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Identification of Tasks to Be Supported by Machine Learning to Reduce Sales & Operations Planning Challenges in an Engineer-to-Order Context

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Abstract. Sales and Operations Planning (S&OP) is a process that aims to align dimensioning efforts in a company, based on one integrated plan and with clear decision milestones. The alignment is cross-functional and connects different operations functions with each other to set an overall delivery ability. There are always challenges connecting different functions in a company which most S&OP practitioners agree with, still, that is one of the things that the S&OP-process should bridge. Digital solutions such as Enterprise Resource Planning (ERP) and other more or less sophisticated tools have contributed to an improved cross functional communication over time. S&OP in an Engineer-to-order (ETO) context, especially where engineering is a major or an equal portion as e.g., make-to-stock (MTS) and make-to-order (MTO) contexts, may experience even further challenges. Technologies within Industry 4.0 are changing the way S&OP is carried out; one of the most relevant ones is Artificial Intelligence (AI), particularly, Machine Learning (ML) that analyses data collected during these processes to find patterns and extract knowledge. The intent with this paper is to, based on S&OP-challenges, see if ML can be used to improve these challenges.

In a brief literature review together with empiric data from a single industrial case (SIC), S&OP-challenges were defined and structured. Based on the challenges in several S&OP-sub-areas, classified into data quality, horizontal and vertical disconnects, specific tasks were specified and structured into anomaly detection, clustering and classification, and predictions. Which exact ML-method to use require further work and tests. Still, this is a good starting point to take the next step and the specified tasks could also be used for other practitioners that want to start using ML/AI in their daily activities.

Keywords. Sales & Operations Planning, Engineer to Order, Machine Learning

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1. Introduction

Most companies continuously need to balance demand and supply (DS) to meet customer demand both on short- and mid-term horizon without e.g., too much inventory or capacity at hand. Sales and Operations Planning (S&OP) is used by a lot companies to manage the DS balance act [1]. S&OP is a cross-functional process that, apart from DS balancing, connect strategic and operational plans, integrate different plans and focus on mitigation of both actual and foreseeable risks on a mid-term horizon up the chain of command [1].

The DS strategy of a product family is of importance to set, not only when establishing the process, but also over time. Wallace and Stahl [1] focus on three DS strategies; make-to-stock (MTS), make-to-order (MTO) and finish-to-order (FTO). The DS strategy is generally defined by where the Customer Order Decoupling Point (CODP) is placed, based on the lead time of the product and the customer required delivery time [2, 3]. Activities before the CODP is seen as forecast driven and the activities after the CODP are customer order driven. Wikner and Rudberg [4] contributed to expand the DS strategies to also incorporate engineering activities before the CODP, engineering-to-stock, and after, engineering-to-order (ETO). Companies with ETO-products typically have complex products with high variability, low volume and long lead times [5, 6]. When customer demand is moving from standard products to more customized products, more and more companies are then moving towards ETO-products since this gives a competitive advantage [7].

S&OP in an ETO-context is rarely documented [8], which indicates that companies with ETO-products either do not use S&OP as the process for the DS-balancing, either is calling it something else or that S&OP is not well suited for ETO-products. Going towards a higher degree of customization in Companies that already have an S&OP process, might however move towards a higher degree of customization, leading to that even more companies must cope with the increased complexity that ETO brings [9]. Engineering capacities incorporate e.g., resources but also competencies which might give uncertainties both in time and cost.

The use of Information Technology (IT)-tools in S&OP is usually seen as a prerequisite for an effective and mature S&OP [10]. Even if there are studies saying that IT both can work as an enabler and a barrier for S&OP [11], most studies concludes that IT is an enabler for an effective S&OP. In recent years, Machine Learning (ML) techniques has also been used in S&OP context [12] but also for tasks that has relevance for S&OP [13]. In a recent paper [14] it was concluded that the use of ML-techniques is rarely used for S&OP. The main S&OP-area were ML-techniques are used is forecasting in MTS-context. The most common ML-technique used is supervised learning with mainly Artificial Neural Network (ANN). S&OP is a process where a lot of data is gathered and ML-techniques should therefore be suitable for finding patterns and extract knowledge for e.g., risk mitigation and decision making. Still there is a gap in literature here. To clarify which different S&OP challenges can be solved or helped by which ML-techniques, the following research questions (RQ) has been defined.

RQ1. Which are the main challenges that potentially can be solved by ML-techniques for each sub-area in the S&OP-process in an ETO-context?

RQ2. What tasks, based on the identified challenges in RQ1, can be supported by ML

2. Method

This paper is a continuation of a brief literature study regarding the documented use of ML-techniques in S&OP [14]. This paper turns the perspective around and has its starting point in the challenges that can be found in S&OP and which of those that can be improved or even solved by ML-techniques. Out of the two general objectives of research, either theory-building or fact-finding research [15], this paper should be seen as fact-finding in two different areas, S&OP and ML-techniques. A brief literature study will give documented challenges in S&OP. The main base for documented challenges will be done via some of the S&OP maturity models since the different maturity levels indicates gaps which can be seen as challenges. The documented challenges will then be complemented with longitudinal empirical data collected in the context of a single industrial case (SIC) with an ETO-context. The information from the SIC will be obtained in a workshop with the S&OP-team at the SIC. The different challenges will then be grouped based on their S&OP-sub-areas, defined in a recent brief literature study [14], see Figure 1. Challenges from literature and S&OP-sub-areas relevant for the SIC will then be categorized. The categories chosen will be (i) data quality, due to the importance to be able to use ML and to S&OP, (ii) horizontal and (iii) vertical disconnect since two of the main aims of S&OP is to integrate different function plans, horizontal integration, and to connect the gap between different planning levels, vertical integration. Data integration might be a reason for some of the challenges in all the categories and it will most certainly be critical once the challenges shall be taken care of, however this will not be a category of its own. If the challenges do not fit into the three defined categories, they will not be considered. Tasks for ML-techniques will then be specified and categorized into the aim of the respective task, (i) anomaly finding, (ii) clustering and classification, and (iii) prediction, based on the identified challenges. The challenges will eventually be tagged back to the S&OP-sub-areas. The result will serve as a starting point for choosing suitable ML-techniques, this will however not be made in this paper.

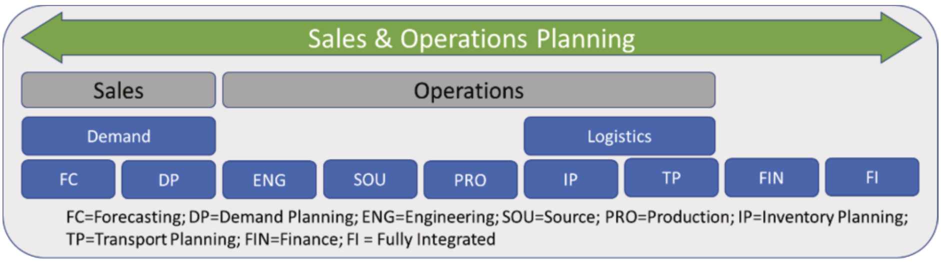

Figure 1 Structure to be used for categorizing both challenges and suitable ML-techniques based on [14]

3. Literature Review

The brief literature review is executed for two areas, (i) the S&OP-area to find challenges in general and in an ETO-context and (ii) ML-techniques in general to see which ML-techniques are valid for solving which problems.

3.1. S&OP-challenges

S&OP is a cross-functional process which mainly aim to balance demand and supply, and to connect strategic and operational plans in a company [1]. The cross-functional parts of the process can be seen as a horizontal alignment and to bridge the gap between strategic and operative plans can be seen as vertical alignment. Kathuria, Joshi [16] concludes that horizontal alignment is less documented than vertical, and the studies made are usually between two different functions. Seeing S&OP as a cross-functional process from sales, different parts of operations as well as finance, indicates that the more functions involved the more complex alignment. Several literature studies regarding S&OP have been performed over time (e.g., Thomé, Scavarda [17], Kristensen and Jonsson [8]), which indicates a wide spread of S&OP, even though the design of an implemented S&OP depends on e.g., the industry itself and differences in company and product complexity [8].

In the existent literature general challenges are usually documented, even though they are not always expressed as challenges. Implementation of S&OP is often critical and is well documented. Wallace and Stahl [1] point out why implementation can fail and list: Top Management are not enough involved. The stakeholders have insufficient education. Insufficient discipline and self-discipline as well as conflict aversion and silo-thinking hinder a good implementation. Continuous data problems, inadequate demand planning and supply planning processes along with inadequate Pre-meeting. Unfocused executive meetings without formal decisions and a too narrow horizon and too many details.

In one of their three RQ's, Tuomikangas and Kaipia [18] raised the question of how the coordination is treated in the S&OP literature. S&OP aim to coordinate both demand and supply, different planning levels, and the integration of plans between different functions. Six mechanisms were defined in the S&OP coordination framework with connected objectives. Out of the six mechanisms two can be looked at from a challenge perspective related to the aim of this paper namely (i) S&OP process, where the mechanism includes how different sub-plans are defined and communicated and (ii) S&OP tools and data, where the objective includes good quality data.

Bower [19] presented twelve S&OP pitfalls which also can be seen as challenges. The challenges relate to vertical disconnect, management attention/indecision, real/non-real forecasts, continuous/annual focus, meeting regularity, S&OP-team neutrality, mid-term horizon, new product coverage, including/excluding of business trends, process metrics, silo-thinking, and meeting procedures.

There are also several maturity models for S&OP which can be a source for S&OP-challenges. Five maturity models are focusing on integration of plans both internally and externally [10, 20-23]. The use of IT itself is described in three maturity models [10, 21, 23] and financial integration is the focus in one maturity model [24] but is also somewhat covered by Grimson and Pyke [10]. The perhaps most extensive S&OP maturity model is the S&OP Integration Framework, addressing five different areas in each of the five maturity stages [10].

S&OP in ETO-context is rarely documented. Looking at tactical questions, which either can be handled in S&OP or separate, Shurrab, Jonsson [9] conclude nine tactical decisions required in an ETO-context related to five areas. The areas involved are (i) order screening, (ii)order customization, (iii) order workload analysis, (iv) order review, and (v) order contracting. These imply an even wider coordination and integration need with further functions, which adds complexity and thereby challenges.

3.2. ML-techniques and their use

ML relate to the study of computer algorithms that automatically improve through experience [25]. ML as a research field is genuinely multidisciplinary, and originates from work carried out in statistics, mathematics, biology, cognitive science, control theory, information theory, psychology, etc. It is generally considered a subfield of Artificial Intelligence (AI).

ML covers a diverse set of learning tasks, from learning to classify emails as spam, recognizing faces in images, and learning to control robots to achieve targeted goals [25]. Each ML problem can be defined as the problem of improving a "Performance" when executing a "Task", through some type of training "Experience". For example, in learning an email spam filter, the "Task" is to learn a function that maps from any given input email to an output label of spam or not-spam [25].

ML-techniques can be classified in different ways. A broadly used classification considers the need of labels in the training data or not, that is, whether the output values are required to be present in the training data (supervised learning) or not (unsupervised learning) [26]. Supervised learning techniques are generally used for classification and regression tasks, through employing, for instance, Support-vector machines (SVM), K-Nearest Neighbor, Naïve Bayes, Logistic regression, ANN, etc.

Clustering and dimensionality reduction techniques belong to the unsupervised learning category and are used for more exploratory tasks. A group of techniques of relevance for this paper that has demonstrated a significant impact due to its results in several areas is Deep Learning (DL). DL is part of a broader family of ML methods based on ANN (inspired by biological neural networks of animal brains); the adjective 'deep' refers to the use of multiple layers in the network. Another relevant category of ML-techniques is, for example Reinforcement Learning, a group of methods based on rewarding desired behaviors and punishing undesired ones.

4. Empirical data in the context of a SIC

The SIC is a company that has been using S&OP for almost 20 years to balance demand and supply but also to establish an integrated plan on a mid-term horizon. The company produces complex and customized, high value products with long lead time and long delivery time. The products can be divided into an MTS-part, an MTO-part and an ETO-part which can vary in scope from project to project. The annual volume is generally between 40 and 60 units and each project includes 2 units in average but can vary from one to up to 10+ units. According to the S&OP Integration Framework [10] going from stage 1 to 5, the SIC has a self-rated S&OP maturity as follows. Stage 2 in Measurement, stage 3 in Meetings and Collaborations, Information Technology and S&OP Plan Integration, and stage 4 in Organization.

In a workshop with the S&OP-team, challenges in their S&OP process were reviewed according to the structure in Figure 1. General challenges, hard to place in the structure, has been categorized as General (GEN). The identified challenges have been summarized related to its area in Table 1. Apart from the identified more general challenges there were also challenges such as organizational issues and complexity, varying S&OP-maturity in the organization, stakeholder buy-in, and in some extent lack of trust of S&OP. These challenges were not considered because they are seen as very company specific.

Table 1 Compilation of the experienced S&OP-challenges in the SIC

Area	Challenge
GEN (generic)	(a) Too much time spent on checking data quality and visualize results
	(b) Input data gets old before the process is finalized
	(c) Input timing issues and continuous input format change
FC (forecasting)	(d) Financial focus rather than planning focus
	(e) Lacking update of sales data
DP (demand planning)	(f) Demand basically using stomach felling rather than facts
	(g) General slippage of Order Intake
ENG (engineering)	(h) Short planning horizon
	(i) Different planning entity (Number of project)
	(j) Backlog capacity utilization hard to predict
SOU (sourcing)	(k) Weak connection between decisions and bullwhip effects
	(l) Late sourcing decisions of outsourced machine hours
	(m) Low visibility of constraints at suppliers in MTO- and ETO-context
	(n) Capacity issues related to sourcing activities for new products
PRO (production)	(o) Low visibility of consequences from disturbances
	(p) Understanding of moving bottlenecks
IP (inventory planning)	(q) Hard to forecast inventory physically and financially
TP (transport planning)	N/A
FIN (finance)	(r) Connect financial measures to S&OP and the plan
FI (full integration)	N/A

5. Analysis and Discussion

Structuring of the challenges from both the brief literature review and the empirical data from the SIC will be covered here. The focus has been to investigate S&OP challenges in an ETO-context but since ETO basically adds complexity compared to e.g., S&OP in an MTS-context the result will in most aspects be relevant for S&OP in general as well. Eventually all relevant challenges have been compiled.

5.1. Structuring of S&OP challenges

Starting from what has been found in the literature, the challenges are too general to relate to the different S&OP sub-areas according to Figure 1. The described challenges can be categorized, and three different areas can be identified. Data Quality refers to requirement of real time data, and how a forecast is defined or intended to be used. Vertical Disconnect refer to the information flows from e.g., strategic to tactical to operative plans and can be exemplified by having a too operative focus or a too short time horizon in S&OP. Horizontal Disconnect refers to the information flows between different functions including integration of plans, extracting sub-plans and co-ordination between different functions in the company.

Doing the same exercise on the empirical data from the SIC, the same groups can be used, and all the S&OP sub-areas can be included in the groups. Most of the challenges for GEN are related to data quality and the work for data checks and visualization. The timing challenge can be seen as a problem regarding horizontal disconnect. The FC challenges relates to data quality and depending on how the FC is interpreted it is rather a vertical disconnect than a horizontal disconnect since the forecast is mid-term but used for different purposes. DP challenges relates, as for FC, to data quality and vertical disconnect. The timing challenges for ENG relates to vertical disconnect. The lack of capacity data refers to data quality. SOU challenges mainly relate to a horizontal disconnect where purchasing comes in too late. Capacity data from suppliers is limited which goes into the data quality area. PRO also see a horizontal disconnect and a limited ability to see consequences of disturbances which relates to data quality. The IP challenge is basically a data quality problem which is worsened by time effects based on long lead times. FIN is both a vertical and horizontal disconnect since they are not a part of the S&OP-process itself and have a vertical plan of their own.

A categorization of the challenges both from the literature and the SIC (Table 1), can now be summarized into the three groups, see Table 2.

Table 2 Categorization of all relevant S&OP challenges from literature and empirical data

Area	Source	Comment
Data Quality	Tuomikangas and Kaipia [18] Wallace and Stahl [1] Empirical areas: GEN (a,b,c), FC (e), ENG (i), SOU (m), PR (o), IP (q)	Required data quality in the different steps and requirement of real-time data as well as correct definition of a forecast
Vertical Disconnect	Wallace and Stahl [1] Bower [19] Empirical areas: ENG (h), FC (d), DP (g), FIN (r)	Vertical addresses operative focus rather than mid-term and the over-lap between these two
Horizontal Disconnect	Tuomikangas and Kaipia [18] Bower [19] Shurrab, Jonsson [9] Empirical areas: GEN (b), SOU (l), PRO (o,p), FIN (r)	Challenges between involved functions including integration of plans, extracting sub-plans and co-ordination between functions in the company

5.2. *Analysis of S&OP challenges and task elicitation*

To apply ML and solve some of the challenges listed in section Table 1, specific tasks must be defined. This is usually an iterative process based on what shall be achieved, the data available, data possible to be gathered and other constraints like computational power available. Therefor this section extracts specific tasks based on the challenges presented in Table 1 and Table 2 that ML can support.

The three types of challenges identified in section 5.1 relate to several areas of S&OP based on the SIC. The first area, Data Quality, is of crucial importance for the application of ML. There are possibilities to use ML-techniques to find inconsistencies and propose solutions. Thus, the following task is formulated as *"Find errors and inconsistencies in the data and eventually correct or propose corrections of the data"*. For the remaining areas of vertical and horizontal disconnect, useful examples from the SIC are explored to find specific tasks.

For GEN there is an overall challenge to reduce non-value-add time to speed up the process as a whole and shift the focus in each step to become more efficient; however, most of this is related to data quality and possibilities to visualize data. If time can be re-distributed, there would be time to create scenarios. To automatically produce different scenarios is usually an optimization problem rather than something where ML-techniques can be used unless the optimization is done via ML. The optimization task could then relate to, e.g., earliest possible, maximized order intake, best usage of resources. In S&OP, all plans should be connected, but usually, it is an iterative process when one change affects something else. The connection is sometimes clear, and sometimes it is not. Validation of plans and their connections to other related plans needs

IT-support and is also a learning process. Finding disconnects between different plans and amending them are complex and ill-defined tasks that can hardly be solved using only ML.

Forecasting is the starting point for S&OP and if the accuracy can be improved, demand planning will be enhanced as well as operations; eventually, both the customer and the company will benefit. DP is using the forecast as a base and in an ETO-context intel from the tendering phase can be of importance. The focus is generally more on the demand of products, but the challenge in FC and DP is connected. In an MTO- or an ETO-context, history plays a less critical role [1] unless there is a possibility to see patterns of e.g., continuous over- or under-forecasting, or systematic slipping of order intake estimates. Global input such as the world economy may add information to forecasts. The first task for FC, as for the DP-area, can be defined as *"Find patterns in historical data and mirror them on the future forecast and/or demand plan"*. There might also be ways to find patterns of which sales projects a company is more likely to win based on history. Manual probability estimations of the likelihood of an order to take-off at all combined with likelihood to win orders is usually in place. If these probability estimations could be complemented with calculated probabilities it would give a better base for decisions. Patterns related to markets, country of installation, product, application, industry or maybe even sales responsible might be revealed. The second task for FC and DP is *"Estimate a projected probability for future projects based on historical data"*.

The S&OP sub-areas ENG, SOU and PRO focus on capacity and capability in an S&OP-context; to understand such capacity is of crucial importance. Usually, ETO-products have high complexity and relatively low volume, which also means that data is limited. Starting with ENG, engineering is the first thing that happens in a new project and usually engineering is involved to a higher or lower extent until the delivery is completed, which usually is for a long time. To investigate finalized orders from an engineering perspective, it can be used to forecast forecasted coming orders but also to forecast remaining work in ongoing back-log orders. Finding patterns in different engineering areas for different type of orders can improve forecasts of resource requirement for new orders but also on existing back-log-orders. Thus, the task for ENG can be formulated as *"Predict capacity utilization over time and identify bottleneck resources"*.

The main challenge for SOU is also capacity related, both internal and external. If there are data available for external capacity this can be investigated further and a similar task as for ENG can be specified. In an ETO-context there can be a lot of dependencies and iterations between engineering and sub-suppliers via purchasing which sometimes makes it hard to use e.g., serviceability from supplier, since changes might appear late, etc. For the experienced bullwhip-effect there would be a possibility to find patterns of bullwhip-effects and relate them back to decisions made in S&OP. Thus, the task for SOU can be formulated as *"Estimate future bullwhip-effects related to S&OP-decisions based on historical data"*.

Looking at data availability, PRO usually have a lot of data if there is an enterprise resource planning (ERP)-tool available and used. To be able to better understand the capability of the PRO-area, historical data is crucial to identify e.g., bottlenecks but also to understand consequences from disturbances. The task for PRO can be formulated as *"Estimate future capacity utilization, serviceability and location of future bottlenecks based on historical data"*.

The IP area for ETO-products should be limited, however the product may include forecast driven material so it can be valid there as well. Inventory forecasting, both from a physical and financial perspective, is generally based on order forecast accuracy. The higher order forecast accuracy the higher inventory forecast accuracy. Inconsistencies in actual inventory can still appear. There might be unknown patterns which can be valuable to understand. A lot of changes of a product together with a badly controlled end-consumption or a high level of non-conformances could be a source of an inconsistency. The task for IP can be formulated as *"Estimate future inventory based on future operations plan and inconsistency patterns in historical actual inventory"*.

The TP-area did not have a specific challenge in the SIC. Traditionally both inbound and outbound transport planning is about optimization. Also, in an ETO-context optimized inbound and outbound transports can be beneficial, however the logistical complexity is quite high with a lot of uncertainties of e.g., scope, size, weight, and coordination of schedules from suppliers and to customers. Depending on available data a task for using ML could be specified here as well, however this has not been done since the SIC did not see this as a challenge. The same applies for the FIN-area, however all tasks above will impact the FIN-area in a positive way.

5.3. Structuring of tasks

All the tasks defined in section 5.2 can be supported by different ML-techniques, including data quality (a step of crucial importance when analyzing data). The tasks described previously can be grouped into various categories, see Table 3. Considering ML tasks, some are related to finding outliers (using anomaly detection methods), others are more of a predictive nature (predictive modeling), classification or finally, some are more of an exploratory nature looking for similar groups (clustering).

Table 3 Summary of identified tasks related to S&OP-challenges

Area	Task	Type of Task
GEN	*Find errors and inconsistencies in the data and eventually correct or propose corrections of the data*	Anomaly detection, regression
FC/DP	*Find patterns in historical data and mirror them on the future forecast and/or demand plan*	Clustering, dimensionality reduction, pattern mining, association rule mining
FC/DP	*Estimate a projected probability for future projects based on historical data*	Prediction modeling (regression, classification, neural networks, SVM's ensembles)
ENG	*Predict capacity utilization over time and identify bottleneck resources*	
SOU	*Estimate future bullwhip-effects related to S&OP-decisions based on historical data*	
PRO	*Estimate future capacity utilization, serviceability and location of future bottlenecks based on historical data*	
IP	*Estimate future inventory based on future operations plan and inconsistency patterns in historical actual inventory*	

5.4. Discussion – ML-techniques for specified tasks

The choice of ML-technique and where it should be used, is connected to many factors e.g., the quality and size of the data available, the number of features, the complexity of the task, the real-time operational requirements the computational power precent etc. In a recent investigation of where ML-techniques have been used in S&OP-context [14] mainly using two structured literature reviews [12, 13], the conclusion was that there is an underuse of ML in S&OP-context. The majority of ML-techniques used in this domain belong to the class of supervised learning methods, except for one case where a hybrid supervised, and unsupervised learning solution was used.

Some examples of the use of ML-techniques in this domain is listed here. ANN has been used for classification in the DP-area [27]. For predictions in the FC-area there are some examples [28-30], but all of these are in an MTS-context where historical data is relevant for finding e.g., seasonal trends. The ML-techniques used in these examples are basically supervised learning methods such as ANN but also Self-Organizational Maps, Radial Basis Function, Fuzzy Neural Network and Cluster and Forecast model. The hybrid solution mentioned above, employed an Auto Regressive and Integrated Moving Average along with Long Short Term Memory Network for solving tasks both in forecasting but also in inventory planning [30]. For DP, a majority of solutions employed ANN [31-34] but also SVM together with ANN [35]. In another example, a Decision Tree (DT) was used for forecasting inventory optimization and price prediction [36]. In the PRO-area prediction of output was made by using DT, Neural DT and ANN.

When finding a ML-technique for a specific task there are many aspects to consider. The size of the dataset is of importance. Usually there is a tradeoff between accuracy of the output and the interpretability of how the result was produced. Usually, a high accuracy gives a low interpretability and vice versa. How much time available for training the model can also be of importance. After building a model additional real data is used to continuously learn the model e.g., when there are long cycle times, it takes a long time to proceed with the learning-phase. The number of features or variables also must be considered, as well as the computational power available to build models from data

6. Conclusions

In this paper challenges based on literature and from empirical data in a SIC has been extracted based on different perspectives, see Table 2. Data quality is one challenge type, e.g., lacking updates of sales data. Horizontal disconnects between different functions e.g., finance focus rather than planning in forecasting or vice versa. Vertical disconnects between strategic plans and operative plans e.g., short planning horizons in engineering. The challenges extracted from literature are more general and unspecific, hence most challenges used were taken from the SIC, see Table 1. From the seventeen specified challenges in most S&OP-sub-areas, in total seven ML relevant tasks were defined e.g., *Predict capacity utilization over time and identify bottleneck resources*. The tasks were then categorized in different types, relevant for ML; anomaly detection, clustering, classification, and prediction, see Table 3. The types can now serve as a base for trying out different ML-techniques. If a specific ML-technique can enhance S&OP in general or in an ETO-context and exactly which ML-method to use for a specific task cannot be determined before practical tests. Further steps will be company specific and will rely on data quality, accuracy versus interpretability, available time for training etc. This means that the used ML-method and the enhancement will differ from case to case.

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