

Predicting equipment failure on SAP ERP Application using Machine Learning Algorithms

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Abstract—A framework model to predict equipment failure has been keenly sought by asset intensive organizations. Timely prediction of equipment failure reduces direct and indirect costs, unexpected equipment shut-downs, accidents, and unwarranted emission risk. In this paper, the author has proposed an equipment reliability model, for equipment type pumps, designed by applying data extraction algorithm on equipment maintenance records residing in SAP application. Author has initially applied unsupervised learning technique of clustering and performed classes to cluster evaluation to ensure generalisation of the model. Thereafter as part of supervised learning, data from the finalized data model was fed into various Machine Learning (ML) algorithms where the classifier was trained, with an objective to predict equipment breakdown. The classifier was tested on test data sets where it was observed that support vector machine (SVM) and Decision Tree (DT) algorithms were able to classify and predict equipment breakdown with high accuracy and true positive rate (TPR) of more than 95 percent.

Index Terms—Machine Learning, SAP, Enterprise Resource Planning, Condition based monitoring, Predictive maintenance, Corrective maintenance, Equipment failure, Reliability maintenance, ERP, SAP, HANA, CBM, Plant Maintenance, clustering

I. INTRODUCTION

Plant maintenance function is strategic to asset intensive organizations operating in sectors such as utilities, healthcare or manufacturing [1]. Mismanagement of maintenance program can lead to critical equipment failure disrupting production lines and essential services such as power supply or healthcare. Faulty maintenance processes can lead to loss of revenue, reputation and can endanger human life and environment [2]. Unplanned equipment outages can result in frequent breakdowns, restoration services, higher budget costs, lower equipment life and MTBF (mean time between failures)[3].

The majority of large organizations or SME (Small and Medium Enterprises) deploy ERP(Enterprise Resource Planning) applications such as SAP to manage business processes, implement controls and segregation of duties across various functions such as procurement, manufacturing, maintenance, invoicing and collection [4].

Asset maintenance programs can usually be categorized into four areas: preventive, corrective, predictive and shut-down [5]. These four maintenance processes can be configured and managed successfully in SAP Plant Maintenance application with strong integration to purchasing and cost controls [6] function. However SAP application does not offer

any functionality to predict equipment reliability and early warning system that can be used by maintenance planners to timely implement corrective actions that can avoid unplanned equipment shut-down.

Various business problems have been resolved in functions such as medicine [7], operations [8] and finance [9] by implementation of ML algorithms and AI techniques. As 80 percent of fortune 1000 and 60 percent of fortune 2000 companies [10] use SAP application, data mining and ML (Machine Learning) algorithms can be applied to data residing in the SAP application to build classification model that can predict equipment reliability.

Therefore author has proposed an equipment reliability model on Artificial Intelligence (AI) platform in which historical equipment maintenance data existing in SAP application from preventive, breakdown, spare part usage, condition based measurements is integrated with Machine Learning algorithms. The research outcome suggests a decision support model that can be used by maintenance planners to predict equipment reliability and take pre-emptive corrective actions to overcome unplanned equipment outage.

The next section of the paper lists associated literature review. The problem statement and associated hypothesis is stated in section 3, proposed classification data model to test hypotheses is stated in section 4 and experiment results in section 5 and 6 of this paper.

II. LITERATURE REVIEW

Optimization of Plant Maintenance processes has been a topic of interest actively pursued by various researchers. Various maintenance processes such as breakdown, preventive and condition-based are practiced by organizations and each method has associated benefits and drawbacks.

Breakdown maintenance is performed as a result of unplanned equipment failure and is considered as a costly and reactive measure. Usually, reactive maintenance is five to eight times costlier than preventive or predictive maintenance [11].

Planned maintenance approach reduces the failure probability of an equipment irrespective of its condition. The planned maintenance approach can either be time-based or performance based. Many a times, work orders triggered via scheduled maintenance process may not be necessary and also not capable of avoiding equipment breakdown [12]. The planned maintenance process is usually carried out based on

a recommendation of the equipment manufacturer. However, the process misses capturing conditions during equipment operations that may have led to equipment degradation and may lead to subsequent failure [13].

Condition based monitoring can offer enough insight on equipment health and can significantly contribute to an equipment reliability prediction model [14]. The equipment starts displaying 'out of range' condition measurements such as temperature, pressure, vibrations and so on for certain time interval before failing.

There are numerous works that have been carried out on equipment diagnostics leading to the importance of predictive maintenance practice. Young et al. [15] evaluated the implementation of data mining algorithms to improve maintenance procedures for F-18 aircraft. The researcher presented data mining models incorporating failures, diagnoses, and repair data to mitigate critical situations leading to improved reliability of the asset. Pan et al. [16] suggested that the machines effective age and remaining maintenance life should be assessed to predict the future degradation rate of machines.

Clustering is another approach where set of features representing each instance are logically grouped by algorithm without any label assignment. Clustering has been successfully used by researchers to perform market segmentation [17] and risk analysis [18].

SAP application can handle configuration of maintenance processes for varied industry sectors. The application can successfully handle breakdown, corrective and condition based maintenance processes of an equipment and can hold large amount of master and transactional data related with the maintenance processes [6]. When it comes to workplace safety, the integration of SAP Planet maintenance and incident management aids improving workplace safety [2].

Emerging technologies such as in-memory databases and high performance computing have transformed the arena of research analytics [19] making vast amount of information available to ML algorithms. With advent of in-memory database systems, specifically with SAP HANA, classification models can be build [20] by integrating equipment historical maintenance data with ML algorithms with an objective to predict equipment reliability.

III. RESEARCH OBJECTIVE AND HYPOTHESIS FORMULATION

Reliability maintenance is an effective tool that can predict equipment failures before it occurs. The majority of machines, almost 99 per cent, convey sufficient condition based signals suggesting a forthcoming system failure [21]. Reliability models can save one-third of an equipment maintenance cost that is otherwise unnecessary and may not add any value.

Using SAP application equipment reliability cannot be predicted, therefore the author has taken equipment reliability as a research problem and proposed a predictive model integrated with SAP application to timely predict equipment failure, leading to improved production lines performance, workplace safety and cost savings for an enterprise.

A. Research problem

SAP application can be configured to run preventive, corrective, breakdown and shut-down maintenance processes for an enterprise. For preventive maintenance process maintenance plan can be configured that generates maintenance orders for an equipment when fixed time or equipment running schedule has elapsed. The deadline monitoring functionality in SAP application allows maintenance planner to foresee next preventive maintenance order scheduled date.

The corrective maintenance processes can record information related to unplanned maintenance processes.

Various condition based measurements for an equipment such as pressure, temperature, vibration can be recorded directly in the application or via an interface. A maintenance order generated as a result of either preventive, corrective or breakdown maintenance process captures information about costs, spare parts, man power usage and so on.

To overcome the research problem of predicting equipment reliability, author has proposed a decision support model by integrating maintenance data residing in SAP application with both supervised and unsupervised AI learning techniques. The decision support model can timely predict equipment health and allow maintenance practitioners to take corrective actions to improve equipment reliability.

B. Hypothesis Formulation

The author has hypothesized that equipment breakdowns can be predicted by integrating ML algorithms and selected data points generated from various maintenance processes such as preventive, corrective, condition based measurements and so on. Based on the literature review, author has short-listed set of important features, listed in table 1, to design a data model useful to perform equipment reliability analysis.

C. Model Application and Benefits

The main advantages of equipment reliability model proposed in this paper are:

- **Iterative:** The ML algorithms learn with incremental data that becomes a part of the SAP application database over time.
- **Flexible:** The model can be enhanced with additional features from SAP database or third party application via interface to improve accuracy and reliability of the model.
- **Adaptive:** The proposed algorithm and approach can be adapted on any ERP or IT application including SAP.

The success of the model relies largely on integration between maintenance department, BI (Business Intelligence) and SAP function in a business organization as shown in figure 1. Each function is expected to have following high level responsibilities:

- **Maintenance Department:** Responsible for proposing set of features for an equipment type that may be useful to perform equipment reliability analysis.
- **Business Intelligence:** Design and Build the data model by implementing ETL (Extracting Transformation and

Loading) methodology on SAP application. The integration between SAP and ML algorithms using ETL methodology can be done using web services, extractors or remote function calls (RFC).

- **SAP Application:** Use classifier model as decision support system, to predict equipment breakdown and communicate with maintenance department to take corrective actions.

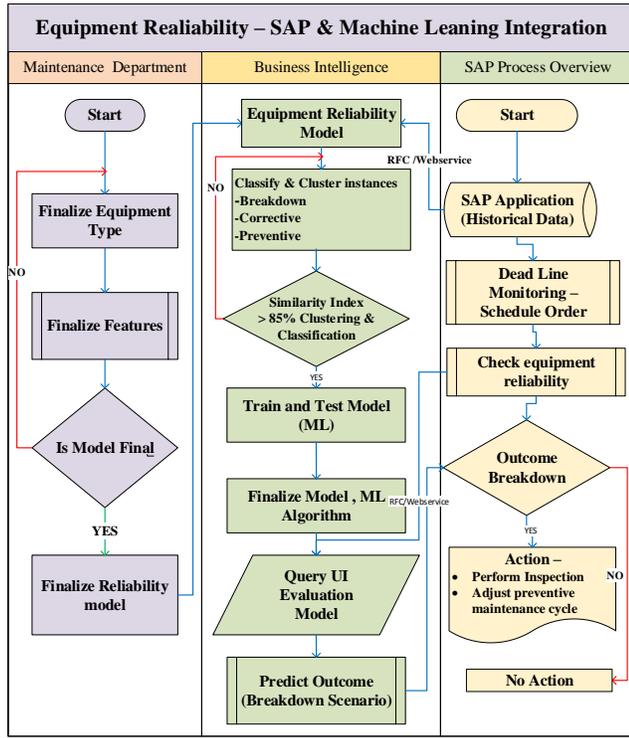


Fig. 1: Equipment Reliability Model- Multiple Functions
Source: Author

IV. DATA MODEL AND FEATURE FINALIZATION

The author has finalized data model following steps mentioned below. The data was extracted from both master and transactional maintenance records residing in SAP application for equipment type pumps.

- Using inputs from industry experts and literature reviews, relevant set of features were identified, as specified in table 1, that were useful to predict equipment breakdowns.
- Used data extraction algorithm (Algorithm 1) to build data model.
- Perform data manipulations on equipment maintenance records to build a fact table.

A. Data extraction and cleaning

Data was collected from SAP Internet Demonstration and Evaluation System (IDES) application for equipment of type pumps. SAP IDES is a model SAP application that is usually used for demo purpose.

The data extraction logic that was applied by author to build the data model is mentioned below in five steps. The algorithm 1 highlights the data extraction logic from various maintenance related tables in SAP. Figure 2 shows how various maintenance objects and tables in SAP are logically connected.

Step -1: In SAP application, a plant Maintenance order is generated to carry out inspections, preventive maintenance tasks and restore equipment normalcy in case of unplanned or corrective repairs. The preventive maintenance process can be configured to generate a work order based on elapsed fixed time interval or schedule as recommended by the equipment manufacturer. To build data model author has selected all the work orders created for equipment type pumps. The work orders were selected resulting from both corrective and preventive maintenance processes. For corrective maintenance order, a further subdivision was performed classifying each order into breakdown and otherwise. Each instance in the data model with assigned either preventive, corrective or breakdown classification depending on the type of work order that generated that instance.

Step -2 : The lifespan of the pump was assumed to be 15 years [22]. The remaining equipment life was calculated as a difference of equipment life (15 years) and the date of equipment acquisition and date of maintenance order.

Step -3 : To calculate Time in days since last maintenance, number of days were calculated when the order was generated and the last maintenance order was completed. The calculation was performed by finding difference of the order start date and last work order technical completion date.

Step -4 : To calculate Time in days for next Planned Maintenance order, number of pending days were calculated as a difference of order start date and the next scheduled preventive maintenance order in a future date. SAP deadline monitoring functionality was used to calculate next preventive maintenance work order date in future.

Step -5 The condition measurement recordings were used in the data model by calculating the deviation of the recorded measurements from the average. We observed a high correlation between instances those had higher than the threshold value condition measurements resulting in breakdown. The condition based measurement readings were calculated as a percentage deviation of from the mean of upper and lower threshold calculated for 7 days time period before order creation date.

Each instance in the fact table was assigned a classification as either Preventive, Corrective or Breakdown on the reasons listed by author in Table 2.

B. Data Cleaning and Finalization

The database prepared for model consisted of 274 instances for 39 equipments and each instance was associated with 11 features. Each instance in the data model was classified either as preventive, corrective or breakdown based on origin of the maintenance process that generated the maintenance order for the instance. This data was split into 75 percent into the training set (n=205) and 25 percent into test set (n=52)

Algorithm 1: Data extraction Algorithm to build Fact Table

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1 Data: tableEQUI, EQKT(EquipmentMaster)
    VQMEL, QMUR(Notification)
    IMPTT, IMRG(Conditionmeasurements)
    AFIH, AFKO, AUFK(OrderMaster)
Result: Data Model to predict equipment reliability and
    breakdown
2 table perform selection initialization
    // Find all pumps from equipment record and
    their acquisition date
3 while Select All From EQKT where EQKT-EQKTX
    contains *PUMP* do
4     read EQKT-EQUNR (Equipment Number ) and pass
    EQKT-EQUNR into EQUI-EQUNR and get
    EQUI-ANSDT (Equipment Acquisition date)
5 end
6 ; // Find planner group, work center, basic start
    and end date, Plant, Notification, Maintenance
    Plan
7 while Select from AFIH passing EQUI-EQUNR into
    AFIH-EQUNR do
8     read AFIH-IWERK (Plant), AFIH-INGRP (Planner
    group), AFIH-GEWRK(Work Center),
    AFIH-ADDAT(reference date),
    AFIH-QMNUM(Notification),
    AFIH-WARPL(Maintenance Plan)
9 end
10 ; // Fetch Basic start and end date for
    Maintenance Orders
11 while Select from AFKO passing AFIH-AUFNR do
12     read AFKO-GSTRP (Basic Start Date),
    AFKO-GLTRP (Basic Finish Date)
13 end
14 ; // Calculate Condition Monitoring measurements
    Percentage deviation from mean value
15 while Select from IMPTT passing EQUI-EQUNR INTO
    IMPTT-MPOBJ do
16 end
17 read IMPTT-MRMAX (Upper range Limit),
    IMPTT-MRMIN (Lower Range limit),
    IMPTT-POINT(measuring point)and pass IMPTT-POINT
    into IMRG-POINT and Read
    IMRG-READG(Measurement Reading)
18 If IMRG-READG(Measurement Reading)
    >IMPTT-MRMAX then High CBM= Mean(IMPTT-
    MRMAX),(IMPTT-MRMIN)-(IMRG-READG)
19 Last Maintenance completed- Perform (AFKO-GSTRP)-
    (AFIH-ADDAT) Calculate number of days since last
    maintenance completed
20 Asset Life Left= Perform
    (15X365)-((EQUI-ANSDT)-(AFKO-GSTRP))
21 Number of days for next Preventive order= Find
    difference of end date of the order and next
    preventive maintenance order(IP10) /* iterate
    over all examples */
22 Exit

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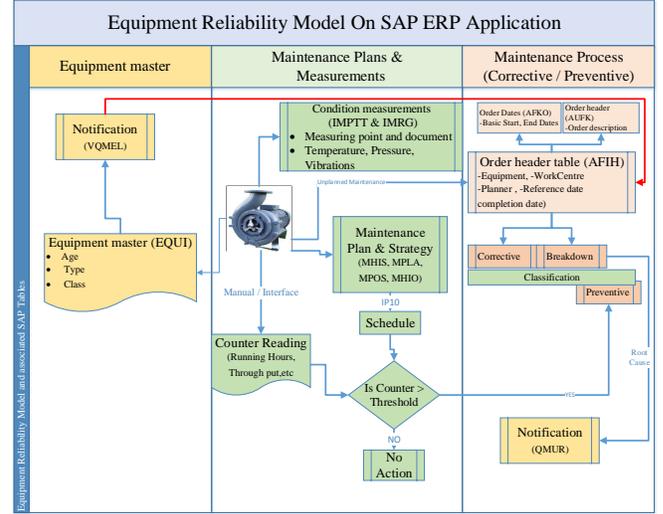


Fig. 2: SAP Maintenance Processes, Objects and Tables
Source: Author

TABLE I: Data Model:Features used in Equipment Reliability Model

Feature	Feature description
Plant	The Physical location where equipment is located. <i>Attribute-Nominal</i>
Equipment	The equipment or the location tag on which failure is to be predicted. <i>Attribute-Nominal</i>
Main WorkCtr	Center or a workshop responsible for maintenance of pumps. <i>Attribute-Nominal</i>
Planner Group	An organization unit or a person who is designated responsible for maintenance of pump. <i>Attribute-Nominal</i>
Asset Life Left	Calculated based on the asset/equipment life left in number of days. <i>Attribute-discrete in 10 bins</i>
Time(days)for next Planned Maintenance	Time in days remaining for next closest scheduled preventive maintenance date in future. <i>attribute-discrete in 10 bins</i>
Time(days) since last maintenance	Time elapsed since last maintenance was completed. Calculated as a difference of basic start date of the order and previous maintenance order completion date. <i>Attribute-discrete in 10 bins</i>
Spare part Used	If spare part was used in the maintenance process (Y/N). <i>Attribute-Boolean(Y/N)</i>
Condition based measurements	The percentage deviation of the measure document from the mean value of upper and lower limit. <i>Attribute-discrete in 10 bins</i>
Root Cause	The cause codes populated in the notification object indicating the reason of equipment failure. <i>Attribute-Nominal</i>
Classification	Either preventive, breakdown or corrective based on work order that generated the instance.

using WEKA resample filter with Invert selection and No replacement filter settings. Each feature in the data model was assigned an attribute highlighted in italics in table 1. The dataset split for class distribution is listed in Table 3.

C. Validating results with Clustering

Clustering technique was applied to the data set in order to validate classification outcome with independent clustering learning to generalize application of equipment reliability model. The table 3 shows that K means clustering algorithm was able to cluster datasets with accuracy of 85 percent. The accuracy percentage was observed to be higher, 88 percent, for

TABLE II: Data Model Instances Classification Rules

Classification	Remarks
Breakdown	Classify instance as breakdown if breakdown Indicator is allocated to the Notification associated with order $VIQME\text{-}MSAUS=X$
Preventive	Classify instance as preventive if the Order is generated with reference to Maintenance plan $AFIH\text{-}WARPL \neq Blank$
Corrective	Classify instance as corrective if Breakdown Indicator is not allocated, order is not generated from subcontracting process

breakdown classification which was the main research problem targeted in the paper. Author has evaluated application of clustering algorithm to ensure generalization of the equipment reliability model if classification labels are not assigned.

TABLE III: Validating Classification label with Clustering Outcome

Cluster to class evaluation	Preventive	Corrective	Breakdown	Total
Observed Classification	102	51	121	274
Instances correctly clustered (%)	83	85	88	85
Instances correctly clustered (Number)	83	43	106	232

V. EXPERIMENT RESULTS - IMPLEMENTATION OF MACHINE LEARNING ALGORITHMS

Author has applied six ML algorithms: Naive Bias, Logistic Regression, Support vector Machine, KNN, Decision Tree and SVM that are part of supervised learning on the data model and evaluated the results. Each ML algorithm was trained using the training data set and the model was tested on the test data set. The WEKA software tool was used to perform training and testing of classifier model.

Salzburg [23], states that cross-validation is an effective method for the reduction of data dependency thereby improving the reliability of the results acquired. In this regard, ML algorithms used to built classifier model were subjected to 10 fold cross validation which is deemed to improve generalization of the model and avoids over-fitting. The results recorded are mentioned in Table 4 and 5 for training and test sets listing accuracy, precision, recall, true positive rate (TPR) and F-score of each algorithm.

The results observed on test data showed that Decision tree, SVM, and LR showed higher accuracy rate of more than 94.5 percent. The true positive rate of the model for DT, SVM, and LR was also observed to be more than .95 and .98 for DT. The False positive rate (FPR) was observed to be very low for these algorithms, confirming to the paper objective to correctly and timely predicting equipment failure.

Based on the results, it can be assumed that LR, SVM, and Decision tree are suitable to perform equipment reliability and predicting breakdowns for equipment on SAP database. However, to negate bias and variance factors, researchers implemented ensemble methods that are detailed in the next section of the document.

TABLE IV: Results of ML Algorithm-Training Dataset CV 10 Fold

Algorithm	Accuracy	Precision	Recall	F-measure	TPR
NB	84.39	0.85	0.844	0.844	0.844
DT	80.01	0.78	0.80	0.78	0.80
KNN, K=4	84.78	0.842	0.849	0.836	0.849
SVM	84.39	.839	.844	0.841	0.844
SVM Breakdown	91.1	.891	.911	0.901	0.911
LR	82.44	.812	.824	0.814	0.824

TABLE V: Results of ML Algorithm-Test Dataset

Algorithm	Accuracy	Precision	Recall	F-Measure	TPR
NB (CV 10 Fold)	92.30	.925	.923	0.922	0.923
DT	94.23	0.951	0.942	0.942	0.942
KNN, K=1	78.84	0.78	0.78	0.775	0.788
SVM	98.07	0.982	0.981	0.981	0.981
SVM Breakdown	99.98	0.941	1.0	0.97	1.0
LR	100	1	1	1	1

The test results of classification models using various ML algorithms is also shown in figure 3.

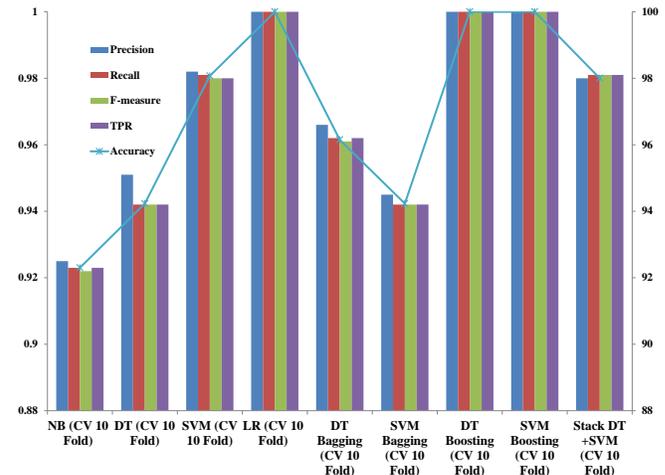


Fig. 3: Test Results of various ML Algorithms

VI. ENSEMBLE METHODS: NEGATING BIAS AND VARIANCE

The negation of bias and variance were managed by Author by deploying boosting, bagging and stacking techniques that are part of ensemble methods with 10 fold cross validation. The bagging technique when called builds multiple models independently and draws sample data sets randomly from the data pool with an objective to decrease variance. However, boosting technique adds new model incrementally to the classifier with an objective to manage bias. The stacking technique was also used by author where SVM, and decision tree models were combined to achieve better prediction and classification results.

The analysis of the results listed in table 6 acquired from the aforementioned examination of the classification algorithms revealed that SVM and Decision Tree are appropriate methods to predict equipment failure. The experiment test results

recorded for these two algorithms were observed to show high accuracy and true positive rate of close to 100 percent.

TABLE VI: Results of ML Algorithm Ensemble Methods-Test Dataset

Algorithm	Accuracy	Precision	Recall	F-measure	TPR
SVM Bagging (CV 10 Fold)	94.23	0.945	0.942	0.942	0.942
DT Bagging (CV 10 Fold)	96.15	0.966	0.962	0.961	0.962
SVM Boosting (CV 10 Fold)	100	1	1	1	1
DT Boosting (CV 10 Fold)	100	1	1	1	1
Stack DT+SVM (CV 10 Fold)	98.071	0.982	0.981	0.981	0.981

VII. CONCLUSION

The present paper proposes a equipment reliability model that integrates historical data from maintenance processes existing in SAP application with ML algorithms. The model identifies set of relevant features useful to predict equipment reliability with accuracy of more than 95 percent. The application of the study highlighted in the paper can also be applied to any other IT application not limiting only to SAP as the rules to design data model will remain more or less same. An additional research is recommended that may lead lead to improved accuracy and generalization of the equipment reliability model by integrating clustering outcomes with supervised ML algorithms to perform classification and predict equipment reliability.

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