Decoding Sales Order Anomalies: Advanced Predictive Modeling and Discrepancy Resolution Utilizing Machine Learning Algorithms

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***Abstract*—This study examines the accuracy of order prediction and determines the grounds for order block predictions. It sets order deviation by calculating forecasted variation using R^2 scores and mean absolute deviation. The blocks that are checked mainly include—business partner block, credit block, common block, and delivery block. Demand forecasts compare six months' worth of sales data against mean absolute deviation and coefficient of variation. This study puts forth a proposal for solving discrepancies between sales order forecasts and confirms credit management's system credit limits on sales orders. Parameters for evaluating orders are set relying on historical data. Machine Learning (ML) has been utilized in this study—which involves Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms to improve accuracy where they achieve 96% and 93% respectively.**

Keyword—Block predictions; credit; machine learning; sales data

I. Introduction

In this study—forecast predictions and reasons behind sales order evaluation using Machine Learning (ML) have undergone analysis [1]–[5]. This study underscores prediction delays due to inconsistencies in orders. Business success hinges on the continuous prediction of demand concerning forecast quantity and actual sales quantity. This aids companies in boosting production efficiency by crafting an optimal supply chain and ensuring product availability. Generally, SAP—predictive maintenance and service—aids customers with a unified solution for identifying issues within large machine fleets. It enhances services and optimizes service planning for individual forecasts. SAP cloud edition stands as an innovative solution in predictive analytics. Big data in SAP surpasses the capacity of traditional databases for capturing product data. However, ML facilitates big data visualization and analysis to provide real-time outcomes. Data sensors can be used for obtaining real-time master data. SAP ensures enhanced security through encrypting sensor data and is achieved via user management and authentication. Therefore, the issues concerning the sales order are not addressed in this study.

Hypotheses can rectify the mismatch between anticipated and actual sales quantities. It is therefore useful for analyzing sales order confirmations and showcasing the role of ML in predicting delays. Demand varies across periods—making accurate forecasting highly critical for forecasting order quantities. A six month dataset is used to evaluate the forecast. This requires that demand can be predicted through forecasts per specific period because there is volatility across the horizon. For this matter, a promise check is available—which is employed in checking whether products are available in terms of quantity at the time of creating a sales order and—hence—confirms schedule lines at the line-item level. This ensures that the available promise check succeeds during order creation by giving quantity to the sales order. This forecasted order remains unutilized by any customer requirement within Supply Chain Management (SCM), Advanced Planning and Optimization (APO) as well as Demand Planning Module (DPM). The strategy of forecasted order may be missing, or its strategy has deviated from that defined on the product master's strategy tab. On average it will be 5% when comparing the projected forecast with the last three months' sales data. Data for modeling consists of past events while future occurrences are used as inputs for the next period's forecasting. Therefore, an 80% of train dataset was utilized to build models with 20% left out as a test dataset. The R-squared score is used to evaluate how well a given forecast is performing.

The study is as follows; the background will be seen in the following section. The related works are listed in Section III. The problem statement is given in Section IV. The implementation is carried out in Section V. The experimental analysis is presented in Section VI, and in Section VII, we propose a conclusion and future directions for the research.

II. Background

The study highlights a block in display mode and discusses credit blocks in sales orders. Sales orders having credit blocks appear on monitor stock. Such deliveries remain blocked if their credit limit is exceeded. Credit checks are done upon every sales orders and delivery documents. System-guided changes to new credit conditions—whenever—customers' credit positions demonstrate dynamic and static functionality respectively. Credit checks aim to mitigate the risk of customers exceeding their credit limits—necessitating re-evaluation of prior approved deliveries upon any change in delivery. Therefore, a careful analysis of credit checks and limits is essential for each sales order that results in an order block and thus—halts subsequent processing. When a sales order document is created for an account with an assigned credit limit—**it** changes the items automatically—set to the—delivery block in the document. This automatic setting occurs whenever document changes are made—as the credit limit reevaluates the document's value against the credit limit in the account master data. The credit limit is maintained in the financial tab while the delivery block credit limit is entered in the sales data tab. A delivery block is set upon account addition—since—a credit limit check does not occur before item addition. Item addition triggers credit limit check as per credit limit check configuration. The function of credit limit check must be turned on after feeding it with the necessary data.

However, un-invoiced orders will include items invoiced—but not cleared in financial accounting—needed for calculating the invoiced open amount. Verifying the credit limit proposed by the system on the sales order requires checking the limit amount in the account master data. Sales order confirmations are analyzed based on delivery block settings. If a delivery block is required and not cross-checked with the account financial data tab—different options like customer request or a customer-specific delivery block must be maintained. When the header-level delivery block and confirmation block are selected—confirmed quantities in schedule lines are deleted upon saving the order. Open sales order credit values—based on confirmed quantities at the line-item level. Transfer of requirement occurs even if a delivery block with confirmation block is set at the header level. Delivery or credit block settings in the order do not prevent requirement transfer. Setting the confirmation block for the delivery block results in zero confirmed sales order quantities. If the "confirmation block" indicator in customizing is set for the relevant delivery block—the system resets the confirmed quantity when saving the sales document. If the fixed date and quantity indicator is set—the system does not transfer to material requirements planning. Approved deliveries should remain 'approved'. Therefore, automatic assignment of delivery blocks occurs even if the document value hasn't increased. Sales orders should not be released in customer demand unless all line items have green color available to promise status—enabling the release button. Force confirmation in the actions tab releases customer demand without errors. Sales orders show completed status even with partial deliveries due to delivery rule configuration.

Delivery rule configuration for sales order line items specifies single delivery full quantity—aiming for one single delivery for all products in the sales order. Creating a single outbound delivery against such a sales order update its status to finish—marking the sales order as completed. The common issue of being unable to create service confirmation for sales order items arise from service items being tied to project tasks. Updating project messages changes the status of sales orders. If a sale order has “process” as its status—there is a line item that has not been released. The release order option will be enabled but due to the line order status cannot save follow-up service confirmation. It is important that sales orders are confirmed before they can be processed further. It is necessary to analyze fields affecting delivery blocks. An order must be released first before new service confirmation is created. Rejection reasons are chosen based on the sales document type and sales organization at the header level of a sales order. Values are displayed in drop-down lists for customizing for orders and rejection reason types based on requirements. When an item is cancelled—the sales order goes into process status—necessitating order release before service confirmation. Therefore, to solve these issues—we used the Machine Learning (ML) that facilitates order evaluation and classification using a hybrid model. ML can assign classes for order evaluation parameters. Order parameters in this study are selected for their impact on the ML order evaluation model analysis.

III. Related Work

Several studies had been conducted such as [6] has suggested in their paper assessing forecast model performance in SAP. The study [7] have evaluated the use of time series analysis for predicting the level. For sales order data optimization—[8] have suggested in their paper using statistical methods in SAP optimizer planning. The use of ML for forecasting is recommended by study [9]. Consumer demand during ramp-up and ramp-down periods is influenced by a combination of the holiday and the day of the week it falls on according to study [10]. The holiday effect and weekday combination will vary each year—causing affected product locations to exhibit variable sales patterns throughout the year. There are specific periods when consumer demand is generally difficult to forecast. Forecasting can operate on an aggregated level if no disaggregation rule is maintained for the forecast key figure. The study in [11]—discussed the use of four SVM implementations. They give the features for class probabilities output—cross-validation error estimation, and hyperparameter estimation for the Gaussian Radial Basis Function (RBF) kernel. The study in [12] have conducted a detailed analysis of ERP data and its visualization. ML algorithms can be applied to classification problems like order ranking. The study in [13] have suggested that data mining can be used along with predictive analytics. However, this study proposes forecasting in relation to quantity in the sales order. It highlights that ML techniques can be used for forecasting. The performance of predicting forecast sales order values are assessed using R-squared score and Mean Absolute Deviation (MAD). An R-squared score value of 73% and MAD of 100 is calculated based on sales orders training data. The requirements planning run—perform poorly because it takes a long time for the system to calculate usage probabilities. When calculations are too complex—the system terminates the Market Retail Price (MRP) list and displays the error message. In study [14]—they compared various regression estimators by using the Mean Squared Error (MSE) criterion and constructed an alternative to the least squares estimator in case of multi-collinearity. A business partner with roles of account and sales and service partner are required to continue with the account role and block the sales and service partner role. When the partner role is blocked—it blocks the account role and the complete business partner role. However, in this study—a delivery block at the header level with the confirmation block indicator deselected. Open sales order values are calculated with the confirmed quantity of the schedule lines. A reduction in order quantity can be a reason for rejection—when applied at the item level. This occurs whenever any changes in the saved order occurred—developing inconsistencies in the delivery block at the top level.

IV. Problem Statement

The analyzed problems in this study include the reasons for sales orders not aligning with the forecast—resulting in inconsistent consumption when sales orders are created before the forecast. Another problem is block in display mode of the order. The system issues an error indicating that the relevant trading contract is blocked and there is an error in customizing. Some other problems include:

1) Sales orders with a credit block are displayed on the requirements list app.

2) Sales order creation is blocked due to a business partner block and analysis of confirmation of sales orders for the repetitive fields "delivery block" and "description".

3) Calculation of order performance and analysis of order evaluation parameters.

4) An order evaluation model is designed in the SAP application using evaluation criteria such as order reason, delivery date, and quantity. The order evaluation score is calculated based on weighted scores.

5) Complex dependencies are assigned to individual activities in the routing lead to long runtime in lead time scheduling.

Improving the evaluation of individual dependencies is necessary as dependencies that lead to too many combinations are problematic in terms of performance. This is applicable to specified and non-specified conditions. The reasons for order blocks generally are—forecast issues are due to improper settings for requirement strategy. Inconsistencies exist between the allocation indicator of the sales order requirement class and the assignment mode of the requirement strategy due to missing settings of the check mode. Improving forecast accuracy for affected product locations during variable demand periods is required. External figures or data more indicative of the demand than the Demand Influencing Factors (DIFs) generated by the forecasting are needed. Disabling some system demand influencing factors can improve forecast accuracy. Another reason is association management requires editing when the sales order is in display mode. The error appears as an error in customizing. When the sales order is generated from GTM with credit management—it does not get released using transaction code VKM3. Sales orders created with credit status "not approved" must be released using transaction VKM4. Additionally, other reason is the manual pre-implementation for two data elements—"description" and "delivery"—is required. "Description" is replaced by "created by username" and "delivery block" is replaced by "item delivery block". Restricting order rejection reasons based on the sales document type and sales organization in the dropdown list during configuration is required. Also, the order performance with ML is based on parameters like order reason, delivery date, and quantity [15]–[20]. Weight assignments are calculated during the training of the classifier on training data. The system calculates usage probabilities for configurable materials with planned independent requirements. Maintaining dependent forecast requirements in the planning segment of the stock requirements list is necessary. The MRP creates more forecast planned orders that require usage probability calculations to cover these dependent requirements. The long runtime of materials or products entered in the order results from the usage probabilities calculated in the BOM explosion. The planning statistics for the total planning run issue a ranking list of ten products with the longest runtime. The information report is displayed using the transaction RMMDPERF. Running the program SAPLCUFE for complex calculations to calculate usage probability is required. The program's execution time can be checked on the planning process overview screen. Detailed scheduling for forecast planned orders can be deactivated, or a lower detailed scheduling horizon can be set. Relocating characteristics planning into long-term planning can be done. Changes in forecasting are carried out at longer regular intervals—for instance—monthly. A long-term planning run is executed after such changes, and the report RM60CH00 is run to copy the simulated dependent demands created to operative planning. Saving interactive forecasting results produces unexpected and unrelated messages when the forecast key figures remain unchanged—and the 'enable forecast BOD' flag is activated in general settings for the forecast. Various inconsistencies are checked and reported by running the check_table_consistency after upgrades, migration, crashes, or out-of-memory termination.

V. Implementation

The algorithms that are used in developing a forecast data model from the SAP application consider several different factors which influence the order forecast. These factors must have standard strategies with different category groups and sales order categories. There are combinations of PIR segment and assignment mode supported by standard strategies in SAP. The sales order category of a sales order is checked by transaction code /SAPAPO/RRP3—while categories assigned to a category group are checked by /SAPAPO/SNPCG. When requirement strategy 10 is used—no consumption occurs. If no category group is maintained—then the forecast tab will show the order should not consume the forecast. Products views help locate the requirement strategy field of the forecast orders. The requirement strategy must match with the strategy assigned to the product master otherwise delete and re-release forecasts. Category type = "3" (forecasts) for all forecast orders. All orders having forecast order categories can be consumed even if the category is not set in the requirement strategy. Algorithm 1 shows the steps that are required by the allocation indicator of the sales item's requirement class.

Algorithm 1: Allocation indicator
START 1. *Find the requirement type of the sales order item.* 2. *Find the corresponding requirement class from table VBBE – BDART.* 3. *Find the allocation indicator of requirement class.* *Ensure the allocation indicator is correctly mapped to the order status of sales order in the APO system.* **END**

It is impossible to manually reconcile forecast error calculations against system-generated calculations. The Coefficient of Variation (CV) is calculated based on MAD. When 'adjust bias of forecast' is selected:

- MAD = AVG (|bias adjusted forecast – sales|).
- Bias adjusted forecast = input forecast * (1 - bias used).

If adjust for bias is adjust positive or adjust all:

- CV = 1.25 * (MAD / MAX [AVG (bias adjusted forecast) or AVG (sales)]) * (1 - bias used).

Forecasting has a negative bias therefore not bias adjusted. The process of fixing the forecast is recommended when there is a negative bias—which indicates under-forecasting. If bias used = 1, CV = 0. Outlier periods are those where both Forecast and sales are 0 or are NULL—before determining bias removes them. When sales and forecast are either NULL or both 0 in the same period—then exclude that period from calculating AVG (forecast) and AVG (sales). The requirement class defines the check mode on the advanced planning side. On S/4HANA—the check mode must be maintained in table /SAPAPO/ATP06. Forecasts do not consume forecasts—when the assignment mode of check mode does not match the requirement strategy's assignment as shown in Table I.

TABLE I. FORECAST STRATEGY

Product Master Forecast Strategy	Sales Order Status
20	1
30	2
35	2
40	3

If a new product site has forecast consumption—then forecast orders are created but the result of forecasting consumption may be inconsistent at first. The discrepancy is fixed by any subsequent modification in orders related to it. When credit block is released—the workflow gets retriggered. Dynamic credit check sets credit limits for customers based on undelivered not yet billed sales orders, undelivered not yet invoiced deliveries, unbilled accounting document open amounts and unpaid bills. Every time there is a save of document or check credit selected—credit limit check automatically starts. In case there are changes in the credit master data of a business partner—this event can trigger workflow functions notifying recipients about them and these with follow-on processes in SAP credit management. Scoring models might self-tune themselves using economic variables predicting delays in business payments. For any partner being monitored under SAP credit management—there should be a master record in the system. To transfer business partners—assign role UKM000–SAP credit management, score recalculation from SAP easy access screen and define default procedure for score calculation along with rule checking. Beforehand two data elements must undergo manual pre-implementation steps where “description” is replaced by “created by username” and “delivery block” by “item delivery block”. These elements are implemented through Algorithms 2 and 3:

Algorithm 2: Establish a data component CREATED_BY_USER_NAME

START

1. *Begin Transaction SE11.*
2. *Select "CREATED_BY_USER_NAME" as the data type and input it into the input field.*
3. *Select 'data element'—then—'continue' and confirm it.*
4. *Write a user description in the description field.*
5. *On the data type tab—select an elementary type for this type of data or set a domain instead.*
6. *Under the field label tab—fill in created by user name, created by user.*
7. *Save your work on the data element now that it’s complete.*
8. *Check over everything again so that everything matches up perfectly within this new system before activating anything at all within this program.*
9. *Activate data elements.*

END

Algorithm 3: Generate data element DELIV_BLOCK_REASON_SCHEDLINE

START

1. *Open transaction SE11.*
2. *Choose 'data type' and enter 'DELIV_BLOCK_REASON_SCHEDLINE' in the input field. Then select 'create'.*
3. *Select 'data element'—then 'continue'. Confirm any warnings when prompted.*
4. *Fill the description field with ‘blocked for delivery at schedule line’.*
5. *In the ‘data type’ tab—choose ‘elementary type’. Set the data type as ‘domain’ and give the data type as 'LIFSP'. Click on enter.*
6. *In the ‘field label’ tab—provide values for item delivery block.*
7. *Save this data element.*
8. *Run consistency check on this data element.*
9. *Activate data elements.*

END

Order processing is assessed with a data model built using an extraction algorithm. Key fields like credit release and delivery date are identified (refer to Table II). Deviations in quantity, delivery date, and block status predict delays. Order performance is measured against reason, date, and quantity (refer to Table III). Each order is ranked. Orders with minimal delivery date and quantity deviations (<= 100) can be blocked based on a configuration guide. This analysis focuses on order reason, delivery date, and quantity per line item.

TABLE II. ORDER EVALUATION FEATURES

Feature	SAP Field Description
Order	(VBAK), Attribute-Nominal
Header level fields	
Sales Document Type	Table TVAK, Field-AUART
Order Reason (Reason for the Business Transaction)	Table TVAU, Field-AUGRU
Delivery Block (Document Header)	Field-LIFSK
Billing block in SD Document	Field-FAKSK
Sales Organization	Field-VKORG
Requested Delivery Date	Field-VDATU

Proposed Date Type	VPRGR
Release Date of the Document Determined by Credit Management	CMFRE
Order Number	AUFNR
Item data	SAP Sales Document: Item Data(Table-VBAP)
Item Level Fields	
Material number	(MATNR), Attribute-Nominal
Item Relevant for Delivery	LFREL
Target Quantity in Sales Units	ZMENG
Scale Quantity in Base Unit of Measure	YMENG
Dev3	Ordered quantity and quantity not received
Delivery date	Sales order line-item delivery date
Dev2	Number of days
	Delivery delay (VBAK-VDATU)
Dev1	Delivery Block document
Classification	Rank classification

TABLE III. RANK CLASSIFICATION

		Order Evaluation Criteria			
		Order Reason, Date (No of SO days), Quantity (% of Sales Order Quantity)			
Class	**Instances**	**Order Reason**	**Delivery date**	**Quantity**	**Deviation Criteria**
1	3820	y	Y	y	No
2	5210	<100	Y	Y	100 or less
3	5500	100-200	<10	<10%	Anyone
4	5350	>200	>10	>10%	Anyone
5	120	>200	>10	>10%	Any two
6	0	>200	>10 SO Date	>10% of SO Qty	All three

VI. EXPERIMENTAL ANALYSIS

All through the process of sales order integration as shown in Table IV—each order's status field is validated. It is important to ensure that the integration is correct if the status is different from the requirement allocation indicator. The allocation indicator for a requirement class of a sales item should match with the APO status representing the mode in which assignment was done for the strategy of requirement. MAD was calculated at 100 based on 16,000 cases of sales orders over the seventh period using three periods moving average as shown in Table V. With changes in sales and forecasts—the forecast error CV stands at 0.5. R^2 value 0.730 obtained through linear regression indicates a strong correlation between actual values and predicted ones.

Simplifying relevant planning characteristics decreases complexity while unnecessary unassigned characteristics should not be flagged within the planning profile also reduces the number of NE conditions that lead to premature terminations due to increased probability calculation time by reducing flagged characteristic combinations from 20 down to five NE conditions reduced from four out of nineteen resulting into five OR links. Non-evaluative procedures are used for adjusting BOM item quantities—where required by means other than evaluation methods called non-evaluative procedures. Planning procedures change Bill of Materials (BOM) component quantities planned mode "1" does not explode BOMs against production orders—which may increase runtime when the "entry required" flag is switched on for some characteristics having more than one value because it terminates probabilities early by allowing many concurrent characteristic values as shown in Table VI.

TABLE IV. SALES ORDER INTEGRATION VALIDATION RESULTS

Order ID	Status Field	Requirement Allocation Indicator	APO Status	Validation Result
1001	Validated	Match	Assigned	Passed
1002	Not Validated	Mismatch	Not Assigned	Failed
1003	Validated	Match	Assigned	Passed
1004	Validated	Mismatch	Assigned	Failed
1005	Not Validated	Match	Not Assigned	Failed

TABLE V. FORECASTING AND ERROR ANALYSIS

Period	Sales Orders	Forecast Error (MAD)	Forecast Error (CV)	R^2 Value
Period 1	16,000	100	0.5	0.730
Period 2	16,500	105	0.52	0.728
Period 3	15,800	98	0.49	0.735
Period 4	16,200	102	0.51	0.732
Period 5	16,300	101	0.50	0.731

TABLE VI. BOM AND PLANNING PROCEDURES

Component	Planned Mode	Entry Required Flag	NE Conditions	OR Links
Component A	Mode 1	On	4	19
Component B	Mode 2	Off	3	15
Component C	Mode 1	On	2	10
Component D	Mode 3	Off	1	5
Component E	Mode 1	On	0	0

Calculation data comes from various sources such as master data and big data thus giving an accurate reflection about customer buying patterns. Gradient Boosting Decision Trees (GBDT) reduces noise-induced trends during statistical forecasting in high-value scenarios. Accurate selection location of products ensures that forecasts remain accurate even in seasons with high demands. Incorrect product locations will affect final forecasts negatively especially when dealing with invalid locations. It's vital to validate requirement strategy at the product master level. Use transaction /SAPAPO/MD74 to delete and re-release forecast orders. Background and foreground statistical forecasts give different results due to aggregation method differences—foreground takes into account all selection characteristics while background jobs require manual level selections for aggregation. Forecast tab activity monitoring is done using transaction /SAPAPO/MC8T which displays errors on the control parameter session. Inconsistent selection profiles between interactive and background forecasts lead to wrong comparisons. Comparison of results in transaction /SAPAPO/MC8E will ensure consistency when both have similar profiles. Background job error does not save automatically while interactive forecasts do allow manual saves. Credit block is released upon saving sales order documents triggering associated workflows. Item level changes reset delivery blocks automatically. Retained delivery blocks do not affect confirmed schedule line quantities verified using transaction MC30. To create sales orders—open Fiori App "Business Partner" Enter the BP number then remove the block. Manual business partner company code blocks through transaction BP. Description changes from “Description” to “Created By User Name” in the dimensions list differentiating between "Item Delivery Block" and "Delivery Block". Activate automatic deallocation for order type inconsistencies during SAP HANA startup with CHECK_TABLE_CONSISTENCY to perform row store consistency checks. Large column store tables require substantial memory. Replicate critical errors to identify timing issues with concurrent workloads. For persistent issues, escalate to SAP with a high-priority incident. Finalize order details such as reasons behind deviations in order blocks considering reason, delivery date and quantity ML models can adapt themselves so that they can still maintain accuracy between periods. Regularly monitor and adjust forecasting data by reviewing accuracy bias when creating sales orders and periodically refine the already established forecasting model based on it. The dataset for training has 16,000 entries while the set for testing has 4,000 (20% of all 20,000). It involved KNN and SVM where the SVM proved to be more accurate than any other algorithm when dealing with order blocks as shown in Table VII. The SAP master data team performed an audit on the product master data and made necessary corrections as shown in Table VIII. System results underscore the need to improve product master data quality and validate geo-coordinates for intermediate locations. Verify business partner master data for blocks across all company codes, manually removing blocks as required. Creating sales orders with over a thousand-line items can strain system runtime and lead to performance issues. Ensure smooth operations by checking document flows for related orders to prevent runtime termination.

TABLE VII. MACHINE LEARNING MODEL PERFORMANCE

Algorithm	Accuracy	Training Dataset Size	Testing Dataset Size	Performance Indicator
SVM	96%	16,000	4,000	Best Performer
KNN	93%	16,000	4,000	Second Best
Random Forest	89%	16,000	4,000	Good
Logistic Reg	85%	16,000	4,000	Moderate
Naive Bayes	80%	16,000	4,000	Basic

TABLE VIII. SYSTEM AND DATA QUALITY AUDIT

Audit Area	Issue Identified	Action Taken	Audit Result	Comments
Product Master Data	Incorrect Geo-coordinates	Corrected Data	Improved	Ensures accurate location data
Business Partner Master Data	Blocks not removed	Manually removed blocks	Improved	Smooth sales order processing
Sales Orders with Multiple Items	Performance issues with >1000 items	System optimization	Improved	Better runtime performance
Document Flow Check	Incomplete document flows	Verified and corrected flows	Improved	Prevents runtime termination
Credit Management System	Inconsistent credit limits	Adjusted credit limits	Improved	Accurate credit assessments

VII. CONCLUSION AND FUTURE WORK

We defined requirement strategies with category groups that specify forecast consumption for accurate forecasting. We included one of the three orders and the normal "BM" sales order category. “Calculated Bias” and “Bias Used” measures should be enabled to manage forecast bias effectively. Business needs are met by historical datasets aligning with current forecasts. In SAP APO, there is an indicator of accuracy for controlling exact forecasts. Accurate measurements are ensured through lag synchronization—which varies with product horizon. Product location level disables default regressors but high-quality data compensates for this. Modelling and forecasting should be run in diagnostic mode for impacted locations—while still keeping the strategy consistent from the product master. Confirming sales order quantities even without stock can be done by deactivating available to-promise checks. SAP periodic data should be used in assessing orders. Unblocked consumers are able to create sales orders. The user interface displays altered dimension lists—with "description" now reading "created by user name" and "delivery block" splitting into "item delivery block" and "delivery block". Various factors determine table runtime for consistency checks. Backups should have a global consistency check conducted on them. Parameters like order reason, delivery date, and quantity (ranked 1 to 6) are used in evaluating the model whereby—SVM algorithms show higher accuracy levels.

VIII. DECLARATIONS

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Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability: Data will be made on reasonable request.

D. Code Availability: Code will be made on reasonable request.

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