistics as the ARIMA algorithm. However, simple statistics often fail while applied for complex non-linear predictions.

Initial results show that even a simple MLP ANN produces better results than traditional statistic methods. Furthermore, a baseline (Implicit Sales Expectation) of the company was used to compare the performance. This comparison also shows that the proposed AI method is superior.

Until the developed method becomes part of corporate practice, it must be further optimized. The model has difficulties with strong declines, for example due to holidays. The authors are certain that the model can be further improved. For example, through more advanced methods, such as a FilterNet, but also through more data, such as external data on holiday periods.

Key words

Artificial Intelligence, Machine Learning, Deep Learning, Artificial Neural Network, Forecasting, Time series prediction

CR-Category

- **Computing methodologies** → *Artificial Intelligence*
- **Computing methodologies** → *Planning under uncertainty*
- **Applied computing** → *Forecasting*

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1 Introduction

Artificial Intelligence is a branch of computer science that deals with the investigation of mechanisms of intelligent human behavior (intelligence). This is done by simulation using artificial artifacts, usually programs on a computer. The term "artificial intelligence" was invented by the American computer scientist John McCarthy (*1927). He used it in the title of a project proposal for a conference lasting several weeks, which took place in 1956 at Dartmouth College in the USA [1].

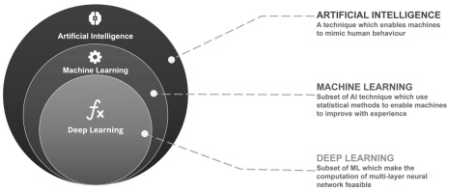

Figure 1: Artificial Intelligence, Machine Learning and Deep Learning [2]

Figure 1 shows the relationship between AI, ML and DL. They are subsections with specific methods and algorithms. AI algorithms are able to act and optimize independently, e.g. the subsection Machine Learning learns through training with huge data sets [3]. Multiple real-life industry and business applications have already shown the potential of this technology.

An important sector is the prediction of future demand not only according to past demand, but also considering factors like economic growth, weather forecasts or social status of the buyers etc. [4, 5]. AI hence can be of positive economic impact for the enterprises that use it. In industry processes for example, predictive maintenance algorithms using Machine Learning (ML) or Deep Learning (DL) methods that analyze data provided by IOT-sensors to predict upcoming defects reliably [6].

A concrete example is the implementation of a forecast model for a spare parts supplier in the agricultural industry. Here, a model was developed which predicts which components will fail or break on a tractor. For this purpose, internal customer data (tractor model, daily running time, GPS data, etc.) as well as external data (humidity, temperature, season, etc.) are used.

This ensures that the right components are ordered and delivered just in time. As a result, the customer has faster repairs and downtime is reduced. At the same time, the supplier's tied-up capital is reduced and customer satisfaction increases.

The following chapters in this paper are structured as follows: The research project with its goals is explained in the following chapter. Chapter 3 will explain the state of the art technics for demand forecasting in greater detail. Afterwards the Solution Approach with an MLP ANN is presented in chapter 4. Finally, we will explain the next steps in the project: How we plan to increase the accuracy of mid-term forecasting and implement a short-term forecast as well. The last chapter leads to a conclusion and outlook.

2 Description of the research project ANIMATE

The acronym ANIMATE stands for: *„**An**wendung der künstlichen **I**ntelligenz im **M**ittelstand: Data **A**nalytics – **T**echnologie, Kompetenz und **E**rfolgsfaktoren in der betrieblichen Anwendung“.*

The project started in March 2019 and will continue until February of 2021. The research project is intended to answer questions about the practical use of artificial neural networks, the associated problem areas, their requirements and the suitability of their prognosis:

- Which requirements exist for the used data (data availability, dataset size, quality, etc.)?
- How can the structuring and preparation of the data be supported?
- How can ANN tools be designed so that they can be used relatively easily by companies in their own context with as few adjustments as possible?

- Can problem clusters be identified for this?
- Are the forecasts of the ANN tools better suited than the methods used in companies to date and how can these be further optimized by practical experience?

This article intends to give insight into the ongoing research, display the already found results and map the future research focus.

2.1 Digitalization in the "Mittelstand"

The German term *Mittelstand* is not only defined by quantitative measures such as the size of the companies, but also by qualitative aspects such as the unity of ownership and entrepreneurial responsibility [7]. Therefore, enterprises that exceed the usual thresholds (250 employees, a turnover of 50 Mio and/or 43 Mio in balance sheet total) that are set to define SME's by the European Union [8] are still considered part of the *Mittelstand*.

One of the largest studies on the topic of digitization in medium-sized businesses was carried out by Becker et al [9]. They conclude that digitization has an important to very important meaning for almost all of the participating companies. In relation to the industry, the importance of digitization is also important. In contrast to the industries of the participating companies, the companies in the areas of financing, leasing and corporate service providers in particular assign great importance to digitization, followed by companies from the manufacturing sector. A minor importance was put on record by companies in the construction industry [9].

Yet only 5% of businesses in Germany used Artificial Intelligence in 2018, and especially in medium-sized businesses it is rarely used [10]. Based on the conclusion that artificial intelligence is rarely used in SMEs, the project aims at the transfer of AI methods to the medium-sized German companies.

To transfer methods that are already proved in larger enterprises and research facilities, so that they are usable for smaller enterprises, poses distinctive challenges. This is caused by the business structure and culture of SMEs, as they often have only limited resources to invest in digitalization and are more risk averse [11].

2.2 Project-Team

The ANIMATE project is a cooperation between the REIFF Group, the management consultancy 4flow AG and the research group "Digitalization & Management" of the ESB Business School at Reutlingen University.

Its aim is to research possible business application for Artificial Intelligence (AI) in the *Mittelstand* by implementing applications to forecast demand of the goods traded by REIFF. The research focuses not only on the technical feasibility but also on the organizational demands posed by the business structure and culture of the *Mittelstand*.

2.3 REIFF Group

The REIFF group is based in Reutlingen, Germany and is one of the leading retailers for technical products in the Business-to-Business (B2B) sector. It has a product portfolio of more than 140.000 various products purchased from more than 10.000 suppliers and about 10.000 customers. With a work force of about 875 it is not a SME, but as a family owned and lead business it qualifies as *Mittelstand* [12].

With a highly diversified and specialized portfolio, managing demand and supply of products is challenging for the buyers, as they must estimate future demand of a large quantity of products and customers by high uncertainty. This demand is influenced furthermore by outside factors like for example economic growth. Currently the estimated numbers of future demand are determined by the buyers' individual experience.

The Project ANIMATE aims to support those decisions by using state of the art methods to forecast demand more accurately and also integrate external factors like economic climate.

3 State of the art

Forecasting of future demand as exact as possible is of high economic value. Erroneous forecast can have multiple negative effects. If demand is underestimated, outstanding orders cannot be fulfilled and therefor revenue is lost. Overestimating demand can lead to excess stock, fixed capital and storage costs [4]. Both scenarios are hence to be avoided.

The state of the art in science still differs significantly from business practice regarding forecasting methods [4, 13]. While companies mainly use judgmental and statistical methods for forecasting, e.g. Autoregressive integrated moving average (ARIMA). Artificial Neural Networks (ANN's) have been used for these purposes in research around the turn of the millennium[14]. For some time now, AI forecasting methods have been gradually finding their way into the business practices of large companies [15].

The main reasons for entering practice are primarily:

- Big Data – The amount of data is increasing rapidly, at the same time the price of storing enormous amounts of data is decreasing [16].
- AI Democratization – Through AI packages from e.g. TensorFlow, AI methods are distributed more widely, which reduces the complex hurdle of using them [17].
- Low-cost computing power – Due to the continuous improvement of computing power, simple applications can be calculated on almost any computer. Flexible cloud computing services, such as AWS (Amazon Web Services), reduce the high investment requirements of companies in their own data centers [18].

Some studies show that medium-sized companies have recognized digitization as an important trend, but are far away from large corporations in terms of implementation [9].

The question arises why especially medium-sized companies do not yet use state of the art forecasting methods such as Artificial Intelligence. The reasons for this are multi-layered, but amount to fundamental technical deficits in the IT infrastructure, the lack of a digital strategy as well as psychological hurdles of the changes and the shortage of skilled IT workers [19].

For this reason, there is the research project ANIMATE, which aims to support small and medium-sized enterprises in the application of Artificial Intelligence. Therefore, the focus in this second chapter is on the description of Artificial Intelligence as state of the art method for forecasting purposes.

3.1 Description of the currently used methods in the field of forecasting

In this chapter, the current forecasting methods used by companies in practice are briefly examined.

Surveys conducted with companies show that companies today still use judgmental forecasting methods based on experience rather than quantitative methods [20].

Research has shown that quantitative methods to be superior to judgmental methods, both in terms of accuracy and timeliness. Moreover, it has been shown that human biases influence the assessment of forecasts, including lack of consistency, tendency to over forecast and wishful thinking [20].

The following table 1 gives an overview of widely used statistical methods for time series prediction based on linear algebra.

Table 1. Overview of classic statistical methods for forecasting purposes [21]

Method	Example
Autoregressive Integrated Moving Average (ARIMA)	Gold price
Seasonal Autoregressive Integrated Moving-Average (SARIMA)	Electricity Consumption
Vector Autoregression Moving-Average (VARMA)	Temperature
Holt Winter's Exponential Smoothing (HWES)	Visitors in Australia
Generalized Auto Regressive Conditional Heteroscedasticity (GARCH)	Stock Market

The advantage of these methods for companies is based on the fact that these methods are widely used since decades and are better understood by companies than artificial intelligence methods [21]. The classical statistical methods can achieve reliable results with a multitude of possible applications. Since these approaches are based on linear relationships, they are clearly limited and fail in complex applications. Artificial Intelligence methods, such as neural networks, achieve significantly better results because they can recognize complex non-linear cause-effect relationships [4].

The presented methods all had their justification in the past, but due to the permanent advancement of technology, software and research, there are new and better opportunities for companies to conduct forecasting today [17]. Overall it can be stated that the current methods of companies can be improved in practice. In the context of relevance, influence and dependencies of good forecasts, companies should constantly adapt and optimize their methods [4].

Due to the developments explained at the beginning of chapter 3, a shift to AI-based forecasts is possible, even for SMEs. For this reason, the possibility of Artificial Intelligence in forecasting will be discussed in more detail in the following chapter.

3.2 Artificial Intelligence for forecasting purposes

As shown in Figure 1 in Chapter 1 Introduction, the generic term artificial intelligence consists of the further subareas Machine Learning and Deep Learning.

Artificial Intelligence enables machines to learn from their experiences. The machines adapt their response to new inputs and thus perform human-like tasks by processing large amounts of data and recognizing patterns in them. Machine Learning is a subset of artificial intelligence. It enables the machines to learn and make predictions based on their experiences (data). ML uses specific algorithms such as Naive Bayes or Multiple Linear Regression. Deep Learning is a subset of machine learning inspired by the functionality of our brain cells. It simply takes data connections between all artificial neurons and adapts them according to the data pattern. More neurons and layers are needed if the data set is complex and not linear. It automatically provides learning at multiple levels of abstraction, allowing a system to learn complex functional mappings without being dependent on a particular algorithm. Different neural network architectures are used, such as Convolutional Neural Networks for image processing [2, 3, 18, 22].

More than 5,000 academic publications have been indexed in the AI forecasting field by ISI (International Science Indexing), which demonstrates the increased interest of AI in the context of forecasting [5].

According to Zimmermann, ANN's are particularly suitable for solving nonlinear problems with a high number of variables [23]. They extend the instruments of conventional methods of linear algebra, which are suitable for the solution of linear systems of equations

with a multitude of linear variables, and the methods of integral and differential calculus, which are suitable for the solution of nonlinear systems with few variables.

Therefore ANN's are particularly suitable for forecasts of complex, non-linear but also linear circumstances as well as time series [24].

Figure 2 illustrates the above-mentioned facts.

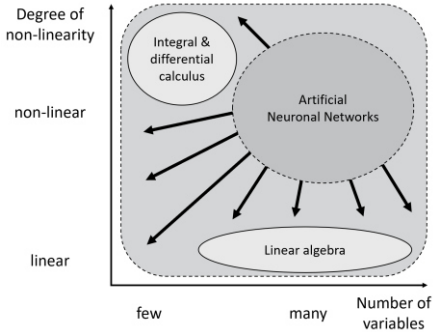

Figure 2: Areas of application of Artificial Neural Networks [4]

Neuronal network-based algorithms have become very popular in recent years and are in the focus of Artificial Intelligence [25]. Artificial Neural Networks (ANN) are systems that consist of many simple units and can process information. They can be programmed individually or an already existing program of an ANN can be used for training and prognosis [22]. Due to the many, often free of charge available programs, which can also be used by people without far-reaching computer science knowledge, the use of the ANN is also practically applicable in enterprises.

Areas of application for Artificial Intelligence include customer loyalty management for forecasting customer departures, credit management for creditworthiness checks, exchange rate forecasts, marketing for sales and demand forecasting, controlling for early warning or in the energy supply sector for load forecasts or electricity price forecasts for day-ahead electricity prices as well as the prediction of the price of CNC turned parts based on the technical drawing [4, 6, 13, 16, 19, 23, 26, 27].

The following figure 3 illustrates an Artificial Neural Network.

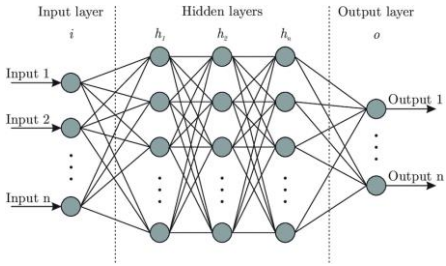

Figure 3: Artificial Neural Network architecture [28]

The network shown consists of the Input Layer, the Hidden Layers and the Output Layer. Since the displayed network has more than one hidden layer, it is a so-called Deep Learning network [29].

The next chapter describes the concrete possibility of Artificial Intelligence to create prognoses in the context of the ANIMATE research project.

4 Solution Approach

The REIFF Group faces numerous challenges. The company serves many customers in different industries with a variety of products. Service is perceived as a decisive competitive feature. For this reason, it is of great interest to REIFF to optimize inventory levels and reduce delivery times for customers.

In the following chapter, the procedure for using an Artificial Neural Network in the ANIMATE research project is explained in more detail in the following structure.

First, the research process is presented. This is followed by the Explanation of the target forecast and the data structure as well as the approach for training the model. This is followed by the model architecture and its parameters. Finally, the forecasting capability is evaluated.

4.1 Research Process

The REIFF group provided the research team with inventory numbers on monthly basis and all incoming orders from 2008 until 2019. After consolidating the data, which was delivered as multiple .csv data files, into an SQL-data base, this data was used to train and test machine learning algorithms, that forecast the demand of product groups and industry sectors.

A baseline was set up to compare the accuracy of the applications forecasting with the status quo. The scope of the forecasting is separated in mid-term and short-term forecasts. Mid-term forecasts study a time range from 3 up to 6 months for different product categories. Short-term forecasts focus on estimating the demand of the individual products on a basis of 1-2 weeks. As a first step, the middle-term forecasts were implemented by training a Multilayer perceptron (MLP) with the data provided by REIFF and several outside factors.

Alongside, we will also research the current business processes of REIFF via a number of qualitative expert interviews to then subsequently conceptualize how an AI application can be integrated in the default business processes.

4.2 Explanation of the target forecast

The present data structure consists of eight divisions of the branches, such as drive technology, hydraulics, sealing technology, plastics, etc.. Sales mainly consists of the number of orders and the articles ordered per month. In the first step, a mid-term forecast of the sales of the internal branches of REIFF is made on a monthly basis. The medium-term forecast was requested by the project leader from the partner company REIFF. This poses the following challenges. Medium to long-term forecasts at product level (n>140.000) are currently difficult to implement, due to the long forecast period and the large number of completely different products and customers.

For this reason, mid to long-term forecasts are realized at the branches level. As soon as the mid-term forecasts on branch level are implemented with a sufficient error rate, we will continue to develop short-term forecasts on product level. Figure 4 illustrates this relationship between short-term, mid-term and long-term forecasts.

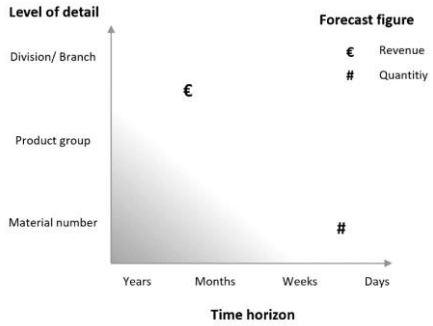

Figure 4: Comparison of the forecast time horizon

The purpose of the graph is to illustrate that a forecast at the lowest detail level with the highest information content can only be made on a very short time horizon. In turn, a forecast at industry level on a significantly longer forecast period is possible

4.3 Structure of the data

For a better understanding, the data structure is now discussed, as this serves as input for the forecast (output). ML and DL algorithms work best if they can use a large set of data that is labeled congruently. Under real-life conditions though, data availability and consistency pose a challenge though, as data sets are often incomplete or repetitive [30].

As already mentioned, the data structure is basically divided into branches such as drive technology, hydraulics, sealing technology, plastics, etc.. The customer order contains information about the order, like the customer, the branches, the ordered article, the quantity, etc. We have access on the stock numbers in a monthly interval and all the customer orders beginning in 2008.

During the project period we will receive regular updates, which means newer data of the future quarters as well.

In addition to the data of REIFF, the following external data has been included: ifo Business Climate Index, DeStatis economic data, Google Trends (using Keywords like “PVC”, “REIFF” or customer names). This data is then combined to a single .csv by a python script. The data is then preprocessed by using the StandardScaler method included machine learning library Sklearn to standardize the input, and then rescaled to values between 0 and 1 by the MinMax-Scaler by Sklearn.

4.4 Training structure

For the training of the neural network the data explained above are used. It should be emphasized that instead of a classical training method, a rolling cross validation training method (Time Series Split) has been used. With a classical training method, the data set is usually divided randomly into a training set (80%) and a test set (20%). The model has access to the full training set from the beginning.

Using the time series split method, the training set (80%) is split once more into training data and validation data. The test set (20%) is used for a subsequent evaluation. The model is trained iteratively, with an increasing amount of data. This has the advantage that the chance of a randomly "simple" data set or division has been reduced. Furthermore, the model becomes less susceptible to the effect of overfitting.

This is a training method which is advantageous for time series prediction because time series modeling and forecasting are tricky and challenging. Cross validation methods must be used to optimize model quality and reduce possible overfitting. Time Series Split is a variation of k-fold which returns first k folds as train set and the (k+1) fold as test set. The idea about the Time Series Split is to divide the training data into 2 parts. In each iteration the training set is used to train the model and at the same time a part of the training set is used directly for validation, with data that the model has not yet used [31].

As an example, it can be assumed that the model is trained with the data for the months January to March. April, which is predicted, serves as validation. In the next iteration the model is trained with the months January to April and predicts the month May for validation. The following figure 5 illustrates the training method schematically.

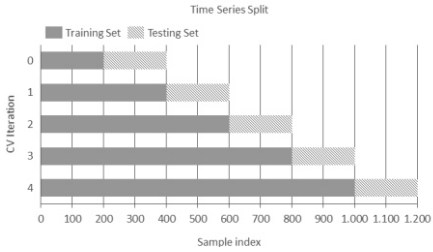

Figure 5: Exemplary representation of the rolling Time Series Split [31]

4.5 Model architecture and parameters

In a first step, a prototype network architecture of the Multi-Layered Percepton (MLP) is tested. The open source library scikit-learn, which is based on the Python programming language, is used to build the neural network. The concrete name of the used function/class is sklearn.neural_network.MLPRegressor.

The model has 3 hidden layers consisting of 500, 100 and 10 neurons each as well as an input and output layer. The activation function rectifier (ReLu) is used. Adam is used as a gradient-based optimization of stochastic objective functions.

The other Parameters are illustrated in the following table 2.

Table 2. Parameters of the MLP ANN

Parameter	Value
Alpha	0.001
Batch_size	Auto
Learning_rate	Invscaling
Power_t	0,5
Max_iter	1000
Shuffle	True
Random_state	1
Verbose	False
Warm_start	False
Momentum	0.9
Nesterovs_momentum	True
Early_stopping	False
Alidation_fraction	0.1
Beta_1	0.9
Beta_2	0.999
Epsilon	$1 * 10^{-8}$

Various hyperparameters were tested on a trial-and-error basis to find the overall best result.

4.6 Outcome and Evaluation

To evaluate the model quality, the neural network is compared with standard forecasting methods as well as a baseline, which represent the performance of REIFF. Since there is currently no explicit sales planning, the warehouse stocks are used to estimate sales expectations. The REIFF baseline is calculated as follows.

$$I = \frac{s\ [€]}{p\ [months]} \qquad (1)$$

with:

I = Implicit sales expectations

s = stock

p = planned delivery time

We use linear regression and SARIMA as classic forecast methods. For the comparison between the methods Root Mean Square Error (RSME) and Coefficient of Determination (R^2) are used.

The following table 3 displays the results of the methods (The row highlighted in gray is the MLP ANN based on Artificial Intelligence).

Table 3: Comparison of different RMSE and R^2 for different models

Model	RSME	R^2
Baseline	99 k€	78%
Lin. Regression	88 k€	87%
SARIMA	137 k€	70%
MLP ANN	46 k€	95%

For a better understanding regarding the prognosis quality, the actual sales and the forecast from the MLP ANN for 2018 are presented graphically in Figure 6.

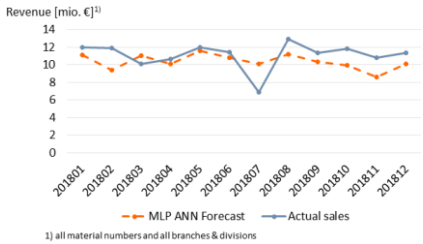

Figure 6: Comparison of the MLP ANN forecast with the actual sales in 2018

The chart shows that the MLP ANN has very similar trends to the current sales trend. However, it can also be noted that the difference of forecast and actual data needs to be improved. Additionally, the July's outlier was not correctly identified by the ANN The outlier itself might be explained by a holiday period.

As a conclusion it can be stated that artificial intelligence has its justification in the field of forecasts.

On the one hand, the MLP ANN was able to achieve better results, i.e. more accurate forecasts, than classical static methods (see Table 3). At the same time, the result is not yet satisfactory. Further research is needed to optimize the result. One is to improve the data basis. Part of this is to increase the amount of data through internal data from REIFF. At the same time, external data such as holiday periods are added. Other deep learning architectures are also being tested, such as FilterNet, a convolutional neural network.

5 Conclusion and outlook

The first implementation of the ANN shows that using an Artificial Intelligence is superior. The ANN performs better than the baseline of REIFF. It also performed better than both the linear regression and the SARIMA algorithm (see Table 3). The current results could already be used by REIFF to estimate which branches will probably increase their order value and can hence be specially targeted by the sales department. Yet, none of the algorithms could exceed the threshold of 40 k€ with the current clustering and the used external input.

The next research step therefor will aim to enhance the accuracy of the mid-term forecast.

5.1 Enhancing the mid-term forecast accuracy

As a first step the quality of the model in respect of the external data will be verified by Principal Component Analysis (PCA), Correlation and Collinearity Analysis. Also, the clustering of the data will be reviewed. The current used clustering methods combined customers by the branches they were assigned to by REIFFs internal guidelines. These guidelines are partially due to historic developments though. Instead of using REIFFs clustering, in a new approach is used to cluster customer groups, as they are clustered by correlation in their time series. This way businesses with similar demand variation are combined in one cluster.

5.2 Short-term forecasts

Reliably forecasting the demand of product groups and/or single products would enable the buyers of REIFF to minimize the costs of wrong order quantities. Short-term forecasting of single products imposes a set of challenges that we aim to investigate. The product portfolio of REIFF with 140.000 various products is not only large but also highly diverse. Computing such numbers of various products with ANNs requires substantial computing power. And as many of the 140.000 various products are sometimes only ordered every few years, the validity and meaningfulness of a demand forecast of such a product has to be called in question. Hence, before implementing any technical solution, there needs to be an evaluation of the products (ABC- and XYZ-Analysis) themselves and an evaluation what kind of output is usable for REIFF. Also, a new baseline must be set up to compare the future results too. After this preliminary work, several types of ML algorithms as well as Neural Networks will be evaluated on the data.

5.3 Integration in business processes

The ANIMATE project not only aims to show the validity of AI algorithms for SME processes but also to integrate them in daily business, as our research goal is to enable REIFF and other SME's to profit from AI technology. As a first step, expert interviews with REIFF buyers will be conducted to understand the status quo: The tools they use, the people involved, the different kind of orders and the corresponding ordering process. The next task is then to conceptualize how to integrate the technology into the daily business. If necessary, current business processes will be modelled with BPMN (Business Process Model Notation). This visualization can then be used to develop process models that integrate AI forecast technology. The needs and worries of both employees and management also has to be taken in consideration and evaluated.

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