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PREFACE

The Journal of Emerging Supply Chain, Clean Energy, and Process Engineering (JESCEE) is published by the Faculty of Industrial Technology at Universitas Pertamina. It fosters communication among researchers, disseminates research findings, cultivates an academic culture, and encourages the development of new ideas in the fields of mechanical, electrical, chemical, and logistics engineering. The journal's Volume 4, Issue No. 1, has attracted significant attention from numerous researchers eager to publish their work.

On behalf of the Editor-in-Chief, I would like to extend my gratitude to everyone who supports this journal, especially the Dean of the Faculty of Industrial Technology for their direct and indirect assistance. I also appreciate the dedicated editors, the reviewers who provide valuable suggestions and constructive feedback on each submitted paper, and the authors who trust JESCEE with publishing their research.

We hope that this publication will continue to grow and present the latest information in the fields of mechanical, electrical, chemical, and logistics engineering. We also welcome collaborations from individuals and organizations that value this journal and wish to contribute to its ongoing development.

Jakarta, October 2025
Editor-in-Chief

Assoc. Prof. Dr. Eng. Ir. Muhammad Abdillah, S.T., M.T.

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DEVELOPMENT OF WEB-BASED GOODS STOCK RECORDING SYSTEM DESIGN: A CASE STUDY IN INDONESIA

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Abstract
In this day and age, technology is something that everyone uses in their daily activities. Web system technology has been widely used. Technology is a tool that can make it easier for users to carry out daily activities. Web System technology is one of the most active technologies in all companies. Pt Ingress Technologies Indonesia still uses the old method of using stock management using Microsoft Excel. This study aims to determine the stock of goods at PT Ingress Technologies Indonesia through the Web System. This research method uses a qualitative descriptive type of research used in this study to obtain an in-depth and comprehensive development of the inventory management record system at PT Ingress Technologies Indonesia. The results of this study are the recording system through the web system is very influential for an organization or company in their management, and in inputting data it is easier when using the web. The development of a recording system that will be carried out by the company through a web system must be realized immediately, in order to increase the effectiveness and efficiency of each employee in carrying out the recording system.

Keywords:
Example; recoding system; web system; good stock

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1. Introduction

Warehouses play a crucial role in the success of a company's supply chain. A good warehouse should facilitate the achievement of its main objectives. PT Ingress Technologies Indonesia is a company that manufactures automotive components and operates in the trading sector, producing spare parts. Despite the rapid development of Information Technology and Information Systems, the warehouse activities at PT Ingress Technologies Indonesia have not yet implemented information system technology. Recording of goods, such as production output and items to be shipped, is still done manually using Microsoft Excel. As a result, the process of locating finished goods becomes time-consuming as employees struggle to find the desired stock items for customers. This manual recording leads to inefficiency in production activities.

Currently, technology is widely used by everyone in their daily activities, including the use of Web Systems. Web System technology is one of the most active technologies in all companies. A web-based information system is a set of interconnected components that function to collect, process, store, and transfer information in the form of text, images, sound, and hypertext, accessible by software to support organizational activities in achieving goals.

Based on the above explanation, the purpose of this research is to determine the stock of goods at PT Ingress Technologies Indonesia through a web system and propose the implementation of web system technology at PT Ingress Technologies Indonesia.

2. Methods

In terms of data type, the approach used in this research is descriptive qualitative research, intended to obtain in-depth and comprehensive development of the inventory management recording system at PT Ingress Technologies Indonesia through the web-based inventory management system.

The data collection methods used in this research are interviews, direct observation, and documentation. Based on the conducted interviews, the problems occurring in all warehouse activities were identified. The direct observation revealed that the current system used is manual and does not utilize a web-based system. The documentation results include stock data records and current condition photos of the storage warehouse, which serve as analytical materials for the development of the web-based system

The data analysis technique used in this research is a qualitative approach using the Miles and Huberman method to address the research objectives. The sequence of this method is as follows:

a) Data reduction
b) Data presentation after data reduction
c) Drawing conclusions and verifying the next process

3. Discussion

A. Interview

Interviews were conducted with pre-determined informants. The results of the interviews were interpreted to draw conclusions.

a) To Facilitate Users

In this case, the use of a web-based system facilitates users in conducting recording activities compared to manual recording systems.

Table 1. Interview Result "Facilitate Users"

Can a web system facilitate users in conducting recording activities?		
Informants	Answer	Verbatim Aalysis
1st Informant (Sir Agus Fauzan)	The use of a web system makes it easier for users to perform their tasks, particularly in terms of recording activities. As known, manual recording systems can be time-consuming for workers to perform their tasks.	It has a significant impact on the recording system through the use of a web-based system.
2nd Informant (Sir Supriyanto)	Compared to manual recording systems, using a web-based system can facilitate and reduce the time for its users. Additionally, a web system can connect users without the limitations of distance or geographical boundaries.	Recording through a web-based system has a significant impact on its users.
3rd Academician (Sir Yusup Rachmat Hidayat)	In my opinion, in a web-based recording system, it would certainly be easier compared to manual recording systems.	It has a significant impact when using a web-based recording system.

b) The effectiveness of recording systems through a web-based system

Recording systems using a web-based system are much more effective and helpful for users who will perform their tasks.

Table 2. Interview Result "The Effectiveness of Recording System Through A Web-Based System"

Is the use of a web-based system effective within a company when conducting recording activities?		
Informants	Answer	Verbatim Analysis
1st Informant	A web-based system can make recording activities within a	The web-based system enhances the effectiveness of

(Sir Agus Fauzan)	company more effective and integrated among its users. Even when users are outside the office, they can access the web system through their mobile phones.	its users in performing recording activities.
2nd Informant (Sir Supriyanto)	The presence of a web-based system can greatly assist and improve the efficiency of workers in recording activities. Additionally, the completion of tasks using a web-based system is faster compared to manual recording systems.	The web-based system is highly beneficial and effective for its users.
3rd Academician (Sir Yusup Rachmat Hidayat)	Recording in a web-based system is more effective and efficient compared to manual recording systems.	Recording through a web-based system is more effective and efficient.

c) Obstacles of the recording system through a web-based system

Despite its ability to expedite and assist in recording activities, web-based systems also have their own obstacles.

Table 3. Interview Result "Obstacles of the Recording System Through a Web-Based System"

What are the obstacles that may be encountered when implementing a web-based recording system?		
Informants	Answer	Verbatim Analysis
1st Informant (Sir Agus Fauzan)	Recording through a web-based system has its obstacles, particularly in terms of network or internet connectivity, which needs to be consistently available.	The presence of network or internet connectivity obstacles can cause delays in the recording system.
2nd Informant (Sir Supriyanto)	The obstacles that occur when using a web-based recording system include the need for users to understand how to use the web system effectively.	Users also need to understand how to use the web-based system before conducting recording activities through it.
3rd Academician (Sir Yusup Rachmat Hidayat)	Recording systems using a web-based system still require data backups in case of any potential troubles or issues.	Recording systems in a web-based system should have data backups in case there are any issues with the web itself.

B. Direct Observation

The recording system through a web-based system can assist and support the performance of its users. In this case, using a web-based recording system is more effective and efficient compared to manual recording systems. Therefore, the web-based recording system is more integrated or connected among its users.

Discussion

a) Development of Stock Management Recording System at PT. Ingress Technologies Indonesia through Web-based Stock Management System
Based on the answers obtained from interviews with several informants, it can be concluded that the recording system through a web-based system has a significant impact on recording activities within an

organization or company. Therefore, many organizations and companies have implemented recording systems through web-based systems.

b) Obstacles in the Recording System through Web-based Systems
In this case, the recording system through web-based systems faces several obstacles, including the requirement for users to understand how to use the web system effectively, the need for consistent network and internet connectivity, and the necessity of data or file backups in case of issues with the web. These obstacles significantly impact the recording system in the web-based system.

c) Efforts to overcome obstacles in the recording system through web-based systems include
Based on the identified obstacles in the recording system through web-based systems, the author concludes the following efforts that need to be undertaken to address these obstacles:
   i. An organization or company should conduct trials or experiments on how to use the web-based system before implementing the recording system through the web system.
   ii. An organization or company must ensure a continuous network connection and internet connectivity to enable the uninterrupted use of the recording system through the web system.
   iii. Each user or user should have backup files to minimize potential issues with the web system.

4. Conclusion

Based on the research findings, the following are the conclusions derived from the data processing:

a) Recording systems through a web-based system have a significant impact on the management of an organization or company, and data input is easier when utilizing such a web system.

b) Recording systems through a web-based system are more effective and efficient in company activities, and they can enhance employee performance.

c) Recording systems through a web-based system are highly integrated with all users, as each user can access the recorded data through the web system, making it easier to search for information

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ENHANCING PATIENT EXPERIENCE IN RADIOLOGY: PREDICTIVE MODELING OF WAIT TIMES USING FEATURE SELECTION TECHNIQUES

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Abstract
The increasing patient flow and overcrowding in critical hospital departments have prompted the need for effective strategies to enhance patient satisfaction. This study focuses on machine learning algorithms to predict patient waiting times for X-ray services using the dataset from a high-volume radiology department. Three regression models, such as Linear Regression (LR), K-Nearest Neighbor (KNN), and Random Forest (RF) were proposed and integrated with the recursive feature elimination (RFE) algorithm to reduce the dimension of the dataset and to enhance the model's efficiency by selecting optimal features. The findings indicate that the LR-RFE model with 30 features predicted waiting time with a mean absolute error of 3.63 minutes as compared to the standard LR model with 63 features. Comparable results were observed with the RF and KNN models, which demonstrated mean absolute errors of 3.77 minutes and 3.81 minutes, respectively. Furthermore, the feature revealed key contributors to waiting times, such as the sum of patient queue wait times, the number of patients waiting in line, and the wait time for the most recent patient. This study underscores the potential of machine learning techniques combined with feature selection to offer actionable insights for better patient queue management.

Keywords:
Machine learning; feature selection, wait time, patient flow, regression

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1. Introduction

In most of the hospitals, dynamics of the patient queues critically shape the clinical workflow. As a result, predicting patient flow and wait times has become one of the most important clinical management techniques. The queuing is caused by variations in supply and demand, as well as a lack of resources at hand [1]. Implementing a tool for planning and control and using operational management techniques are the main goals to improve the operational efficiency in a sector. Radiology departments (RD) are the most important units in each hospital because they help in generating diagnostic information about a patient's condition. The problems of long waiting times among patients are faced due to crowd in the department. Most of the patients visiting RDs face long waiting times due to overcrowding which is a major concern across the hospitals in the United States. The patient flow should be improved by scaling up linked wards to achieve coordinated flow and by considering the total patient flow throughout the wards rather than concentrating on specific wards to prevent irregular flow [2].

When there are no slots available at the RD, the patient must wait in the preceding ward, which causes the queue to grow and seems to be problematic for patient flow. Therefore, the accurate prediction of radiology emergency patient flow is of great importance to optimize appointment scheduling decisions. This requires an accurate and efficient method to model the experienced waiting time for patients visiting an emergency medical services unit.

The main causes for overcrowding at the RD are the excessive number of non-emergencies, unscheduled patients, and the socially recommended cases, in addition to the shortage of specialist radiology physicians. The majority of patients (74.1%) had examinations lasting between one and five minutes, particularly for X-rays, according to the distribution of patients based on examination time. The research shows that many models for estimating waiting time and utilization are available today but not adopted in our country [3]. Our main aim is to evaluate the applicability of machine learning models to predict patient wait time in walk in facility in RD. In this department even for high-priority cases, the hospital is facing a problem of long patient wait times. Due to the interconnectivity of the wards, any problem in the RD ward has a direct impact on the patient at the front of the line, resulting in the formation of a patient queues. There are many stages in healthcare system such as admission time, the in-patient period, and the discharge process. Not all phases of a patient's flow are carried out inside a single ward, and and a well-functioning infrastructure is necessary for the effective performance of these operations [4].

The patient flow is greater and has been worst during COVID 19 outbreaks. Considering the identified issue, the RD is the main area of attention since the flow needs to be changed without causing any harm to the Department. An overcrowded clinic is stressful, whereas an idle clinic wastes resources and is depressing. Realistic and timely prediction helps prevent congestion and idle time. It also helps load-balance by rerouting arriving patients to less-busy sections before it gets too packed. Modelling usually identifies waitline problems and proposes solutions (e.g., hiring more staff, implementing a ticketing system, using electronic patient records,polling patients for feedback) and uses discrete event simulation to prevent patient overcrowding.[5], [6] This study uses different ML models to predict waiting time of patients in walk-in RD for X-ray facility with consideration of different features related to patient queue, exam type and time related information. We constructed three linear and nonlinear models to predict wait times of patients at the time of arrival. The Linear regression, K-nearest neighbors, random forest models were applied on data and then evaluate the results for prediction of waiting time of patients wait for X ray exam.

2. Literature Review

The use of Machine learning techniques is increasingly applied in prediction of various time related aspects, such as patients waiting times for treatment, consultation durations with doctors, payment processing times at counters, delays in scheduled appointments and length of stay in inpatient departments. These applications are critical in optimizing hospital operations and improving the overall patient experience. Penn et al. [7] developed a logistic regression ML model to calculate the wait time from a primary care referral note. By connecting the specialist type from a primary care referral to a complete consultation visit conducted in Ontario, Canada, health administrative data was used to quantify the wait time. In order help future researchers, they also examine how note length (measured in tokens) and dataset size (measured in notes per target specialty) affect model performance. Alternatively, they suggested that electronic medical records (EMRs) can be used to arrive at wait time estimates. However, due to missing labels, target specialty physician labelling is presently a task requiring manual human labelling, something we wish to automate to increase the number of referrals labelled and decrease the cost and time associated with conducting such studies.

Silver et al. [3] investigated the reasons of increasing waiting times in a high-volume outpatient cancer clinic and use some quality improvement tools to reduce waiting time of patients. They analysed the patient flow and scheduling process in the department of head and neck surgery with the use of paired- t test. They found that average patient waiting time is 71 minutes and analysed that scheduling too many patients in a short time interval at the beginning of clinic hours exceeding the physician's patient capacity per hour. By implementing the rules of quality improvement (identifying best practices, standardizing appointment scheduling and load levelling), waiting time of patients significantly decreased. Accurate waiting time estimation was also expected to improve staffing decisions, leading to enhanced patient flow and satisfaction [8].

Susmitha et al. [9] analyse the patient waiting time at OPD, at various diagnostic services through a cross sectional observational study conducted in a tertiary care hospital for the period of 8 months. They found that average waiting time of patients for X-ray was 6.09 minutes and ultrasound 6.9 minutes. They concluded that patients satisfied with the activities of the hospital, but patients are not satisfied with the waiting time in hospital for consultation. Idigo [10] analysed that high patient load and ineffective appointment scheduling causes crowding in hospitals. They used the real time data of 768 patients conducted in a radiology department of tertiary hospital in Nigeria and analysed using MATLAB software. They find the scheduling method, arrival time, treatment time and waiting time of patients in radiology department for different examinations. The average patient arrival per hour (arrival rate) was 7 ± 5.4 patients per hour. Patient arrival rate distribution showed a pattern that resulted in the identification of three segments: 7:00–10:00, 10:00- 13:00 and 13:00-16:00 with arrival rates of 12, 6 and 2 patients per hour, respectively. The mean waiting time was 116.2 minutes.

Anusheel et al. [11] represented an analysis of waiting and treatment times for patients undergoing radiation therapy at a single institution over a 4-year period from Jan 2014 to Feb 2018. They collected a large dataset of patient related times, including waiting time before treatment and actual start treatment. They included many new modern therapy techniques in radiology oncology such as volumetric- modulated arc therapy, three-dimensional conformal radiotherapy etc. They obtained average wait time and average time spent in hospital is 12.1 ± 62.7 min and 52.4 ± 33.0 min respectively. They emphasize the importance of considering waiting times in modern-day radiation therapy and provides insights into the time requirements for different techniques in healthcare.

Goldovac et al . [12] concluded that wait times of more than 30 minutes are negatively associated to patient satisfaction in the orthopaedic department. Furthermore, appointment time, visit time, and whether the visit required an X-ray are the most effective predictors of longer wait time. Li et al. [13] predicted the outpatient waiting time in a Chinese paediatric hospital with the help of machine learning algorithms. They proposed a novel classification model based on statistical analysis and medical knowledge. Then applied four ML algorithms LR, KNN, RF, and GBDT to develop models for predicting waiting time of patients in four department categories. The best model for Internal medicine department was the RF model with MAE 5.03, while for other three departments was the GBDT model with lowest mean.

A study carried out in Northern India in 2020 found that 12% of patients spent more than 30 minutes in the laboratory and 29% of patients in the radiology department[14]. Goswami et al. [15] conducted an analysis on the wait times at a restaurant utilizing queuing theory. Employing Littles theorem and the M/M/1 model, they examined data obtained from Raipur restaurant. At the peak hours, the arrival rate at the restaurant was 3.244 customers per minute (cpm), while the service rate stood at 3.28 cpm. The restaurant typically accommodates an average of 104 customers with an average usage period of 0.989 minutes. This analysis aids in understanding the current scenario and offers insights for forecasting both customer arrivals and their wait times, thereby facilitating improvements for future operations. Grot et al. [16] analyse the dataset and found that random arrival of patients and random consultation times affect waiting time. This increased the average waiting time by up to 30 minutes compared to when patients arrived on scheduled time.

3. Proposed Methodology

This section describes the framework of proposed system to predict wait time. As Fig. 1 shows, the proposed system comprises three steps: Data understanding, Data Preprocessing, Features Selection, and Machine Learning algorithms. All preprocessing steps were performed using Jupyter notebook of Python. To predict the wait time, we used the dataset of a radiology department with walk in facility at Massachusetts General hospital. This dataset is taken from Kaggle to predict patients waiting time for their exam. In this study, one year data from Nov 2017 to dec 2018 including records for around 28870 patients. There are 61 features related to flow of patient such as arrival information of patient, resources used such as number of scanners used, queue information before and after arrival of patient as shown in Table 1.

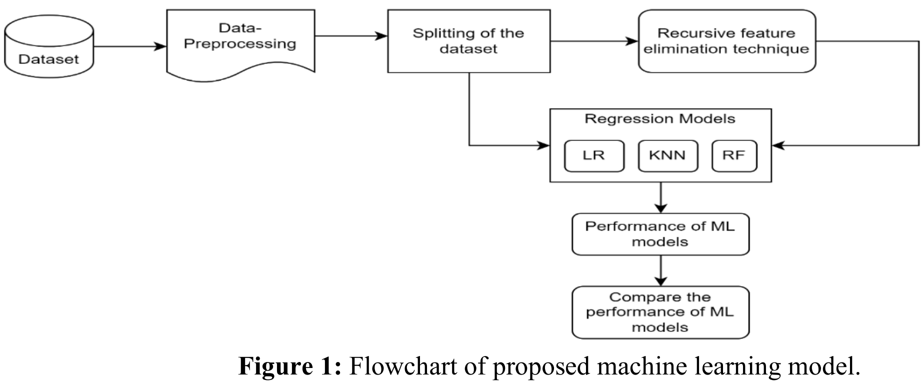

Figure 1: Flowchart of proposed machine learning model.

The patients waiting for different types of exams such as thoracic imaging which detects the diseases involving lungs and chest wall, paediatric imaging detects the diseases in children and musculoskeletal imaging detects

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conditions affecting the bones and muscle ligaments. The average waiting time of patients was 8 minutes and per hour of the day is shown in Fig 2. The average arrival rate of patients on each weekday with respect to each hour of the day shown in Fig 1. A very few patients with wait time greater than 70 minutes were removed from the dataset.

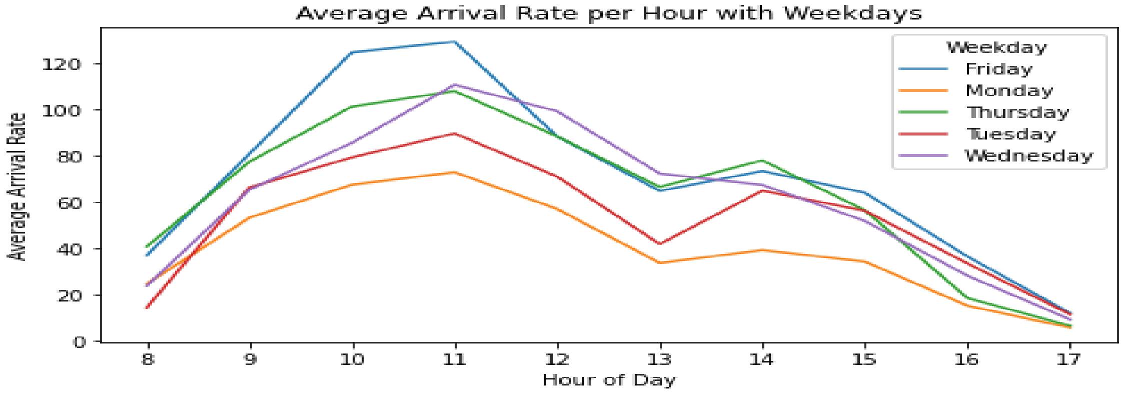

Figure 2: Distribution of average arrival rate per with each hour on each weekday**.**

To enhance the dataset understanding, we derived additional features from these datetime variables, such as arrival hour and arrival time shift, and subsequently removed the original features. The Pearson correlation coefficient was then employed to quantify the correlation between the target variable, wait time, and the independent variables [17].

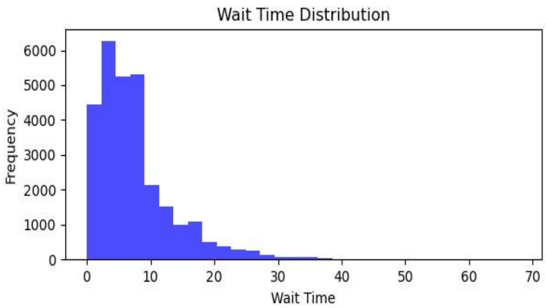

Figure 3: Distribution of patients with wait time.

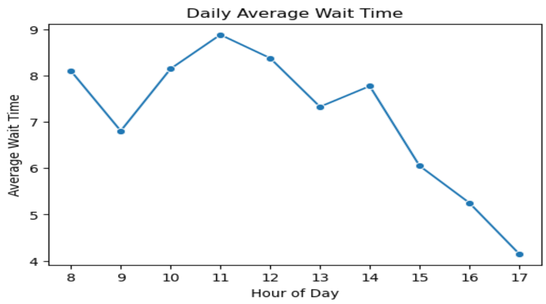

Figure 4 : Average wait time of patients per hour of the day.

A. Data Preprocessing

Data processing plays an important role in the learning process of machine learning models. It consists (1) cleaning of the dataset, (2) feature transformation, and (3)normalization of dataset. The following steps applied in the preprocessing phase, which aims to effectively prepare the data for analysis. There is no missing value in the dataset.

Categorical Encoding. Categorical transformation plays a crucial role in enhancing the learning capability of classifiers that are designed to process only numeric values. In our dataset, the features “Arrival weekday”, and “Time category” contain categorical data that has been encoded into numerical values. To carry out the encoding techniques, we have decided to use one hot encoder [18]. It is suitable with the dataset as it assigns a unique binary column to each unique categorical value. This transformation facilitates the interpretation and learning of encoded variables by the classifier. The “Arrival weekday” feature contains 5 categorical values, such as [‘Monday’, ‘Tuesday’, ‘Wednesday’, ’Thursday’, ’Friday’]. These categorical values have been encoded into five different binary columns. Similarly, the “Time category” feature contains two categorical values, namely [‘Morning’ and ‘Evening’], which are encoded into two variables.

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Data Normalization. The presence of numerical values in different variables is on different scale, affects the learning process of ML algorithms such as LR, KNN, and RF. In this step, Min-Max scaling [19] technique is used to scale the features of the dataset using Equation (1).

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

This scaling technique helps in mapping the original values to a range between 0 and 1, maintaining the relative relationships among the data points. However, the datasets used to train and test the ML classifiers were scaled to get accurate and consistent model performance.

B. RFECV using RF for Feature Selection

The REFCV method is applied to carry out feature selection on the pre-processed dataset, resulting in the identification of the most significant features based on their importance scores. This is a wrapper-type feature selection technique that uses an ML algorithm to select the most relevant features from the dataset [20]. This method combines recursive feature elimination (RFE) and cross-validation (CV) to identify the optimal number of features, and it also maximizes the performance of the model. This algorithm effectively selects the features from the training dataset that are most significant in the prediction of the target variable. It operates by looking for a subset of features in the training dataset, starting with all features and recursively deleting them until the target number of variables. This algorithm employs backward selection for feature selection. It starts with the whole feature set and iteratively eliminates features that do not enhance classification accuracy. Eventually, it identifies the most optimal subset of features.

In this research work, the implementation of RFECV was conducted using the random forest regression model RF-RFECV as an estimator and five-fold cross-validation as a splitting strategy to preserve the percentage of samples for each class. However, the five-fold cross-validation divided the dataset into five folds of equal size. [21]. To assess feature selection performance, the RFECV method computes internal accuracy metrics for every cross-validation iteration.

This procedure builds a model with the predictors, and an importance score is computed for each predictor. The predictors with less significance were removed. Then, the model is built again, and the score is computed. Furthermore, the number of predictor subsets and their size were specified to evaluate a tuning parameter. The optimal subset of predictors obtained from this process can be used to train the model. Thus, the top-ranked features obtained from RFE algorithm can be considered as a group of selected features.

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Algorithm 1 RFECV with RF

input: training dataset X, n number of desired features
output: feature set of tops- n most important features

1: **for** all features in X **do**
2: **Initialize an empty set Selected Features FS**
3: **for $k = 1$ to 5 do** ▹ k is the number of folds for cross validation
4: X is randomly divided into five equal subsets using K-Fold cross validation method;
5: One subset used as validation data, and
6: the remaining four subsets are used as training data.
7: Train a RF model using the training data.
8: Calculate the prediction accuracy using the validation data.
9: Obtain the importance of each feature produced by the RF model.
10: Remove one least important feature in each step and update the training data.
11: **end for**
12: Obtain the featured subset FS with desired number of features.
13: **If number of features in** FS is **n then**
14: Selected features = FS;
15: **end if**
16 **end for**
17 Return list of top n most important feature.

C. Prediction Using Machine Learning Algorithms

Once the top features were selected, several ML regression models were trained using the training set. Then, the performances of the trained models were evaluated using the test dataset. This step demonstrates the wait time prediction model that performs the best. As stated initially, ML plays an important role in predicting wait time features and prediction, which is a main priority for hospital management and patient satisfaction. This subsection presents and describes three regressors utilized in our study.

Linear Regression: This is a supervised learning ML algorithm that predicts the target variable y using linear equation follows in Equation 1

$$\hat{y}(x) = w_0 + w_1 x_1 + \cdots . w_n x_n \quad (2)$$

where $x_1, x_2, \dots, x_n$ are n features, and $\hat{y}$ is the predicted value. The weight vectors $w_1, w_2, \dots, w_n$ are designated as an attribute co-efficient, and w_0 is defined as another attribute 'intercept' in the linear model of sklearn. Usually, there is no need of hyper-parameters tuned in this algorithm. The performance of a linear model's mainly depends on how well the problem follows a linear distribution.

K Nearest Neighbors. KNN is the supervised ML algorithm used for both regression and classification task. In regression, KNN is used to predict continuous numerical value for given input. Assume that training dataset $T = \{(x_i, y_i)\}_{i=1}^{m}$ containing m observations with x_i feature vector and y_i represents numerical target variable. For any test instance x, the predicted value is calculated from Equation 3.

$$y = \frac{1}{k}\left(\sum_{x_i \epsilon N_k(x)} y_i\right) \tag{3}$$

Where, y_i is the target value of the ith nearest neighbors of x, k is the number of nearest neighbors and $N_k(x)$ is the set of k- nearest neighbors of x.

This approach assumes that instances with similar features have similar target values, making the average of their outputs a reasonable estimate for the target value of the test instance. In this algorithm, k is the most crucial hyper-parameter that is considered as number of nearest neighbors [22]. Moreover, the choice of the weighting function during prediction is an additional consideration. Two common options are 'uniform,' where all data points contribute equally to the prediction, and 'distance,' where points carry weight inversely proportional to their distance. The distance metric and the power parameter of the Euclidean metric or Minkowski metric can also be tuned as it can result in minor improvement.

Random Forest (RF). RF is an ensemble learning model consisting of a set of decision trees $\{ f_r(x, \theta_r) | r = 1,2,, \dots n\}$. The specific implementation process involves using a randomized with bootstrap method to extract the training set θ_r from the original dataset θ. Subsequently, this training set θ_r is used to train the decision tree regressor $f_r(x, \theta_r)$. When a new sample set x is given as input to the random forest then each decision trees f(x) predicts the target variable for the new sample and then final prediction determined by averaging the regression results:

$$Y = F(x) = \frac{1}{n}\left(\sum_{r=1}^{n} f_r(x)\right) \tag{4}$$

Where Y is the final result of regression model, $F(x)$ is regression model, $f_r(x)$ is a single decision tree regressor, and $f_r(x)$ is the average predicted value by each decision tree. Random Forest uses Gini importance to calculate the feature importance.

D. Evaluation Metrics

For the comparison of the predicting models, mean squared error (MSE), mean absolute error (MAE), and computation time were used.

Mean Squared Error. It measures of the errors that occurred between predicted values and actual values. The sum of the squares of each error is calculated and then divided by the total number of errors to find the average.

$$MSE = \frac{1}{n}\left(\sum_{i=1}^{n} (y_i - \hat{y}_i)^2\right) \tag{5}$$

Mean Absolute Error. It also measures the errors in a set of predictions. As it is absolute, so it disregards the positivity or negativity of the error and all distinct errors are equally weighted [23][24]. The formula to calculate MAE is shown in Equation 6.

$$MAE = \frac{1}{n}\left(\sum_{i=1}^{n} |y_i - \hat{y}_i|\right) \tag{6}$$

MSE was used to put more effort into outliers. While MAE indicates the average amount of error that may be expected from the prediction.

4. Result and Discussion

We developed three ML models by applying LR, KNN and RF algorithms on training dataset and then obtain the performance of all models on test dataset in terms of metrics MAE, MSE as shown in Table 1. The computational time of each model is also obtained.

In second experiment, REFCV algorithm is used to obtain the optimal number of features. We find 30 optimal features from the dataset and then applied all these algorithms on reduced dataset. Performance of all models with RFECV is shown in Table 1. LR model performed better among all models with and without using feature selection technique. The LR model with RFECV performs best with MAE 3.72 and least computational time with 30 features. KNN and KNN-RFE models performed with approximate same MAE. But computational time decreases with decreases features.

Table 1 Performance of all machine learning models with and without using Feature selection**.**

Models	MAE	MSE	Computational Time(s)
LR	3.823	28.15	0.05
KNN	3.929	31.70	0.03
RF	5.565	45.42	403
LR-RFE	3.717	28.41	0.01
KNN-RFE	3.961	32.07	0.003
RF- RFE	6.121	52.32	101.04

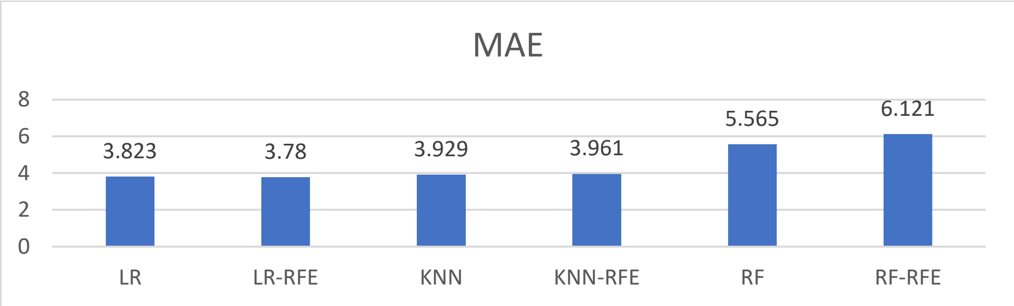

Figure: 5-Accuracy comparison of ML models on the dataset with and without RFE feature selection technique.

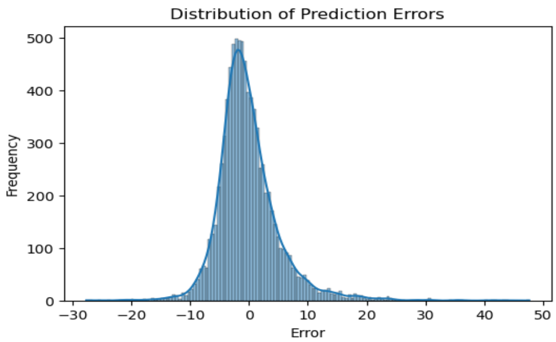

Figure 6: Distribution of prediction errors of best model (LR-RFE).

The actual and predicted values of 200 patients by LR-RFE is shown in Fig. The graph shows that there is in most of the cases, actual value is very close to predicted value which shows that model has good fit for those points.

Table 2 Mean Absolute error of LR model in different classes of waiting time

Classes of wait time	0-5	5-10	10-20	20-30	More than 30
MAE of Linear regression model	3.44	2.09	4.59	10.51	20.22
MAE of Linear regression model-RFE	4.04	2.06	4.12	10.22	20.39

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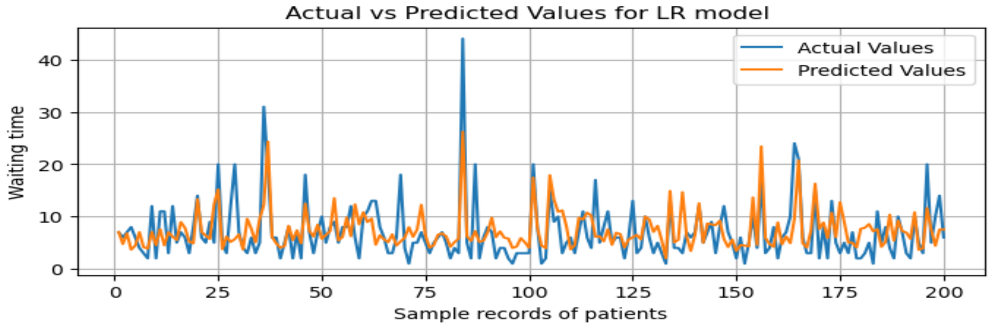

Figure 7: Waiting time predicted vs actual for the LR-RFE model for the sample test data

Table 2 shows that the accuracy of the LR model decreases as the wait time increases. The model is relatively more accurate for shorter wait times and less accurate for long wait times, accuracy indicated by MSE values. The peak of the distribution in Figure 5 shows that it is very close to zero and indicates that most of the predictions are quite accurate, with very less errors. The long tail on the right side of the distribution suggests there are a number of cases where the model has underestimated the target variable. While the short tail on left shows, there are a few instances of large overestimation.

5. Conclusion

This study aimed to demonstrate the ability of machine learning techniques to predict waiting times in hospital radiology departments, a critical issue in the face of increasing patient flow and departmental overcrowding. The integration of LR, KNN, and RF models with the RFE technique has proven not only to increase the predictive accuracy but also to optimize the feature selection process effectively.

Among the tested models, the LR-RFE model emerged as particularly effective, utilizing a reduced set of 30 features to obtain a lower mean absolute error compared to the standard LR model with 63 features. Additionally, the RF and KNN models also demonstrated robust performance, confirming the reliability of machine learning approaches in healthcare operational management. The important features such as patient queue lengths and recent wait times, highlight the areas where hospital administrations can target improvements to enhance patient Satisfaction and efficiency of departments. By applying these findings, healthcare facilities can better manage patient expectations, reduce wait times and optimize resource allocation.

Future research can explore the integration of real time data and the appli9cation of more complex machine learning models to further increase the predictive accuracy and operational responsiveness. This research also provides actionable strategies for healthcare management to increase service delivery in an increasing complex and demanding healthcare environment.

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IMPROVEMENT OF FORECASTING AND INVENTORY CONTROL FOR OPTIMIZING INVENTORY AT PT UNITED TRACTORS SITE MUARA TIGA BESAR

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Abstract
PT United Tractors, Muara Tiga Besar site, is one of the company's sites in Indonesia, responsible for accurately meeting customer demands in terms of timeliness, quantity, and quality. Ineffective and inefficient inventory management leads to idle capital and increased inventory costs, such as storage expenses and other inventory-related risks. Currently, PT United Tractors Muara Tiga Besar site has not yet optimized its inventory management, as evidenced by the Days of Inventory (DOI) performance in 2024 showing an upward trend, with the performance in May 2024 reaching 81.9 days. Therefore, this study aims to improve the DOI performance to meet the established targets. The root cause of the problem was identified using the 5 Why Analysis method, followed by generating ideas and solutions for improvement. The chosen solutions include forecasting using the Simple Moving Average method and inventory control through the Periodic Review and Continuous Review Systems. The research results indicate that forecasting with this purpose method effectively reduces DOI performance to 72 days, while inventory control using the Continuous Review System significantly reduces storage costs by 49%, achieving a more efficient outcome..

Keywords:
DMAIC; 5 why analysis; forecasting; simple; moving average; periodic review system; continuous review system

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1. Introduction

As business competition grows increasingly intense, companies must develop strong competitive advantages and deliver added value to their customers. This requires streamlined and effective operations to support long-term, sustainable growth. For companies involved in manufacturing and distribution, such as PT United Tractors Muara Tiga Besar, efficient product flow and inventory management play a vital role in achieving positive business outcomes. PT United Tractors Muara Tiga Besar handles the distribution of heavy machinery and spare parts from brands like Komatsu, Scania, UD Truck, and others. Poor inventory practices can lead to excess capital being tied up in stock, increased storage expenses, and additional inventory related risks. Currently, the site faces challenges in optimizing inventory—particularly in selecting the right items to stock, determining proper quantities, and setting appropriate safety and maximum stock levels—resulting in a misalignment with actual customer demand.

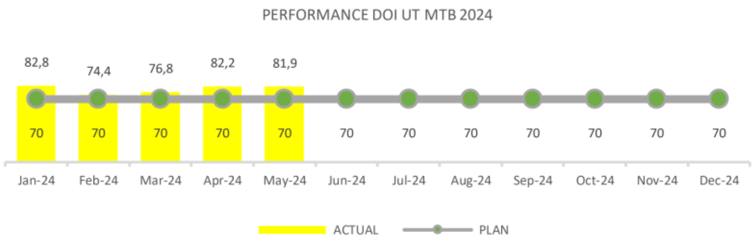

Figure 1. Performance DOI UT MTB 2024

This situation is illustrated by the KPI for Days of Inventory as depicted in Fig. 1, which remains below the targeted benchmark as of May 2024. To address this issue, the company must enhance its inventory control strategies by making more informed product selections and establishing precise inventory thresholds

2. Literature Review

A. *Inventory Management*

Inventory management is the science of maintaining adequate stock levels to meet customer demand. It involves monitoring and controlling inventory to ensure efficient distribution. Poor inventory control can lead to stock shortages, reducing profits and customer satisfaction, while overstocking increases costs. The goal is not just to reduce or increase stock but to optimize profitability. Ukar et al. (2015) emphasize that effective inventory management balances stock levels with customer needs and serves key functions:

1. Decoupling – Ensures product availability without relying too heavily on suppliers.
2. Economic Lot Sizing – Achieves cost savings through bulk purchasing and reduced shipping expenses.
3. Anticipation – Prepares for sudden or seasonal demand with safety stock and planned shipments.

B. *Classification of FSN*

Classifies inventory based on usage frequency and movement in the warehouse. It helps identify high-and low-value stock, aiding in better inventory control, especially for low-value items. The classification uses two key parameters:

1. Average Stay – How long items remain in stock before being used.
2. Consumption Rate – The speed at which items are used over time.
3. FSN Categories:
   a. Fast Moving (F): Used more than once a month.
   b. Slow Moving (S): Used less than once a month.
   c. Non-Moving (N): Not used for over two years.

C. *Forecasting*

Forecasting is the process of predicting future requirements, encompassing quantity, quality, timing, and location to fulfill customer demands. Forecasting involves predicting future events by utilizing historical data, which aids companies in making informed decisions.

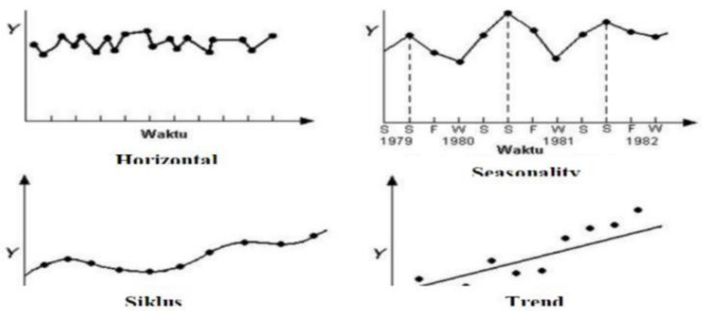

Figure 2 Supply Chain Stages

D. *Periodic Review Method*

The Periodic Review Model is an inventory control approach where orders are placed at fixed time intervals. Unlike continuous review systems, inventory is not monitored constantly but reviewed periodically. At each review point, the order quantity (Q) is determined based on current inventory levels, causing the lot size to vary while the time between orders remains constant.

Demand is uncertain and varies between periods, so each order may be different in size. Although this model simplifies administration and reduces the number of ordering events, it often requires larger safety stock to avoid stockouts between review periods.

This system is useful when:

a. Inventory is checked at regular intervals.
b. Administrative simplicity is preferred.
c. Variable order quantities are acceptable.

Key Points:

a. Fixed review intervals, but variable order quantities.
b. Requires higher safety stock due to potential delays between reviews.
c. Reduces monitoring efforts and simplifies ordering processes.

E. Continuous Review System Method

The Continuous Review Model (Q Model) is an inventory control system where inventory levels are constantly monitored, and a fixed order quantity (Q) is placed whenever stock falls to a predetermined level, known as the Reorder Point (ROP).

Key Characteristics:

a. Orders are triggered immediately when inventory hits the ROP.
b. The order quantity (Q) is fixed, but the time between orders varies depending on demand.
c. Continuous monitoring helps minimize the risk of stockouts, as orders are placed in real time.

F. DMAIC (Define, Measure, Analysis, Improve, and Control)

DMAIC is a structured, data-driven process used for continuous improvement toward Six Sigma goals. It aims to eliminate inefficiencies and optimize performance by relying on facts and analysis. DMAIC consists of five key phases:

1. Define
   a. Set project goals and select Six Sigma projects.
   b. Identify key roles and responsibilities.
   c. Determine training needs.
   b. Define critical processes and customer requirements.
2. Measure
   a. Identify quality factors (Critical to Quality/CTQ) aligned with customer needs.
   b. Create a data collection plan using SIPOC (Supplier-Input-Process-Output-Customer).
   c. Measure current performance to set a baseline.
3. Analyze
   a. Assess process stability and capability.
   b. Set improvement targets for CTQs.
   c. Identify root causes of defects or failures.
   b. Translate defects into the Cost of Poor Quality (COPQ).

G. Days Of Inventory (DOI)

Days of Inventory is a key metric that measures how many days a company's current inventory can meet customer demand, serving as an indicator of inventory management efficiency within the supply chain. A shorter Days of Inventory reflects better performance, indicating that inventory moves quickly and assets are efficiently utilized. This metric is calculated by comparing the current inventory level with the average sales over a specific period, helping management make informed decisions regarding inventory value and control.

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3. Research Methodology

Figure 3 shows the stages of the data processing procedure:

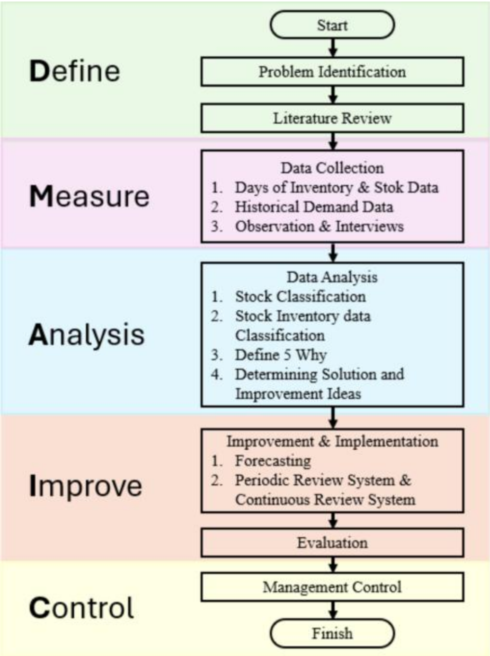

Figure 3 Research Framework

A. Define

The goal of the "Define" step in the DMAIC approach is to identify the stage where the problem statement, research objectives, and scope of the process are determined. In this phase, it is crucial to clearly formulate the main objectives and the issues to be addressed, ensuring the improvement efforts remain focused. A detailed explanation of the "Define" stage is divided into two parts, which can be outlined as follows:

1. Problem Identification
2. Literature Review

B. Measure

The "Measure" phase focuses on collecting accurate data related to the identified problem for further analysis. This step uses factual information to clearly describe the situation, ensuring the solution is relevant. Data is gathered through field studies, interviews, and discussions.

C. Analyse

The "Analyze" phase in the DMAIC methodology focuses on analyzing the data collected during the "Measure" phase to identify the root causes of problems or inefficiencies in the process. The following are the key steps taken during the Analyze phase:

1. Inventory Classification
2. Define 5 Why
3. Determining Solution and Improvement Ideas

D. Improve

The "Improve" phase in DMAIC focuses on designing and implementing solutions based on the analysis of the problem. Success relies on selecting the right solutions, thorough testing, and careful implementation. Continuous evaluation and monitoring are essential to ensure the improvements lead to long-term benefits and increased process efficiency. The following are the key steps taken during the Improve phase:

1. Forecasting
2. Periodic Review System & Continuous Review System
3. Evaluation

E. Control

The "Control" phase in DMAIC is the final step, focused on sustaining long-term improvements. It ensures the stability and consistency of processes after changes are implemented in the Improve phase. The main goal is to prevent issues from reoccurring and ensure that the improvements remain sustainable over time.

4. Result And Analysis

A. Data Collection

The Data Collection phase in thesis preparation is crucial for gathering relevant information that forms the basis for analysis and interpretation. The quality of the data collected directly influences the validity and reliability of the final results. For this research, the data collection process includes the following steps:

1. Days of inventory and stock amount data
2. Historical demand data
3. Observation & Interviews

B. Data Analysis

1. Stock inventory data classification.

The existing stock was classified using FSN Analysis, which identified the number of items, quantities of spare parts, stock percentages, and Days of Inventory (DOI) for each group. This classification allows for targeted analysis of issues and the development of tailored solutions and management strategies based on the unique characteristics of each group. The detailed classification results are shown in Table 1.

Table 1. Stock Inventory Data Classification

Classification	Item	Qty	Amt Stock	Stock Percentage	DOI (Days)
Fast Moving	2.627	90.420	59.350.115.433	67%	75,1
Slow Moving	1.724	11.767	19.602.395.835	22%	86,3
Non Moving	1.092	5.774	9.671.027.251	11%	149,6
Grand Total	**5.443**	**107.961**	**88.623.538.519**	**100%**	**81,9**

2. Define 5 Why.

Using the 5 Whys method, the root causes of the problem were identified, with the fifth "Why" representing the core issue. The process of identifying these root causes is presented in Table 2.

Table 2. Why Analysis

Problem	Why 1	Why 2	Why 3	Why 4	Why 5
DOI above target	High inventory level	Fast moving stock	Ineffective stock management	Excess Stock	Process ordered error
		Slow moving stock	Ineffective stock management	Excess Stock	Process ordered error
		Non-moving stock	Stock has no transactions	Error ordered	Human error

From the 5 Whys analysis table on Days of Inventory (DOI), the main issues identified involve several aspects, namely:

i. The order processing method for stock items.
ii. Human error in the ordering process for stock items.

3. Determining solution and improvement ideas

To develop effective improvement strategies, the next step is to create a Root Cause and Problem Solving table. This table serves to clearly connect each identified root cause with its corresponding solution, ensuring that all issues are addressed in a structured and targeted manner. Tabel 3 is the Root Cause & Problem Solving table:

Table 3. Root Cause & Problem Solving

Problem	Identification	Corrective Action	Methods
The order **processing method (error)** for stock items.	Handling of order items and incorrect quantities (Excess & Shortage)	Improving forecasting accuracy and order quantities.	Forecasting & Periodic Review
Human error in the order processing for stock items.	Lack of accuracy in processing customer orders.	Preventing human errors and improving the order processing flow.	Fish bone diagram

From the table above, table Root Cause & Problem Solving, several improvement activities are identified as follows:

i. Improvement of forecasting methods.
ii. Inventory control using Periodic Review System & Continuous Review System.
iii. Reducing human errors by improving the order processing flow.

C. Improvement & Implementation

1. Forecasting.

Forecasting is performed using the Simple Moving Average method by comparing three specific time periods: the last 3 months, the last 6 months, and the last 12 months. Additionally, error values for each forecast are calculated using the Mean Absolute Deviation (MAD) method. The forecasting calculations will cover both fast-moving and slow-moving classification.

Table 4. Summary Result Forecasting & Error

PN: 600-319-4540		Actual Demand	Forecast Result				Absolute Deviation			
			Naïve	AVG MA12	AVG MA6	AVG MA3	Naïve	AVG MA12	AVG MA6	AVG MA3
2024	01	830	961,0	1189,2	1056,7	932,0	131,0	359,2	226,7	102,0
	02	818	830,0	1163,7	1083,8	925,7	12,0	345,7	265,8	107,7
	03	1085	818,0	1162,3	1195,8	1036,7	267,0	77,3	110,8	48,3
	04	1171	1085,0	1183,9	1306,2	1181,3	86,0	12,9	135,2	10,3
	05	1312	1171,0	1188,4	1374,5	1242,0	141,0	123,6	62,5	70,0
Sum Of Error							637,00	918,67	801,00	338,33
Mean Absolute Deviation							127,40	183,73	160,20	67,67
PN: 6219-11-3100		Actual Demand	Forecast Result				Absolute Deviation			
			Naïve	AVG MA12	AVG MA6	AVG MA3	Naïve	AVG MA12	AVG MA6	AVG MA3
2024	01	108	204	114,8	60,8	60,3	96,0	6,8	47,2	47,7
	02	13	108	120,8	68,7	48,3	95,0	107,8	55,7	35,3
	03	149	13	109,8	48,5	52,0	136,0	39,2	100,5	97,0
	04	271	149	122,3	68,5	61,3	122,0	148,8	202,5	209,7
	05	109	271	144,8	73,5	89,0	162,0	35,8	35,5	20,0
Sum Of Error							611,00	338,42	441,33	409,67
Mean Absolute Deviation							122,20	67,68	88,27	81,93
PN: 17A-27-41761		Actual Demand	Forecast Result				Absolute Deviation			
			Naïve	AVG MA12	AVG MA6	AVG MA3	Naïve	AVG MA12	AVG MA6	AVG MA3
2024	01	2	3	0,6	0,0	0,0	1,0	1,4	2,0	2,0
	02	0	2	0,8	0,0	0,0	2,0	0,8	0,0	0,0
	03	0	0	0,8	0,0	0,0	0,0	0,8	0,0	0,0
	04	1	0	0,8	0,0	0,0	1,0	0,3	1,0	1,0
	05	0	1	0,8	0,7	0,0	1,0	0,8	0,7	0,0
Sum Of Error							5,00	4,00	3,67	3,00
Mean Absolute Deviation							1,00	0,80	0,73	0,60
PN: 6215-61-6700		Actual Demand	Forecast Result				Absolute Deviation			
			Naïve	AVG MA12	AVG MA6	AVG MA3	Naïve	AVG MA12	AVG MA6	AVG MA3
2024	01	0	0	0,7	0,0	0,0	0,0	0,7	0,0	0,0
	02	0	0	0,7	0,0	0,0	0,0	0,7	0,0	0,0
	03	0	0	0,7	0,0	0,0	0,0	0,7	0,0	0,0
	04	0	0	0,7	0,0	0,0	0,0	0,7	0,0	0,0
	05	1	0	0,7	0,5	0,0	1,0	0,3	0,5	1,0
Sum Of Error							1,00	3,00	0,50	1,00
Mean Absolute Deviation							0,20	0,60	0,10	0,20

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Based on the forecasting results and the error calculation that have been performed, the demand for the year 2024 for the four sample materials is as follows:

Table 5. Final Forecast 2024

NO	MATERIAL	DESCRIPTION	Forecasting Demand 2024											
			01	02	03	04	05	06	07	08	09	10	11	12
1	600-319-4540	CARTRIDGE	932,00	925,67	1.036,67	1.181,33	1.242,00	1.355,00	1.431,00	1.507,00	1.388,00	1.212,33	980,00	869,67
2	6219-11-3100	INJECTOR	114,83	120,83	109,83	122,25	144,83	140,92	148,15	151,31	158,46	158,65	12,46	133,96
3	17A-27-41761	COVER	-	-	-	-	-	-	-	1,33	1,33	2,33	1,67	1,67
4	6215-61-6700	TENSION PULLEY	-	-	-	-	0,50	1,33	1,33	1,33	1,33	1,33	0,83	0,17

2. Periodic Review System & Continuous Review System.

Inventory control needs to be implemented because it can reduce inventory costs, minimize stockouts, and make inventory management more efficient.

i. Calculation Without Using Periodic Review

Based on the inventory cost calculations for the four sample materials, the following is the recap of the total inventory costs incurred by the company for the sample materials using the without periodic review method:

Table 6. Summary Inventory Cost Without Periodic Review

MATERIAL	INVENTORY COST
600-319-4540	35.038.848.147
6219-11-3100	20.087.874.189
17A-27-41761	5.382.930.972
6215-61-6700	3.369.845.299
Total	**63.879.498.608**

It is known that the table 6, shows the inventory costs for all materials. The total inventory cost, including ordering costs, holding costs, and the material purchase price, amounts to Rp. 63.879.498.608.

ii. Calculation Using the Periodic Review System

Below is the recap of the inventory cost calculations for all materials using the Periodic Review System method.

Table 7. Summary Inventory Cost Periodic Review System

MATERIAL	INVENTORY COST
600-319-4540	21.808.362.767
6219-11-3100	10.310.656.302
17A-27-41761	238.656.849
6215-61-6700	616.085.080
Total	**32.973.760.997**

Based on the table 7, the inventory costs for all four materials can be seen. The total inventory cost when using the Periodic Review System method is Rp. 32.973.760.997.

iii. Calculation Using the Continuous Review System

Below is the recap of the inventory cost calculations for all materials using the Continuous Review System method.

Table 8. Summary Inventory Cost Continuous Review System

MATERIAL	INVENTORY COST
600-319-4540	21.801.730.827
6219-11-3100	10.274.429.250
17A-27-41761	217.969.318
6215-61-6700	563.359.806
Total	32.857.489.202

Based on the table 8, the inventory costs for all four materials can be seen. The total inventory cost when using the Continuous Review System method is Rp. 32.857.489.202.

3. Evaluation

I Forecasting (Days of Inventory) Evaluation.

After applying the forecasting method recommended by the authors, Figure 4 shows the achievements of Days of Inventory in 2024.

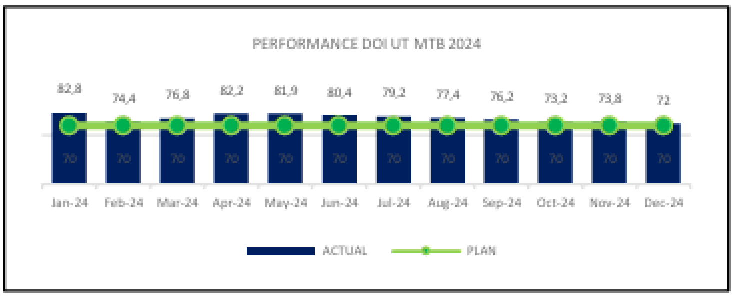

Figure. 4. Performance DOI UT MTB 2024

The figure 4 shows the progress in improving the days of inventory at PT United Tractors, Muara Tiga Besar site, throughout 2024. This improvement is attributed to enhancements in the forecasting process to better prepare inventory for the upcoming period.

II Periodic Review System & Continuous Review System Evaluation.

Here is a summary of the comparison of total inventory costs between the company's policy method, the continuous review system, and the periodic review system.

Table 9. Summary Cost of Inventory

MATERIAL	Without PRS & CRS	Periodic Review System	Continuous Review System
600-319-4540	35.038.848.147	21.808.362.767	21.801.730.827
6219-11-3100	20.087.874.189	10.310.656.302	10.274.429.250
17A-27-41761	5.382.930.972	238.656.849	217.969.318
6215-61-6700	3.369.845.299	616.085.080	563.359.806
Total	63.879.498.608	32.973.760.997	32.857.489.202
Efficiency	-	30.905.737.611	31.022.009.406
Efficiency in %	-	48%	49%

Based on the table beside, the calculations reveal that the continuous review system method incurs the lowest total inventory cost

The total inventory cost for the continuous review system amounts to Rp. 32,857,489,202, which is lower than the Rp. 32,973,760,997 incurred by the periodic review system and significantly less than the Rp. 63,879,498,608 observed when no method is applied.

D. Management Control

Management Control in this research is carried out in 5 ways, namely:

1. Monitoring
2. Reporting
3. Standard checklist inventory procedures
4. Regular Audit Inventory Management

5. Continuous Improvement

5. Conclution And Recommendation

A. Conclusions

The research identified high Days of Inventory (DOI) at PT United Tractors, Muara Tiga Besar site, with performance metrics showing a steady increase from January to May 2024. This issue was mainly caused by "Order Process Errors" and "Human Errors," disrupting inventory management efficiency. To address this, the company decided to enhance its ordering process by adopting reliable forecasting and inventory control methods. After careful evaluation, the Simple Moving Average method was chosen for forecasting due to its simplicity and ability to smooth out demand fluctuations. The Continuous Review Control method was selected for inventory control, improving efficiency by 49%, significantly enhancing inventory operations. As a result, by December 2024, the company achieved a substantial reduction in DOI, marking a milestone in operational efficiency. To ensure long-term sustainability, the company focused on standardizing inventory procedures with comprehensive checklists and regular audits, aiming to maintain inventory performance and uphold operational excellence.

B. Recommendations for Further Research

To ensure future development and align performance with established targets, the following recommendations are made. First, implementing a forecasting and inventory control system using artificial intelligence and data analytics will reduce human errors, enhancing demand prediction accuracy and streamlining inventory management. Second, adopting a system that can accommodate unplanned customer needs will improve flexibility and responsiveness. Lastly, improving supply chain synchronization is essential to enhance inventory turnover, reduce lead times, and minimize storage costs, contributing to more efficient and cost-effective operations, ultimately supporting optimal performance and long-term sustainability.

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REMAINING LIFE AND INTEGRITY ASSESSMENT OF AN ATMOSPHERIC STORAGE TANK (T-125) BASED ON ULTRASONIC TESTING AND API 653 STANDARD

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Abstract
This paper presents a Fitness-for-Service (FFS) evaluation and Remaining Life (RL) prediction for the T-125 Atmospheric Storage Tank (AST), which stores Solar (Diesel) fuel at PT. XYZ. The study utilized data from Ultrasonic Testing (UT) conducted over an eight-year inspection interval (2016–2024) to quantify material loss due to corrosion. The analysis was performed strictly according to the guidelines of API Standard 653, 5th Edition. Key parameters, including Corrosion Rate (CR), Minimum Required Thickness (tmin), and RL, were calculated. While the 1st and 2nd shell courses and the roof plate possess acceptable integrity with RL values ranging from 32.6 to 73.12 years, the 3rd shell course was found to be non-compliant based on the comparison between its calculated minimum required thickness (2.2 mm) and the API minimum plate thickness requirement (2.54 mm). This assessment provides a scientific basis for maintenance planning, emphasizing the need for immediate attention to the 3rd course and continuous monitoring of the 2nd course, which exhibits the highest corrosion rate (0.06 mm/year).

Keywords:
Remaining life analysis; API 653; corrosion; storage tank; ultrasonic testing

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1. Introduction

Storage tanks are critical assets in the oil and gas industry, and their structural integrity is constantly challenged by degradation mechanisms, primarily corrosion. Uncontrolled corrosion can lead to catastrophic failures, resulting in safety hazards, operational downtime, and significant environmental damage [1]. To ensure continued safe operation, periodic inspection and integrity assessment of these assets are mandated by international standards.

The American Petroleum Institute (API) Standard 653 provides the established guidelines for the inspection, repair, alteration, and reconstruction of ASTs, offering a standardized approach for quantitative assessment of service suitability [2]. This study focuses on an in-depth integrity assessment of the T-125 atmospheric storage tank, a vertical, welded steel tank, by analyzing its corrosion history and projecting its remaining service life in compliance with API 653 criteria. The primary objective is to determine the current corrosion status, predict the tank's Remaining Life (RL), and identify any structural non-compliance based on thickness measurements.

2. Method

A. Data Collection: Ultrasonic Testing (UT)

Data was collected through Non-Destructive Testing (NDT), specifically Ultrasonic Testing (UT), which is the preferred method for accurate measurement of material thickness to monitor corrosion and erosion loss in steel structures [5]. Two sets of minimum thickness data were acquired: previous wall thickness from the initial inspection in 2016 and actual wall thickness from the current inspection in 2024. The elapsed time between inspections (Δt) was 8 years. The minimum thickness values were recorded at designated Thickness Measurement Locations (TMLs) on the three shell courses and the roof plate.

B. Remaining Life and Corrosion Rate Calculation

The integrity parameters were calculated using the formulae obtained from API Standard 653:

1. **Corrosion Rate (CR):** The uniform metal loss rate was calculated by dividing the material loss by the inspection interval.

$$CR\left(\frac{mm}{year}\right) = \frac{T_{previous} - T_{actual}}{\Delta t(years)} \quad (1)$$

Where: $T_{previous}$ is minimum thickness measured from the previous inspection, T_{actual} is minimum thickness measured from the current inspection which shows the actual condition after experiencing metal loss due to corrosion during operation period, Δt is the time period between the previous inspection and current inspection.

2. **Minimum Calculated Thickness (t_{min}):** The minimum required plate thickness for the shell courses, based on circumferential (hoop) stress, was determined based on APT 653[2].

$$t_{min} = \frac{2.6(H-1)DG}{SE} \quad (2)$$

where: *H* is the liquid height (ft), *D* is the tank diameter (ft), *G* is the specific gravity (0.81 for Solar), *S* is the material allowable stress (psi), and *E* is the weld joint efficiency.

3. **Remaining Life (RL):** The predicted operational time until the plate thickness reaches the minimum required retirement thickness (t_{req}) was calculated. The minimum retirement thickness (t_{req}) is defined by the absolute minimum thickness specified by API 653 (which is 2.54 mm for shell plates and 2.286 mm for the roof) or the calculated t_{min}, whichever is greater [2].

$$RL(years) = \frac{T_{actual} - T_{req}}{CR} \quad (3)$$

where: T_{actual} is minimum thickness measured from the current inspection which shows the actual condition after experiencing metal loss due to corrosion during operation period, T_{req} is the minimum thickness required as stated by API 653; and *CR* is the corrosion rate

3. Result and Discussion

A. Integrity Assessment Result

The core integrity parameters determined for the T-125 tank components are summarized in Table 1.

Table 1. Calculated Integrity Parameters and Fitness For Service (FFS) Status

Component	T_{actual} (mm)	CR (mm/year)	T_{min} (mm)	T_{req} (mm)	FFS Status	RL (years)
1st Shell course	4.0	0.05	7.9	2.54	Acceptable	37.2
2nd shell course	4.0	0.06	6.2	2.54	Acceptable	32.6
3rs shell course	3.9	0.025	2.2	2.54	Non acceptable	62.4
Roof plate	3.1	0.0125	3.1	2.286	Accptable	73.12

B. Analysis of Corrosion and Remaining Life

On the shell Courses 1st and 2nd, both courses retain acceptable integrity. The measured current thicknesses (4.0 mm) are well above the API absolute minimum thickness (2.54 mm). However, the 2nd shell course exhibits the highest corrosion rate (0.06 mm/year) and the lowest RL (32.6 years) among all shell plates. This elevated corrosion rate is attributed to localized corrosion around the manhole area, where coating damage often occurs, facilitating greater exposure to atmospheric moisture and corrosive agents in the stored product [1].

Shell Course 3rd (Critical Finding): This course has the lowest measured tactual (3.9 mm) and the lowest CR (0.025 mm/year). Despite the actual thickness being greater than the API absolute minimum, the course is flagged as Non-acceptable because its calculated minimum thickness based on design load (t_{min}=2.2 mm) is compared against the mandatory API treq of 2.54 mm. Although the tactual is 3.9 mm, the design calculation indicates a structural non-compliance based on the API 653 assessment criteria for fitness-for-service, suggesting a potential inadequacy in the original design input or an over-reliance on the stress calculation for this specific course [2]. This finding necessitates a thorough re-evaluation of the design basis parameters (e.g., allowable stress or joint efficiency) or application of an advanced FFS procedure (e.g., API 579-1) [3]. Roof Plate: The roof plate shows minimal corrosion (0.0125 mm/year) and the longest RL (73.12 years), affirming its robust current condition.

4. Conclusion

The integrity assessment of the T-125 storage tank, performed in accordance with API 653, indicates that the asset is largely fit for continued service but highlights one critical non-compliance issue and one high-risk area for monitoring.

1. The 3rd shell course is technically non-acceptable due to its calculated minimum required thickness (t_{min}) being below the API 653 absolute minimum plate thickness requirement (2.54 mm). A detailed engineering review is mandatory to confirm the basis of the tmin calculation and to determine if structural reinforcement or an FFS exemption is justified.

2. The 2nd shell course, despite having an acceptable RL of 32.6 years, exhibits the highest CR (0.06 mm/year), concentrated around the manhole. It is recommended to implement an aggressive maintenance plan for coating repair in this localized area and reduce the inspection interval for the 2nd course to manage this accelerated corrosion rate.

3. The tank's overall projected service life remains substantial, confirming that the current corrosion management program is generally effective, provided the identified structural and high-corrosion risks are mitigated promptly.

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Short-Circuit Disturbance and Distribution Network Protection Electric Power System in Human Resources Development Center for Oil and Gas

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Abstract
The power system is a very vital part of the industry, serving as the source of electrical energy up to the distribution of electric power, which must be protected against various types of disturbances that may affect the equipment in use. Power system protection is the protection provided to electrical equipment installed in a system against abnormal operating conditions of the system itself. These abnormal conditions include short-circuit faults, overload faults, and overvoltage disturbances. Breaking capacity, or the maximum interrupting capacity, is the highest short-circuit current value that a circuit breaker can withstand without sustaining damage.

Keywords:
Power system; electric power distribution; power system protection; short-circuit faults; circuit breaker

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1. Introduction

The electric power system is a fundamental backbone of industrial operations, serving not only as the primary source of electrical energy but also as the infrastructure that ensures its reliable transmission and distribution to end-users. Given its critical role, the power system must be provided with robust protection schemes to guard against disturbances that may threaten equipment integrity, operational reliability, and personnel safety. Disturbances in power systems, such as short circuits, overloads, and overvoltage conditions, can cause severe damage to electrical equipment, interrupt industrial processes, and even lead to large-scale system instability if not addressed promptly. Therefore, protection systems are not optional but are indispensable elements in modern electrical networks, designed to isolate faults, minimize damage, and maintain service continuity. Among the most essential analyses in power system protection is the short-circuit current study.

A short circuit introduces a low-resistance path that allows fault currents to escalate rapidly to values many times higher than the normal operating current. Such high fault currents, if not interrupted quickly, can cause overheating, mechanical stress, insulation failure, and catastrophic equipment damage. Short-circuit studies provide engineers with critical data for planning, designing, and expanding power systems. Specifically, these studies are used to determine protective relay settings, verify system coordination, and establish the required interrupting capacity of circuit breakers. Without accurate short-circuit analysis, it is impossible to ensure that protective devices will operate reliably under fault conditions. Circuit breakers, as primary protective devices, must be carefully selected not only based on their normal current-carrying capacity but also with respect to their ability to withstand and interrupt maximum fault currents. The concept of breaking capacity—also known as rupturing capacity—is central to this process. Breaking capacity defines the highest short-circuit current a breaker can safely interrupt at its rated system voltage without sustaining permanent damage. Choosing breakers with insufficient breaking capacity may result in catastrophic failures during fault conditions, while appropriately rated breakers ensure system safety, reliability, and stability. For this reason, standards and guidelines emphasize the importance of selecting protective devices that correspond to the maximum prospective fault currents at their installation points.

Protection systems must also be designed to operate selectively and reliably. Selectivity ensures that only the protective device closest to the fault operates, isolating the affected section while allowing the remainder of the system to continue functioning. This principle minimizes service disruption and enhances overall system reliability. In practice, protection can be achieved using devices such as fuses or circuit breakers. While fuses are simple and cost-effective, circuit breakers are generally preferred in industrial power systems due to their higher fault-handling capacity, coordination capabilities with protective relays, and ability to be reused after operation. Importantly, protective devices must be capable of eliminating disturbances without damaging themselves during the process, which underscores the necessity of selecting equipment rated for the expected short-circuit conditions.

2. Method

The reliability and continuity of an electric power system in delivering electricity to consumers is strongly determined by the protection system that is implemented. A reliable power system is not only expected to meet the growing demand for electrical energy but also to ensure that supply is maintained safely and with minimal disruption. For this reason, the design of a protection system requires careful attention to potential disturbances and fault conditions that may arise within the network. These considerations are addressed through fault analysis, which serves as the foundation for planning protection schemes, selecting switchgear, and determining the specifications of essential equipment such as circuit breakers (CBs) and protective relays. The results obtained from a fault analysis are used to establish critical parameters, including the relay settings that dictate how and when relays will operate under abnormal conditions. Furthermore, the analysis ensures that the ratings of circuit breakers are appropriate for the maximum fault current levels expected in the system. Faults may occur in different parts of the power system, including generators, power transformers, transmission networks, and busbars, each of which requires a tailored protection strategy.

A. Power System and Distribution Protection

Delivering electricity to consumers involves a relatively complex process that spans from generation at the power plant to transmission through high-voltage lines, and finally to distribution networks before reaching end-users. The last stage, distribution, is especially critical, as it directly impacts the reliability and quality of supply received by consumers. Distribution system protection refers to the protective measures and equipment installed along the distribution network to ensure that electricity is safely transferred from the power generation station through substations and finally to households, industries, and commercial consumers. Without proper protection, disturbances within the distribution network could result in widespread outages, equipment damage, or even hazards to human safety. Effective protection ensures that disturbances are isolated promptly, allowing electricity to be supplied reliably, safely, and at the required quality standards [2].

B. Power System Protection

In general, power system protection can be defined as the coordinated application of protective devices to safeguard electrical equipment and maintain system stability under abnormal operating conditions. This includes protection of generators, power transformers, transmission and distribution lines, and other essential components of the power system. Abnormal operating conditions may take several forms, including:

1. **Short-circuit faults** (line-to-line, line-to-ground, or three-phase faults)
2. **Overload conditions** caused by demand exceeding equipment capacity
3. **Overvoltage disturbances** due to switching surges, lightning strikes, or system instability

Among these, short-circuit faults are particularly significant. When a short circuit occurs, it creates a very low impedance path that allows extremely high currents to flow through the system. These currents may be several times higher than the normal operating current, posing serious threats to equipment and system stability. Short-circuit faults can be classified as either permanent or temporary. Permanent faults typically occur due to insulation failure, equipment breakdown, or mechanical damage, and include three-phase short circuits, double-phase-to-ground faults, interphase faults, and single-phase-to-ground faults. On the other hand, temporary faults are often caused by environmental conditions such as flashovers between conductors and ground, between conductors and poles, or between conductors and grounding wires. Temporary faults may clear themselves once the disturbance is removed, but protective systems must still respond quickly to prevent damage [2].

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C. Short-Circuit Current and Breaking Capacity

The magnitude of the maximum short-circuit current is a critical parameter in power system protection. This current value is compared against the breaking capacity (or interrupting capacity) of protection equipment such as circuit breakers to ensure that the equipment can safely operate under fault conditions. According to the ANSI C37.010-1999 standard, the instantaneous fault current I_m for systems with voltage levels above 1.5 kV can be calculated as:

$$I_m = 1.6 \times I_{SC}$$

For systems operating at voltage levels below 0.6 kV, the equation is:

$$I_m = 1.5 \times I_{SC}$$

where I_{SC} is the symmetrical short-circuit current.

The instantaneous power capacity of a circuit breaker can be determined by:

$$S_m = \sqrt{3}\, V_p \times I_m$$

where V_p is the system's phase-to-phase voltage. These equations provide the basis for evaluating whether a circuit breaker is adequately rated to handle the worst-case fault scenarios. Using underrated breakers could result in catastrophic equipment failure, while properly rated breakers ensure safe interruption of fault currents and protect the stability of the entire power system [3].

D. The Function of Protection

Understanding the magnitude and characteristics of fault currents at different points in the system is essential for designing an effective protection system. Since fault currents can reach dangerously high values in a very short time, the protection system must be capable of detecting and isolating them almost instantaneously. This requires the use of detection devices, such as protective relays, that continuously monitor system conditions. When an abnormal condition is detected, the relay issues a trip signal to the appropriate circuit breaker. The circuit breaker, in turn, disconnects the faulty section from the rest of the system, thereby preventing damage and maintaining stability. A circuit breaker is defined as a mechanical switching device capable of making, carrying, and breaking currents under normal operating conditions. Additionally, it must also be capable of making, carrying for a specified duration, and interrupting currents under abnormal conditions, such as those caused by short circuits [4].

The primary functions of power system protection can be summarized as follows [2]:

1. Prevent or minimize equipment damage caused by abnormal operating conditions. The faster the protective devices respond, the smaller the potential for equipment failure.
2. Localize faults to the smallest possible area, ensuring that unaffected parts of the system continue to operate normally.
3. Maintain service reliability and power quality, ensuring uninterrupted electricity delivery to consumers.
4. Protect human safety by preventing exposure to dangerous electrical conditions.

3. Result and Discussion

Pusat Pengembangan Sumber Daya Manusia Minyak dan Gas Bumi or Human Resources Development Center for Oil and Gas (PPSDM MIGAS) is a Central Government Agency under the Human Resources

Development Agency for Energy and Mineral Resources, Ministry of Energy and Mineral Resources [5]. The majority of the load at PPSDM Migas consists of induction motor units used in crude oil processing within refinery and utility units. In addition, the power plant also supplies loads for lighting systems. The installed load data at PPSDM Migas are presented as follows:

Table 1. Total Operating Load of Refinery and Utility Units

Load Unit	Maximum Operating Load (kW)
Power Plant Unit	38.55
Water Treatment	145
Boiler Unit	5.9
Refinery Unit	323.03
Total Load	**512.48**

The protective equipment used at PPSDM Migas includes fuses, Oil Circuit Breakers (OCB), Disconnecting Switches (DS), Load Break Switches (LBS), relays, and grounding systems. Following the processing of field study data on the existing conditions of the PPSDM Migas power system, a Single Line Diagram (SLD) model was developed using ETAP 16.0 software. ETAP was used to analyze power flow and short-circuit disturbances with high accuracy. Figure 1 shows the single line diagram of the PPSDM Migas power system developed using ETAP Power Station 16.0 based on the collected data. When Generator 2 operates, the power flow distribution at each bus bar is as follows:

Table 2. Power Distribution on Bus Bars

Bus ID	kV	Load (%)	MW Loading	Amp (A)
Bus 1	0.4	100	0.692	1134
Bus Dist. Boiler	0.38	99.72	0.0076	13.27
Bus Dist. Kilang	0.38	98.19	0.373	642.8
Bus Dist. P.Plant	0.38	99.36	0.0438	71.43
Bus Dist. Water Treatment	0.38	97.24	0.159	285.5
Bus T.Kilang	6.1	98.35	0.473	50.9
Bus T.Utilitas	6.1	98.35	0.216	23.48
Bus T8	6.1	98.3	0.465	50.05
Bus T9	6.1	98.35	0	0
Bus T10	6.1	98.35	0.0076	0.843
Bus T13	6.1	98.34	0.172	18.98
Bus T14	6.1	98.35	0.044	4.535
Main Bus	6.1	98.35	0.689	74.37

The maximum short-circuit current was obtained from a three-phase short-circuit simulation with 4 cycles, while the minimum short-circuit current was obtained from a two-phase short-circuit simulation with 30 cycles. The short-circuit current values at each bus bar supplied by Generator 2 are shown in Table 3.

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Table 3. Short-Circuit Current Magnitudes

Bus ID	3-Phase (kA)	L-G (kA)	L-L (kA)	L-L-G (kA)
Bus 1	10.529	14.824	9.309	14.999
Bus Dist. Boiler	2.056	1.883	1.783	2.04
Bus Dist. Kilang	4.151	0.975	3.591	3.688
Bus Dist. P.Plant	3.516	3.328	3.061	3.551
Bus Dist. W. Treatment	3.641	3.065	3.155	3.702
Bus T.Kilang	0.62	0	0.546	0.546
Bus T.Utilitas	0.62	0	0.546	0.546
Bus T8	0.619	0	0.545	0.545
Bus T9	0.618	0	0.544	0.544
Bus T10	0.618	0	0.544	0.544
Bus T13	0.619	0	0.545	0.545
Bus T14	0.62	0	0.545	0.545
Main Bus	0.62	0	0.546	0.546

Simulation results using ETAP 16.0 under full-load operating conditions show that the largest fault is a Line-to-Line-to-Ground (L-L-G) fault at Bus 1, producing a short-circuit current of 14.299 kA. The fault current values at the load distribution buses are larger than those in the distribution lines, because as more loads operate, the positive- and negative-sequence impedances decrease, resulting in higher short-circuit currents. On the other hand, zero-sequence impedance is not affected by the number of loads in operation [3]. The Breaking Capacity (or maximum interrupting capacity) of a circuit breaker is the highest short-circuit current that the device can interrupt without damage. Circuit breaker performance is rated by two key parameters: interrupting duty (the ability to break fault current) and momentary duty (the ability to withstand the first half-cycle fault current surge) [6].

Table 4. Circuit Breaker Breaking Capacity during Short-Circuit Conditions

Bus ID	kV	SCmax (kA)	Im CB (kA)	Sm (kVA)
Bus 1	0.4	14.999	239.984	16626.5
Bus Dist. Boiler	0.38	2.04	3.264	2148.29
Bus Dist. Kilang	0.38	3.688	59.008	3883.78
Bus Dist. P.Plant	0.38	3.551	56.816	3739.51
Bus Dist. Water Treatment	0.38	3.702	59.232	3898.52
Bus T.Kilang	0.38	0.546	0.8736	574.98
Bus T.Utilitas	0.38	0.546	0.8736	574.98
Bus T8	6.1	0.545	0.872	9213.12
Bus T9	6.1	0.544	0.8704	9196.21
Bus T10	6.1	0.544	0.8704	9196.21
Bus T13	6.1	0.545	0.872	9213.12
Bus T14	6.1	0.545	0.872	9213.12
Main Bus	6.1	0.546	0.8736	9230.02

From the short-circuit simulation, the maximum fault current in the distribution system was found to be 9.938 kA. The largest fault current occurred during an L-L-G fault, which was then used to calculate the momentary current duty—the maximum current that may flow through a circuit breaker in the first half cycle after a fault. Once the short-circuit currents and nominal load currents were obtained from ETAP simulations, they were compared with the ratings of the existing circuit breakers at PPSDM Migas. The comparison included maximum short-circuit current (IM), nominal current (IN) from load flow analysis, and the existing CB rating and breaking capacity (ICU).

Table 5. Existing Circuit Breakers, Nominal Currents, and Short-Circuit Currents

Bus ID	Nearest CB	Im CB (kA)	IN (A)	Existing CB Rating (A)	ICU (kA)
Bus 1 (ACB 2)	ACB 2	239.984	1134	2000	65
Bus 1 (ACB 6)	ACB 6	239.984	1134	1600	65
Bus Dist. Boiler	CB Ts10	3.264	13.27	400	36
Bus Dist. Kilang	CB Ts8	59.008	642.8	400	36
Bus Dist. P.Plant	CB Ts14	56.816	71.43	400	36
Bus Dist. Water Treatment	CB Ts13	59.232	285.5	400	36
Bus T.Kilang	OCB 3	0.8736	50.9	630	30
Bus T.Utilitas	OCB 4	0.8736	23.48	630	30
Bus T8	CB T8	0.872	50.05	630	30
Bus T9	CB T9	0.8704	0	630	30
Bus T10	CB T10	0.8704	0.843	630	30
Bus T13	CB T13	0.872	18.98	630	30
Bus T14	CB T14	0.872	4.535	630	30
Main Bus	OCB 1	0.8736	74.37	630	30

The comparison results indicate that most circuit breakers are appropriately rated and are capable of protecting against short-circuit faults in the system. However, it was found that the circuit breaker in the refinery distribution unit requires replacement with a minimum rating of 800 A, since the existing 400 A breaker is inadequate to withstand the fault current under full-load conditions. The overload towards the refinery distribution occurs due to load transfer from Transformer 10 (Boiler Unit) to Transformer 8 (Refinery Unit), which increases the current beyond the rating of the existing circuit breaker.

4. Conclusion

The distribution network at PPSDM Migas uses a radial distribution system, which makes the power system less reliable when disturbances occur. However, the generation system is relatively quick in meeting the electricity demand of the refinery and utility units. The transfer of load from Transformer 10 to Transformer 8 has resulted in a nominal current exceeding the circuit breaker rating under full-load conditions (when all loads are operating). Therefore, it is necessary to replace the circuit breaker from a 400 A rating to an 800 A rating.

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