Improving the Prediction and Accuracy of Parts Marketing Promotion Program for Heavy Equipment Spare Parts Business Through Digitalization Approach

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Abstract*—In the face of changes in customer policy that are very fast due to changing market conditions, a promotional approach and a customer approach are also needed that are in accordance with existing conditions. This also occurs in the field of heavy equipment spare parts trading, where the spare parts offered and promoted to the customer must be in accordance with what the customer needs. It often happens now that what is trying to promote to customers is not in accordance with the needs due to the condition of the unit that is not operational or has even been standardized. In this research, the author tries to propose a prediction method for customer spare parts needs with a digital technology approach, where the purpose of this research is so that parts salesmen can easily find out customer needs quickly and continue with promotions to increase sales. In this research, the Author used a Focus Group Discussion (FGD) with the team and DMAIC analysis in finding the necessary improvements. The findings of this research are that by using a historical demand and sales approach and analyzed with a machine learning algorithm, it will obtain a prediction of the opportunity needed, besides that the Author also uses the End of Life (EOL) Spare Parts approach to predict when there will be a change. With these two approaches, it can be used effectively in predicting the needs of heavy equipment spare parts.

***Keywords*—machine learning, parts prediction, heavy equipment parts, opportunity prediction. parts sales opportunity.**

I. Introduction

The decline in coal prices has greatly affected the business in the heavy equipment sales sector, this is because the coal mining business has the largest contribution in heavy equipment sales compared to other sectors such as the construction sector or the agro-business sector. This can be seen when the coal price of USD 120/ Ton in July 2018 continued to move down and became USD 60/Ton in September 2019 which had an impact on heavy equipment unit sales, which decreased by almost 40% in 2019. This was due to the sluggishness of the coal sales business. This is because the coal mining contractor company is holding back heavy equipment investment even if there are many existing equipment on standby to match the decreasing production target. Fluctuations in coal prices not only affect coal companies but also directly affect economic growth [1]. With its standby capacity, this tool has an impact on the sales of spare parts which have also decreased. As data taken in the last five years from one of the Komatsu heavy equipment distributor companies in Indonesia regarding the sales of heavy equipment spare parts, it shows that sales have decreased by around 11% in 2019 compared to the previous year. For this research Author focus to Komatsu Product because this product is the biggest contributor sales of the company and the Pareto method by looking at the Ranking and Selection can represent finding the best solution for overall improvement in this research [2].

The decline in sales of heavy equipment spare parts also adds to the tighter competition for sales of heavy equipment spare parts because at the same time spare parts suppliers have high inventory stock, so they are competing to win the market with their respective sales strategies. One of the strategies launched by the company is how to increase the prediction of customer spare parts needs so that they are right on target in conducting follow-up opportunities and creating promotional programs. Currently, the prediction of opportunity is still done manually by parts salesmen so that it is often inaccurate and not in accordance with customer needs. As explained in Fig. 1 below, in carrying out sales activities to customers, a parts salesman will offer spare parts needs according to customer needs, where the list of needs is made manually by parts salesmen using both historical and deterministic approaches.

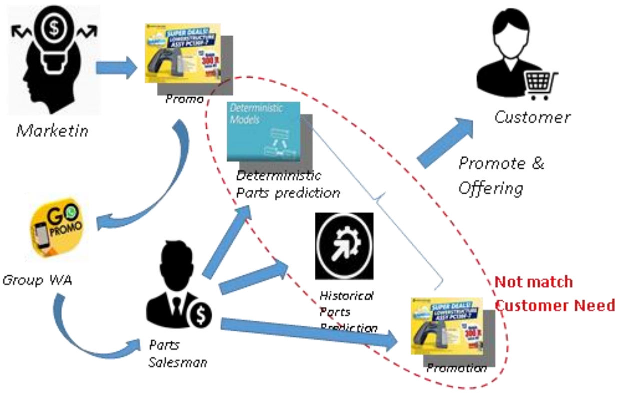

Fig. 1. Flow process promotion approach to customer (Source: Internal Data Company)

II. LITERATURE REVIEW

A. *Machine Learning and Big Data Analysis*

In conducting this research, the author tries to study several journals related to how to predict customer needs. The first approach is to use Big Data Analysis and algorithms using historical data analysis. Many industries and large companies use this approach because it is considered very helpful in making predictions with a high degree of accuracy. With the help of technology, it will be easier to carry out Big Data analysis so that it can generate Value for future business development [3]. Several industries that use this approach include the Transportation Business which studies customer behavior predictions in ordering transportation equipment. In this case the algorithm used is Support Vector Machine (SVM). where this algorithm is one of the methods in supervised learning that is usually used for classification (such as Support Vector Classification) and regression (Support Vector Regression). In classification modelling, SVM has a more mature and clearer mathematical concept compared to other classification techniques. SVM can also solve classification and regression problems linear and non-linear.

In the Banking Business, deeper customer data analysis is also very much needed, because with the right big data analysis, the company can carry out a strategy according to what the market needs in winning the competition [4], especially with uncertain market conditions. Start by analyzing how customers do transactions, how do customers interact with bank officers, whether by telephone or customers coming to the office to make transactions. This data can be used as material for analysis to improve services, create a new product and can be used as a new strategy in marketing. In this research, Jaiswal used three algorithmic methods, namely; Logistic Regression, Artificial Neural Network and Boosting Algorithm (XG Boost), where the main objectives of using this algorithm are:

- Help create key features that help predict future transactions.
- The probability that the customer will complete the transaction.
- Determine the perfect model for predicting customer behaviour.

From the results of the analysis carried out using these three algorithms and using anonymous data from Standard Bank, prediction data is generated as in the Table 1 below:

TABLE I
COMPARISON OF BANK CUSTOMER PREDICTION WITH LR, ANN AND XG BOOST ALGORITHM [4]

Measure of Comparison	Logistic Regression	Artificial Neural Network	XGBoost
Positive Class	1	1	1
Train Accuracy	90.85%	81.90%	99.28%
Test Accuracy	91.13%	81.84%	91.68%
Overfitting	No	No	Yes (slight)
NIR	0.9018	0.8993	0.8993
Kappa	0.275	0.369	0.4964
Precision	0.6586	0.3274	0.6083
Recall	0.2012	0.7615	0.48796
F1	0.3083	0.4579	0.54152
Balanced Accuracy	**0.5949**	**0.7931**	**0.72638**
AUC	0.8313	0.7999	0.8875
Correct 0 Predictions	98.863%	82.475%	96.480%
Correct 1 Predictions	20.127%	76.148%	48.792%

From the Table 1, it can be seen that the accuracy data using the Artificial Neural Network algorithm and XG Boost needs to be considered, because it produces predictive data with a high level of accuracy, besides that both methods can predict the number of satisfactory transactions that customers will make.

in other journals that do research on customer demand predictions in the transportation sector also explain that that by analyzing the Top 10 Important Features, predictive data will be obtained for customer behaviour in the next 14 days [5].

Furthermore, the author wants to see the correlation of the prediction of demand for heavy equipment parts in this research with the prediction method of remanufacturing parts in the mining industry, where comprehensive data can be used as an approach to get a prediction of demand for remanufacture products which is then used to develop a marketing strategy [6]. Some of the algorithmic methods used in research on remanufacturing this product include; SVM, Artificial Neural Network (ANN), Key Nearest Neighbors (KNN) and Random Forrest (RF). It is hoped that using this algorithmic approach will obtain the most accurate predictive data for the remanufacturing industry.

B. *End of Life approach*

Traditionally, forecasting is based on simple extrapolation from historical data. This method is commonly referred to as the black box method and is very popular because it is very simple, as the information required is limited to historical demand data. This method only takes historical data series whether weekly, monthly or yearly, this method has become widespread in business since the work of Box and Jenkins (1976). As a development in forecasting parts at this time, apart from using the historical demand forecast which is considered a traditional way of predicting parts, it is also developed using the Install Base Concept, this is to get better accuracy. Because basically spare parts technically have a predictable lifespan, some are long life and some are short life. This forecast approach method is also used to determine the warranty period of these spare parts. In this research, the writer tries to use the Install Base Information and End of Life forecast approach of spare parts to predict customer needs for spare parts as written by [7]. In simple terms, if the sales of the product to the customer is S (t) in weeks (t), R (t) is the return from the customer in that week and L shows the average product service life in general. The Install Base Life time can be formulated as follows:

$$IBL(t) = \sum_{i=t=L+1}^{t} (S(i) - R(i) \qquad (1)$$

In considering the accuracy of demand in sales, you must also consider the warranty period given, because sales will occur if the spare parts are out of warranty period. Therefore, if it is related to the warranty period given, the Install Base Warranty IBW (t) can be formulated as follows:

$$IBW(t) = \sum_{i=t=W+1}^{t} (S(i) - R(i) \qquad (2)$$

So that after a sales product is sold, it is connected to the Install Base lifetime (IBL), Install Base warranty (IBW) and the Demand that will occur in the future, the diagram (Fig.2) data can be drawn as follows:

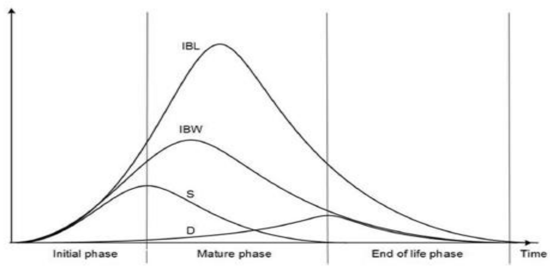

Fig. 2. Sketch of product sales (S), install base (IBL and IBW) [7]

III. Analysis

On the Depth analysis process author using a Focus Group Discussion (FGD) which in this discussion involved all members of the CSSD (Customer Support and Sales Department), in addition to involving the DAD (Differentiation and Digitalization) teams as a development of existing ideas. In this discussion, the analysis method we use is DMAIC (Define, Measure, Analysis, Improve and Control). There are two analysis approaches, namely the historical data approach that will use machine learning and the end-of-life approach of spare parts by studying the installation data and the results of the inspections.

A. *Machine Learning*

Analysis using algorithmic and machine learning approaches requires Big Data preparation first, in this case to predict the opportunity for heavy equipment and data required, among others; Demand and Sales Spare parts Data, Interchange Parts Number, Customer Running Hour Unit and Customer Clustering.

- Demand and Sales Data

Demand data referred to here is a request from the customer for spare parts that are equipped with a purchase order document. Before there was a purchase order, it could not be said as a demand but it was still in the inquiry phase in the Sales Funnel. Furthermore, this purchase order document will be inputted into the SAP system by the COP (Customer Order Processor) so that customer demand data in all branches and sites can be stored in the SAP system. For the needs of analysis in this research, the demand data taken is data for five years backwards, it aims to be able to enrich the data needed, taking into account changes and market conditions in that year, what changes in demand data will be read.

- Interchange Parts Number

The meaning of the Interchange Parts Number is the replacement parts number supplied to the customer, this replacement comes from the principal's database who has indeed replaced a parts number. Replacement of parts number is usually carried out by the principal due to the improvements made to the spare parts, it could be that the spare parts with the old parts number have a problem with quality, so the parts service news will be issued along with the replacement parts number. Replacement of parts numbers can also be done because there is a change in the vendor of the principal so that it is easy to trace the part number from which vendor.

- Machine Operating Hour

In this research the author wants to make a different approach in predicting spare parts, in this case Author wants to take advantage of big data that has been available so far but has not been utilized optimally. The data in question is Komtrax data. Komtrax is one of the digital technologies available in the Komatsu unit, Komtrax is installed in all Komatsu units when the new unit begins delivery from the factory. It will connect units located throughout Indonesia with servers connected via satellite. With Komtrax the latest data can be known and taken from the unit, the data include, the location of the unit, the unit's operating hours, fuel consumption, oil temperature and the condition of the components if they experience abnormal conditions. With Komtrax technology, it can be detected earlier if damage occurs so that even greater damage can be avoided. In this research the author wants to use the data on the number of unit operating hours to determine whether this unit is active or in standby. From this data, it will be developed if the unit is operating, what spare parts will be replaced according to the number of units currently operating.

- Customer Clustering

Customer clustering is used so that the company can map the strategies that will be implemented in accordance with the customer clusters and segments. This strategy is to build an excellent Customer Relationship Management (CRM) concept because with excellent CRM it can increase sales and profits for the company [8]. Customer clustering is made by considering the number of unit population the customer has and the customer's key buying factor. from the existing sales data, it can be seen that the Cluster Customer A group with 251 customers has a sales contribution of 83% and customer cluster B with the number of Customers 1926 has a contribution 12% while the customer cluster C with the number of 2010 customers has a sales contribution of 5%, and in this research the focus will be implemented to Customer clusters A and B.

- Algorithm Selection

The next process is to choose an algorithm that will be used in machine learning. After studying several algorithms that are commonly used to predict customer needs in several companies and industries, the Author decided to test several algorithms on the demand and sales patterns of heavy equipment spare parts. Some of these algorithms include; XG Boost, Logistic Regression, Naïve Bayes, Random Forest and SVM Classivier. By considering the demand and sales data for five years, the following data as shown in Table 2 are obtained:

TABLE II
RESULT ALGORITHM TEST FOR DEMAND PARTS HEAVY EQUIPMENT

Machine Learning Algorithm	Accuracy Training	Accuracy Test	Precision	Recall	AUC
XG Boost	88,10%	88,00%	90,00%	97,00%	73,00%
Logistic Regression	85,00%	84,90%	88,00%	94,00%	66,00%
Naïve Bayes	85,50%	85,50%	86,00%	97,00%	62,00%
Random Forest	97,90%	86,40%	87,00%	94,00%	73,00%
SVM Classifier	87,50%	87,40%	89,10%	95,50%	72,00%

It can be seen from the graph and data above that the XG Boost Algorithm has the highest Accuracy test, namely 88.00%, 90% precision and 97% recall. So, it can be concluded that the algorithm that is most suitable for use as machine learning to calculate the prediction of Demand for heavy equipment spare parts is the XG Boost Algorithm.

B. *End of Life Spare Parts*

Another approach in predicting the opportunity for spare parts is to use the End-of-Life Concept, where the approach uses a prediction of when the spare parts will be damaged by looking at data from the measurement inspection data that has been carried out previously. For heavy equipment spare parts, this approach is used specifically for Spare Parts Under Carriage (UC). The undercarriage is a very important spare part for heavy equipment, because the price is expensive, almost 30% of the unit price and the supply takes a long time. The undercarriage is attached to the Dozer and Excavator units. Undercarriage types ranging from Track link, Shoe plate, Track Roller, Carrier Roller, Idler and Sprocket. Special treatment is required in Undercarriage preparation in order to obtain an accurate plan. The special treatment referred to is the inspection carried out by the Undercarriage inspectors at all branches and sites. They are equipped with an ultrasonic tool to determine the wear rate that occurs on the undercarriage surface, with this data and compared with the factory standard wear data, it can be predicted when the undercarriage must be replaced, making it easier to carry out preparation. This concept is the concept of Preparation spare parts with the Install Base and End of Life (EOL) approach, which is to try to complete the data on the installation and inspection of these parts to get a prediction about when spare parts will be replaced [7].

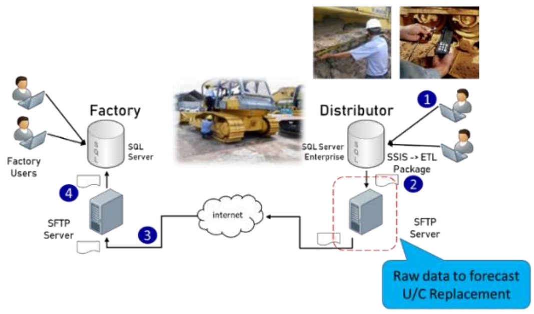

Fig. 3. Undercarriage management system (UMS) Source: Internal Company Data (SPM Department)

Fig. 3 is showing the concept of the UMS, all data from the inspection results carried out by the Undercarriage Inspector are inputted into the UMS system. Basically, all Undercarriage inspectors are equipped with a laptop facility arm and are integrated with the internet to speed up inspection reports. The data that is input into the system will be directly extracted into a text file according to the required data row. The text file is in the form of data information: Date of measurement, Customer Name, Model Unit, Work Location, Name of the undercarriage parts being measured and the measurement results. Then the data will be stored on the server and scheduled will be sent to the Factory FTP server, where the previous FTP connection has been set for synchronization. After the data is entered into the Factory server, the data will also be processed in a scheduled schedule to become row data to forecast undercarriage production at the Factory. This has been done so far in cooperation between distributors and factories. This data is what the Author tries to use to be processed into promotional opportunity data to customers. Where before the data is sent to the factory, we try to access the data so that it can be processed as well as very important data for opportunities to customers. In this undercarriage management system concept, the data downloaded from the UMS system will be prepared first together with other data for further processing. In this processing, a simpler machine learning is made which we call the Undercarriage Analytics Engine. As shown in the Fig. 4 below that the Undercarriage Analytics Engine will analyze the data from the Undercarriage measurement results, where the measurement results will determine the level of wear and when the undercarriage requires replacement.

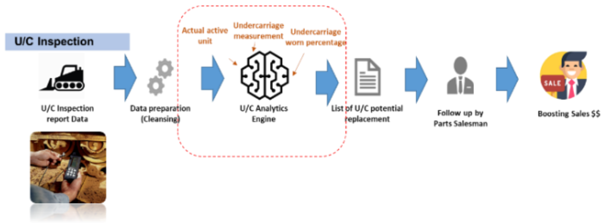

Fig. 4. Undercarriage Prediction Concept (Source: Internal Company Data)

Furthermore, the data will also be processed with Active Unit feature data from customers, with the hope that we will only follow up opportunities for units that are still actively operating, where we get this data from Komtrax Server. From this data, a data output will appear in the form of an undercarriage list that has the potential to be replaced. The data will be continued by the parts salesman team as opportunity sales data and offered to customers.

C. *Monitoring Impact to Sales*

To ensure the implementation and impact of machine learning made, control and monitoring are carried out for three months on opportunity parts sales. As shown in Fig. 5 below, it can be seen that there is an additional sales average of five billion Rupiah which comes from opportunities generated by machine learning. This will continue to be monitored and developed for further machine learning improvements.

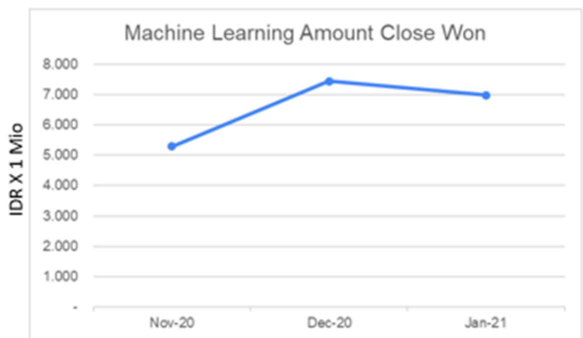

Fig. 5. Close won opportunity from machine learning (Source: Internal Company Data)

IV. CONCLUSION AND SUGGESTION

Finally, at the end of this research, the author makes the following conclusions:

1. This paper is prepared by taking into account the existing Macro conditions, especially those related to heavy equipment industry, as well as Micro conditions regarding the business performance of the sale of heavy equipment and its spare parts. To help analyze existing problems, the Author uses interrelationship diagrams and DMAIC Concept in order to obtain the desired solution analysis. In addition, the most important thing here is the direction of the resulting solution is the digitalization technology approach.

2. Findings from this research are:

   a. In forecasting demand for heavy equipment spare parts machine learning with the XG Boost Algorithm has a Test Accuracy of 88%, 90% Precision and 97% Recall, the highest compared to the Logistic Regression algorithm, Naive Bayes, Random Forest and SVM Classifier.

   b. Comprehensive undercarriage inspection data that was previously only used to forecast production at the factory can also be used to forecast future opportunities for demand.

   c. With the concept of Pareto and contribution, we can make customer clustering for project focus

3. Contributor to academics:

   This paper has an academic contribution by providing a method to predict the opportunity for heavy equipment spare parts with a digital technology approach

4. Practical Contributor are:

   a. Improvement of Parts Sales Operation

   With the digital approach in making opportunity predictions, in general this is an improvement in parts sales operations. Because previously this activity was done manually by the Parts Salesman, now it is done by machine learning.

   b. Help increase sales with accurate promotion and sales planning

   The ultimate goal of research is to increase sales of heavy equipment parts. With good opportunity accuracy, it will be possible to make a good sales plan as well, this will be very helpful in making a promotion strategy and preparing stock parts to be sold, so that it will increase sales.

5. The Future of Opportunity Prediction:

   a. Further developed the concept of machine learning with complete external features

   b. Make better use of big data with deeper analysis for developing opportunity predictions (Backlog Recommendations, Overhaul Plan)

V. REFERENCES

[1] X. Wang, C. Liu, S. Chen, L Chen, K. Li, and N Liu, "Impact of coal sector's de-capacity policy on coal price," *Applied Energy*, 265, 2020. https://doi.org/10.1016/j.apenergy.2020.114802

[2] S. Andradóttir, J. S. Lee, "Pareto set estimation with guaranteed probability of correct selection," *European Journal of Operational Research*, 2020. https://doi.org/10.1016/j.ejor.2020.10.021.

[3] S. C. Wang, Y. T. Tsai, and Y. S. Ciou, "A hybrid big data analytical approach for analyzing customer patterns through an integrated supply chain network," *Journal of Industrial Information Integration*, 20, pp. 100177, 2020. https://doi.org/10.1016/j.jii.2020.100177

[4] D. P. Jaiswal, S. Kumar, and P. Mukherjee, "Customer transaction prediction system," *Procedia Computer Science*, 168, pp. 49–56, 2020. https://doi.org/10.1016/j.procs.2020.02.256

[5] L. M. Kieu, Y. Ou, L. T. Truong, and C. A. Cai, "A class-specific soft voting framework for customer booking prediction in on-demand transport," *Transportation Research Part C: Emerging Technologies*, 114 , pp. 377–390, 2020. https://doi.org/10.1016/j.trc.2020.02.010

[6] T. V. Nguyen, L. Zhou, A. Y. L. Chong, B. Li, X. Pu, "Predicting customer demand for remanufactured products: A data-mining approach," *European Journal of Operational Research*, 281 (3), pp. 543–558, 2020. https://doi.org/10.1016/j.ejor.2019.08.015

[7] T. Y. Kim, R. Dekker, and C. Heij, "Spare part demand forecasting for consumer goods using installed base information," *Computers and Industrial Engineering*, 103, pp. 201–215, 2017. https://doi.org/10.1016/j.cie.2016.11.014

[8] C. H. Cheng and Y. S. Chen, "Classifying the segmentation of customer value via RFM model and RS theory," *Expert Systems with Applications*, 36 (3 PART 1), pp. 4176–4184, 2009. https://doi.org/10.1016/j.eswa.2008.04.003