A Simulation study of availability analysis on a chemical process industry considering spare part inventory

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Abstract. A maintenance strategy is an important factor in the production activities of the process industry. Since the process industry consists of many components, the failure mode is relatively complex. This paper observes one of the petrochemical companies in Indonesia which produces Pythalic Anhydride. The company is able to produce in 20.69 days every month. In reality, during 2017, the company produced 23 days every month on average. Production, known as the calendar day, which cannot achieve the target can affect customer service level. This research focuses on evaluating availability in order to minimize Mean Time to Repair (MTTR). One of the best strategies is to control the spare part inventory policy so that the spare part must be available when an equipment downtime occurs. We will use two modeling techniques to solve the problem: (a) reliability block diagram will be used to model the failure mode and (b) the simulation model will be used to model the entire system, including random variables and variable inter-dependency. After conducting scenario analysis by varying some parameters, the availability increased to 91.8% and average calendar days decreased to 22.64 days per month.

1. Introduction

A maintenance strategy is an important factor in production decision-making, especially in a process plant [1]. Some examples of process industries include chemical fertilizer, oil and gas, cement, iron, and steel. The process industry is composed of several kinds of elements so that the failure mode is relatively complex. In line with this complexity condition, reliability, availability, and maintainability (RAM) parameters are considered as critical factors in order to fulfill production quality and operational cost [1].

This paper studies one of the petrochemical companies in Indonesia that produces Pythalic Anhydride (PA). PA is usually used for resin mixture in paint and plastics production. This industry is one of the priority industries in Indonesia based on the National Industrial Development Master Plan (RIPIN) because the company produces raw components and auxiliary materials to support other industries [2].

The company has a production capacity of 70,000 Metric Ton per Year (MTPY) with an average production realization of 4,967.61 tons every month in 2017. In the process industry, there are two terms used in measuring production time: namely calendar day and stream day [3]. Calendar day is the time needed by a process industrial facility to meet production demand, which includes a variety of constraints that can delay, disrupt, or slow down production, such as downtime production and decreased production rates, whereas stream day is the time needed by a process industrial facility in normal capacity, but does not consider the constraints that delay. In 2017, this company's total calendar days...
was 276 days, which means the calendar average day in each month is 23 days. But, based on production capacity, every month this company can produce 20.69 days. This difference is caused by several factors, such as material stock out and production shutdown at the factory. Calendar days that do not meet the target can cause delays in delivery, which will affect customer service level. In order to decrease the operational cost and reach the customer service target, the calendar day must be decreased.

One factor that can affect the calendar day is the availability of production. Every year, this company always experiences unplanned shutdown with mean time to failure (MTTF) for 24.5 days and mean time to repair for 74 hours. Forty percent of the shutdown causes are machine breakdowns, which are triggered by failures to the electrical system, mechanical systems, instrumentation systems, operational systems, and electricity supply problems. These facility disruptions are also known as supply disruption because it affects the distribution chain [4]. In overcoming this problem, we can evaluate the parameters of reliability, availability and maintainability to improve availability and calendar days. The evaluation and improvement, using reliability, availability, and maintainability analysis (RAM analysis), can result in increased throughput, increased asset availability, and cost savings [5].

The study on RAM analysis of a process plant has not received much attention. However, reliability, availability, and maintainability are important parameters to maintain the operational cost and production quality of a process plant. Many studies have carried out an analytical and simulation approach. Bikram and Scott performed RAM analysis by determining the critical component that has the lowest availability in the system [6]. This study attempts to conduct ABC classification and simulation modeling by experimenting with the spare part inventory parameters. Herder et al. implemented RAM analysis by allocating resources to achieve optimal production parameters [7]. Aijaz and Adamantios compared predictive maintenance strategy with both simulation and an analytical approach. Their study is about improving availability of a natural gas company, which is also a process industry [8]. Wang et al. studied RAM analysis for minimizing unplanned downtime by modeling Markov chain and reliability block diagram. These conventional tools are used for probabilistic behavior and failure mode in a hybrid cooling system [9]. A different concept was studied by Schryver et al. who used an endogenous availability parameter. Endogenous availability does not consider uptime and downtime as a parameter. However, the parameter is calculated by the ratio of actual production with planned production [10]. Comparing both analytical and simulation approaches was done by Alrabghi et al. In this study, they used two different case studies. The simulation approach was implemented in a continuous manufacture company while the analytical approach was implemented in a discrete manufacture company [11]. Different case studies were observed in order to solve a supply disruption problem. This study used a discrete event simulation model in order to develop mitigation scenarios against supply disruption problems [4]. Other supply disruption effect was studied by Siswanto et al. on customer service levels in the maritime transportation problem. The purpose of this study is to maintain inventory level, both in the supply and destination warehouses, during a predetermined planning horizon [12].

According to previous studies, RAM analysis uses both simulation and analytical approaches. Several equations are used in the analytical approach in order to evaluate the availability and capacity in a system. Generally, the analytical approach only considers deterministic variables; the random variables are ignored or assumed to be deterministic. The simulation approach, on the other hand, predicts the system availability by simulating the system during a period of time based on each component failure rate. The simulation approach generates and models random behavior or stochastic event on a system. The analytical approach provides cheaper and faster computation, while the simulation approach provides more flexible and accurate information to the system parameters [13]. Prior studies implement several strategies, such as identifying bad actors, resource allocation, developing spare part inventory policy, and adding redundant machines. RAM analysis generally requires conventional reliability analysis to support modeling, such as fault tree analysis, reliability block diagram, and Petri net [13]. Spare part inventory is one of the practical solutions in order to decrease MTTR. In line with this, an experiment in spare part inventory policy in order to increase availability and minimize calendar day will be conducted in this study.
2. Problem Description
The case study is based on a petrochemical company in Indonesia. This paper will focus on the production and reliability system from raw material until finished product. However, only solid product is observed. The system is assumed remains unchanged and the raw material never starves.

As seen in Figure 1, the PA production starts with the oxidation process with the liquid form of raw material. The oxidation process is a reaction process between raw material and oxygen using a catalyst in a reactor machine. This process will result in gas formed of impure PA with 365–375°C temperature. When the reaction is completed, the temperature will be decreased by a super heater and economizer machine. Both machines use saturated steam to cool down the material. This process results in 170°C of impure PA. The material is then processed into a sublimation process to convert the gas impure PA into liquid. The sublimation process starts from the liquid condenser, which produces a liquid form of 140°C crude PA and a gas form of 137°C crude PA. Since the material is not completely condensed, a second sublimation is required. A switch condenser consists of three parallel condenser machines. This process results in a liquid form of crude PA with 140°C temperature. The liquid crude PA then flows into three crude PA tanks with capacity 100MT. The next process is the distillation process. The purpose of this process is to purify the crude PA into 180°C of pure PA. After the distillation process completed, the pure PA flows into the bagging process. In this process, the liquid form of pure PA is converted into solid form and packed into bags.

This company currently implements continuous review inventory policy with \( s \), \( S \) parameters. \( s \) represents the reorder point or the minimum requirement of replenishment. This means the order will be placed after the stock levels reach \( s \) value. \( S \) represents the target level or the maximum capacity of each spare part. The stock level is not allowed to exceed \( S \) value. The rule of this inventory policy will be discussed further in the next section.

3. Model Development
This study used the flow diagram and reliability block diagram to model the system qualitatively.

3.1 Reliability Block Diagram
Reliability block diagram is a graphical representation of components in a system and how the systems correlates with each other [14]. The case study described in the previous section consists of four units arranged in a series configuration. Failure of one unit interferes with the whole system, whereas each unit consists of several components that are connected in parallels and series configurations. Figure 2, Figure 3, Figure 4, and Figure 5 describe the reliability block diagrams of the related units. For example, the bagging unit consists of two parallel sub systems have two series components, as seen in Figure 5.
Thus, in this configuration, a failure of one component will not interfere with the bagging unit as long as the two components in the other parallel sub-unit are working well.

All units are connected in a series system. If one unit fails, the whole system cannot operate.

3.2 Flow Diagram

Flow diagrams are used to model the system logic, which represents the failure logic and spare part inventory replenishment. The failure logic is generated based on the configuration model (series and parallel system). To simplify the modeling concept, we use three subsystems’ (A, B, C) notations as an example to represent the subsystems of each unit configuration, as depicted in Figure 2, Figure 3, Figure 4, and Figure 5.

3.2.1 Series System. Suppose we have A, B, and C subsystems which are connected in a series configuration. As seen in Figure 6, the corresponding flow diagram starts from the input process of the failure rate (MTTR and MTTF) based on the distribution fitting result. If a subsystem fails, then the subsystem status will be updated to 0, which represents a code as a failed system. The next step is to evaluate the failure of subsystem A, B, and C. If a subsystem fails, the whole system cannot be operated.
Therefore, the subsystem needs to be repaired at the next stage. Repairs are made until all the three systems are working well. After repairing, the system status will be updated to 1, which represents an operated system code.

3.2.2 Parallel System. Let us consider the flow diagram of a parallel system composed of A, B, and C subsystems, as seen in Figure 7. The basic logic of a parallel system is that, if a subsystem fails, the whole system still can be operated as long as at least one subsystem is working well. However, the whole system will shut down if all three subsystems fail. The model starts with the input process of the failure rate (MTTR and MTTF) based on the distribution fitting result. If a subsystem fails, then the subsystem status will be updated to 0 as a failed system code. The next step is to evaluate the failure of subsystem A, B, and C. If all subsystems fail, the system cannot be operated. Therefore, the subsystems need to be repaired at the next stage. Repairs are made until one of the three systems can be operated. After repairing, the system status will be updated as an operated system.

![Figure 6. Flow diagram of series system.](image)

![Figure 7. Flow diagram of parallel system.](image)

3.2.3 Spare part Inventory Model. A model of spare part inventory is shown in Figure 10. This model describes how the spare part inventory will be replenished when the stock level reaches the minimum position. In this case, the inventory policy applied by the company is S, s policy. S means the target level or the maximum stock level stored in the spare part warehouse, while s means the minimum stock level in the spare part warehouse or Reorder Point (ROP).

The first step is to input the spare part stock level information during the simulation. The information required is S, s parameters and the initial stock level. The next step is to evaluate the stock level of each spare part. If the spare part stock level is less than s or ROP value, then O number of a spare part will be ordered. O denotes the number of spare parts to be ordered, which is calculated by subtracting the target level S with the current stock level. After O is identified, the next step is the ordering process. In the ordering process, the delay time occurs based on the shipping time. After the spare part arrives, the next step is to update the spare part inventory level by adding the O value to the current inventory level.

After the conceptual model is generated, the next step is generating the simulation model. The simulation model is generated based on the conceptual model. The simulation model provides the random number generation that will be used to represent the MTTR, MTTF, production delay, and order
shipping delay. There are two important stages in the simulation model, verification and validation. The purpose of model verification is to avoid simulation error, while the model validation is to ensure that the simulation model truly represents the real system. The input system of the simulation model is generated by random value, thus, the output system will be random. Therefore, several replications are required to represent the real system.

4. Results and Discussion
The simulation is conducted in two steps; the first is to evaluate the performance of the existing condition. Based on the existing simulation result, the scenarios are developed to improve system performance. Each experiment is conducted in 10 replications.

### 4.1 Existing Condition
In the existing condition, the company implements the $S$, $s$ spare part inventory policy. Spare part replenishment will occur if the spare part stock level is less than ROP ($s$). The stock level should be less than the target value ($S$). After the simulation, existing calendar day and system availability are obtained.

Based on Table 1, it can be seen that the average system availability is 0.8843 and the calendar day average is 279.25 days. The next step is evaluating system availability in each unit to find out which unit has the lowest availability. The whole system is connected in a series configuration. In line with this, the system availability is calculated by multiplying each of unit availability.
Table 2. Existing Condition Performance Summary

| Replication | Oxidation Availability | Sublimation Availability | Distillation Availability | Bagging Availability |
|-------------|------------------------|--------------------------|--------------------------|---------------------|
| 1           | 0.9457                 | 0.9940                   | 0.9902                   | 1                   |
| 2           | 0.8884                 | 0.9824                   | 0.9961                   | 0.9937              |
| 3           | 0.8791                 | 0.9988                   | 1                        | 0.9953              |
| 4           | 0.9281                 | 0.9963                   | 0.9836                   | 0.9935              |
| 5           | 0.8837                 | 0.9952                   | 1                        | 0.9968              |
| 6           | 0.8973                 | 0.9870                   | 0.9974                   | 0.9953              |
| 7           | 0.9242                 | 0.9975                   | 0.9984                   | 0.9942              |
| 8           | 0.9221                 | 0.9585                   | 0.9949                   | 0.9928              |
| 9           | 0.8901                 | 0.9899                   | 1                        | 0.9910              |
| 10          | 0.8665                 | 0.9904                   | 1                        | 0.9948              |
| Average     | 0.9025                 | 0.9890                   | 0.9961                   | 0.9947              |

Table 3. Existing Condition of Spare Part Availability

| No | Spare part | Availability Average |
|----|------------|----------------------|
| 1  | 001125.4   | 0.97308              |
| 2  | 001268.2   | 0.99642              |
| 3  | 001265.8   | 0.97634              |
| 4  | 001267.4   | 0.99868              |
| 5  | 004005.6   | 0.98953              |
| 6  | 001623.8   | 1                    |
| 7  | 004873.3   | 0.99944              |
| 8  | 002790.0   | 1                    |
| 9  | 005760.0   | 0.99186              |
| 10 | 004255.5   | 1                    |
| 11 | 004881.1   | 0.97973              |
| 12 | 002958.1   | 0.99356              |
| 13 | 001473.8   | 1                    |
| 14 | 001265.3   | 1                    |
| 15 | 003003.4   | 0.98768              |
| 16 | 000643.7   | 1                    |
| 17 | 000938.1   | 1                    |

Referring to Table 2, it can be seen that the lowest availability is oxidation unit. Therefore, we need to conduct an experiment to improve the oxidation unit availability. The experiment for other units might be unnecessary because all units are connected in a series configuration. The average calendar day to fulfill demand every month is 23 days. Meanwhile, based on the target, the calendar day to fulfill the request should be 20 days every month. Therefore, the improvement of spare part inventory policy is required to improve the system performance.

The next step is determining which spare part contributes to the low oxidation unit availability. We can obtain this decision by evaluating each of spare part availability. Spare part availability means the availability of each spare part whenever required during the corresponding machine failure. Based on Table 3, spare part 001125.4 has the lowest availability followed by 001265.8 and 004881.1. To discuss further these spare parts availabilities, we can analyze the stock level behavior based on Figure 9, Figure 10, and Figure 11.
Referring to Figure 9, the spare part stock average during 1,100 days of simulation is 14 units. Six times replenishment is made for approximately three years. Because ROP inventory policy is not applied to spare part 001125.4, replenishment is often made when stock runs out. In line with this policy, the MTTR will be in a high-risk situation. Only one replenishment is made before the stock level reaches the ROP (s), this means that the spare part required is less than the available stock. Spare part 001265.8 shows a different behavior during approximately three years of the simulation. The replenishment is made five times. In one out of five, a replenishment is made before the stock level reaches ROP (s). The average stock level is 58. Figure 11 shows that the replenishment of the spare part 004881.1 is made six times. All these replenishments were made after the stock level reached ROP (s).

4.2 Scenario Development
Referring to the existing condition, three spare parts contribute to the low oxidation unit availability. This is caused by the small value of s or ROP parameter; therefore, the risk of the replenishment during the downtime is high and it can cause a high value of MTTR. In this case, in order to improve system availability, the s value must be increased. Since the inventory cost and ordering cost are neglected during the decision-making, the s or S value can be set to a higher value depending on decision-maker preferences.

We decide to consider the stock level behavior to determine new spare part inventory parameters. Referring to Figure 9, a replenishment is made when the stock level is 5. Therefore, we can change the s value to 5 or above. We decide to change the s value to 10 and the S value to 40. This approach is also implemented for spare part 001265.8 and 004881.1. The s, S parameter of spare part 001265.8 is changed...
to 40 and 120 consecutively, while the $x$, $S$ parameter of spare part 004881.1 is changed to 4 and 8 consecutively. Table 4 shows the experiment result of the scenario development.

### Table 4. Scenario Development Experiment Summary

| Replication | Calendar Day (in Days) | System Availability | Oxidation Availability | Sublimation Availability | Distillation Availability | Bagging Availability |
|-------------|------------------------|---------------------|------------------------|--------------------------|--------------------------|----------------------|
| 1           | 266.34                 | 0.9303              | 0.9444                 | 0.9910                   | 1                        | 0.9940               |
| 2           | 270.54                 | 0.9160              | 0.9318                 | 0.9883                   | 0.9997                   | 0.9950               |
| 3           | 271.88                 | 0.9118              | 0.9210                 | 0.9971                   | 1                        | 0.9929               |
| 4           | 274.38                 | 0.9040              | 0.9202                 | 0.9862                   | 1                        | 0.9961               |
| 5           | 273.71                 | 0.9012              | 0.9124                 | 0.9793                   | 1                        | 0.9952               |
| 6           | 273.63                 | 0.9098              | 0.9125                 | 0.9957                   | 0.9996                   | 0.9930               |
| 7           | 269.5                  | 0.9207              | 0.9207                 | 0.9925                   | 1                        | 0.9948               |
| 8           | 272.08                 | 0.9790              | 0.9962                 | 0.9924                   | 0.9949                   | 0.9953               |
| 9           | 271.17                 | 0.9117              | 0.9331                 | 0.9855                   | 1                        | 0.9914               |
| 10          | 273.71                 | 0.9000              | 0.9280                 | 0.9753                   | 1                        | 0.9944               |
| Average     | 271.7                  | 0.9184              | 0.9352                 | 0.9883                   | 0.9994                   | 0.9942               |

### Table 5. Hypothesis Testing Result

| t-test Hypothesis Testing | Calendar Day | Availability |
|---------------------------|--------------|--------------|
|                           | Existing     | Developed Scenario | Existing | Developed Scenario |
| Mean                      | 279.86       | 271.71       | 0.884 | 0.918 |
| Variance                  | 1307.43      | 143.79       | 0.001 | 0     |
| Observations              | 10           | 10           | 10    | 10    |
| Pearson Correlation       | 725.62       | 0.001        |       |       |
| Hypothesized Mean Difference | 0          | 0            |       |       |
| df                        | 18           | 18           |       |       |
| t Stat                    | 3.321        | -3.222       |       |       |
| P(T<=t) one-tail          | 0.002        | 0.002        |       |       |
| t Critical one-tail       | 1.734        | 1.734        |       |       |
| P(T<=t) two-tail          | 0.004        | 0.005        |       |       |
| t Critical two-tail       | 2.101        | 2.101        |       |       |

The result of this scenario is 271.7 days a year or approximately 22.64 days in every month for calendar day and 0.9184 for system availability. The calendar day was reduced by 8.17 days and the system availability was increased by 3.41%. Conducting t-test is required in order to evaluate the experiment significance compared to the existing condition. Table 5 shows the hypothesis testing result. Based on this result, there is a significant difference between existing condition and developed scenario for both parameters. This can be proven from the $t_{stat}$ value, which lies outside the $t_{critical}$ two-tail.

### 5. Conclusion

Based on the simulation result, the current availability of production at the company is 88.43% and the calendar day is 279.86 days a year or 23 days every month. These two performance indicators still have not reached the target, which is 90% for availability, and 20 days for each month. Oxidation unit has the lowest availability; therefore, we need to conduct an experiment to improve the oxidation unit availability. The experiment for other units might be unnecessary because all units are connected in a series configuration.

In this study, a scenario was developed by increasing the spare parts availability by changing the ROP value and spare part capacity on three types of spare parts that have the lowest availability. Based on the experiment result, the improvement of the spare part inventory policy can produce significant changes to the availability and calendar day. The resulting calendar day is 271.67 days a year and the resulting availability is 91.8%. The availability reaches the target, but the calendar day does not reach
the target. The calendar day average for each month, which was originally 23 days, decreased to 22.64 days.

In managerial aspects, the spare parts inventory management strategy gives a significant impact to the manufacturing performances without incurring the investment cost. As we can see from the experiment result, the calendar day and availability were improved significantly. The calendar day was decreased to 8.19 days, if we convert this duration to the throughput parameter, this strategy will increase the production to 1,965.6 Ton in a year.

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