# Comparison of Discrete Event Simulation and Agent Based Simulation for Evaluating the Performance of Port Container Terminal

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***Abstract*—Event log obtained from Port Container Terminal (PCT) Surabaya is an asynchronous event log. This event log needs to be run in a simulation to reflect the real world performance which contains both time and cost. From the event log we gathered, we use forecast methods to predict the number of container for the following month. Several forecasting methods are evaluated; whereas discrete event simulation and agent based simulation are compared to handle asynchronous processes.**

**The results of the experiments show that moving average have the lowest MSE compared to other forecast methods such as Simple Exponential Smoothing, Double Exponential Smoothing, and Linear Regression. Then, from the forecast results we successfully generate the event log for the following month and simulate it using agent based simulation and Discrete Event Simulation. The results of the simulation show that agent based simulation can handle the communication process which discrete event simulation cannot handle. Both the simulation results are depicted in Gantt charts.**

***Keywords—Simulation; Event log; Forecast; Discrete Event; Agent Based Simulation***

## I. INTRODUCTION

Port container terminal receive container from all over the world every day. The infrastructure for the current situation might still be able to handle the current number of daily incoming container. This does not guarantee that in the future they may still be able to handle those incoming container. Thus, a precaution act is an important task to do. When a company does not take the future into consideration, the company may suffer loss of profit because the company service time is increasing.

To prevent those kind of problem, forecast measure can be taken. Since the event log we gathered from the port container terminal have time attributes, time series forecast methods is implemented. Some forecast methods are Simple Exponential Smoothing, Brown's Double Exponential Smoothing, Holt's Double Exponential Smoothing, Moving Average, and Linear Regression. From the result of the forecast, then the performance of the forecast result can be analyzed to determine further action. We use simulations for the forecast results to analyze the performance of the generated log.

Simulation is widely used to reflect real world processes [1], [2]. With simulation, some unseen problem can be found. Other benefit of simulation is the information on the resources of the running processes such as time and cost will be discovered.

This paper analyzes the performance of Port Container Terminal (PCT) on the existing condition and the future condition. The performance is then analyzed using agent based simulation and discrete event simulation. we try to predict the number of container and event log for the following month by Simple Exponential Smoothing, Brown's Double Exponential Smoothing, Holt's Double Exponential Smoothing, Moving Average, and Linear Regression. Gantt chart is then used to shows the difference on agent based simulation and discrete event simulation. Agent based simulation results on Gantt chart shows that the communication process can be modeled successfully. Agent based simulation result is closer to real world process since the discrete event simulation results on Gantt chart cannot show the communication processes.

## II. LITERATURE REVIEW

A simulation based on CPN has been used to simulate two cases by Rozinat et.al[3]. In the paper, they provide the difference of the data used to build the simulation by building three models. On the first case, the first model and the second model use the decision miner to discover the decision rule, while the third one used the probability method to define the choice of the activities. Hence, the second model and the third model uses 95% of the waiting time while the first model used no waiting time. In the second case, they build 2 models. The first model, use resources to determine its waiting time. On the other hand, the second model use twice of the mined waiting time. The paper shows that automatically generate simulation model from the event log.

Other works on simulation tried to simulate the performance of scalable business process[4]. Three alternative business processes which scalable to the base business process were made to be compared with the base business process. This study uses colored petri net (CPN) tools to do simulations for a process of refueling gas in a gas station. The results show the difference of execution time of the base business process and the alternative business processes.

Moving average (MA) was used by Nhita et.al[5] to predict rainfall which help decide which plant to grow based on mobile device. Several modified moving average methods that has been used on this paper are centered MA, double MA, weighted MA, and modified MA.

Simple exponential smoothing is also a common method which is best used for data without trend or seasonal data[6]. This paper presents the forecast result for patient of oro-maxillo-facial traumas using simple seasonal exponential smoothing and simple exponential smoothing.

Simple exponential smoothing is compared with artificial neural network (ANN) and Group Method of Data Handling (GMDH) by Bon-gil Koo et.al.[7].

Double exponential smoothing (DES) used by Adamuthe, Gage, and Thampi[8] on cloud computing. On the paper, they forecast the growth trend of SaaS, PaaS, and IaaS of cloud computing service providers. Their research shows that DES method with two parameters is better than DES with only one parameter.

## III. Methodology

The event log that we have gathered is useful to build a simulation which simulate the current condition in the port container terminal. Therefore, the data for the simulation of future events is gathered by doing forecast. First, we forecast the number of containers for the upcoming month. Since the number of container is the number of case for the future event log, the traces is defined by doing random normal method. After we get the generated log, we simulate both the existing event log and generated log with discrete event simulation and agent based simulation. The result from the simulations will show the performance of both the existing event log and the generated event log.

To achieve the above results, we have arranged the processes. The method proposed on this paper is covered in the Table 1.

Table 1. The proposed method

| Process | Input | Output |
|---|---|---|
| Forecast<br>1. Simple Exponential Smoothing<br>2. Double Exponential Smoothing<br>3. Moving Average<br>4. Linear Regression | Existing Event Log | Generated Event Log |
| Simulation<br>1. Discrete Event Simulation<br>2. Agent Based Simulation | Existing Event Log, Generated Event Log | Performance Report |

### 3.1. Forecast

Input for the forecast methods here is the event log we gathered from port container terminal. The log is forecasted using each of forecast method to find the lowest error value. Then, the forecast result with the lowest error value is simulated along with the forecasted log in the simulation process.

#### 3.1.1. Simple Exponential Smoothing (SES)

Simple exponential smoothing is a common time series method for forecasting. This method uses a constant alpha ($\alpha$) between 0 to 1 to determine the weight of previous data. The more weight (closer to 1) assigned to this method, the more weight is given to the recent data compared to the older data. The equation for simple exponential smoothing are shown in Equation 1.

$$F_t = \alpha A_{t-1} + (1-\alpha)F_{t-1} \quad (1)$$

$F_{t-1}$ = Forecast result of last period
$A_{t-1}$ = Actual data of last period

For data with a pattern, a high alpha value should minimize the error in the forecasting. While for data with variations, alpha value should be keep lower since the lower the alpha value, the algorithm will weigh the older data more.

#### 3.1.2. Double Exponential Smoothing (DES)

Double exponential smoothing is a statistical method based on simple exponential smoothing. In double exponential smoothing, there is two methods which are commonly used. The first method uses only one weight constant which is alpha (a). The second method use alpha (a) and beta (β) as the weighting constants.

The first one is also called brown's double exponential smoothing. The formulations for this method are shown in Equation 2 through Equation 6.

$$F_t = \alpha_t + b_t \quad (2)$$
$$a_t = 2A_t - A''_t \quad (3)$$
$$b_t = (\tfrac{\alpha}{1-\alpha})(A_t - A''_t) \quad (4)$$
$$A_t = \alpha y_t + (1-\alpha)A_{t-1} \quad (5)$$
$$A''_t = aA_t + (1-\alpha)A''_{t-1} \quad (6)$$

$y_t$= Actual data of the current period
$F_t$= Forecast of the current period

The second double exponential smoothing use two constants. By using two constants, this method can freely weight the series of previous data using alpha (a) and beta (β) as the constant to weight the trend. The formula for double exponential smoothing with two constants are shown in Equation 7 to Equation 9.

$$F_t = A_t + T_t \quad (7)$$
$$A_t = \alpha y_t + (1-\alpha)(A_{t-1} + T_{t-1}) \quad (8)$$
$$T_t = \beta(A_t - A_{t-1}) + (1-\beta)T_{t-1} \quad (9)$$

$T_t$= Trend of the current period
$y_t$= Actual data of the current period

3.1.3. Moving Average (MA)

Moving average is a smoothing technique which calculate the average data of several periods prior to the forecast target[9]. The methods can be implemented by using Equation 10.

$$MA = \frac{1}{K}(Y_{t-1} + Y_{t-2} + \cdots + Y_{t-K+1}) \quad (10)$$

K= the amount of data
$Y$= actual data

3.1.4. Linear Regression

Linear Regression is a basic forecast method on time series forecast[10]. The formula for linear regression are shown in Equation 11.

$$LR = a + bx \quad (11)$$

3.2. Simulation

The simulation on this research is useful to compare the performance of the event log we gathered and the log from the forecast methods. This allow us to analyze the performance from the performance report.

3.2.1. Discrete Event Simulation

Discrete event simulation is a simulation method which is one of the four main method[11]. Thus, this method is widely used for the development of simulation model. Researches on discrete event simulation on various case to identify the performance [12], [13] has been conducted. The research shows that discrete event simulation proves to be reliable on identifying the performance and provides insight on the operation of the activities.

For the case of port container terminal, the event log we gathered has messages which is the form of communication of the customer, bea cukai, quarantine and the port container terminal. In discrete event simulation, this message will not be included.

3.2.2. Agent Based Simulation

Agent based simulation can simulate the behavior of the agents based on the real world[14]. An agent have 4 basic characteristics[11]:

- Autonomy: agents works on its own without the interference of the user.
- Pro-activeness: agents have the initiative to change the environment to reach the goal.
- Reactivity: agents respond to the change of its environment.
- Social ability: agents can interact with other agents.

Agents based simulation can communicate with each other. Therefore, the agent based system can handle the message contained in the event log we gathered from the port container terminal. This characteristic made agent based simulation is more realistic than discrete event simulation.

3.3. Generating Event Log

The results of the forecast will only show the number of container each day of the next month. Therefore, we cannot use the container data as it is. To overcome the problem, we generate future event log using random normal distribution. We decided to use random normal distribution based on the lowest error results of curve fitting process. The random normal equation is as Equation 12 shows.

$$y = ae^{(-\frac{(x-b)^2}{2c^2})} \quad (12)$$

$e$= standard deviation
$a$= average value

## IV. Experiments and Results

In this section, we start the experiments by utilizing the existing forecast methods to forecast the number of container for the next month on the existing event log we gathered from the port container terminal of Surabaya.

The data we got from port container terminal is still in the form of database with the range of date from January 2016 to March 2016. To gather the event log, the data must be transformed. The transformed data reveal the activities occurred on the port container terminal.

The structure of the event log we gathered are shown on Table 2.

Table 2 Existing event log

| CASE_ID | ORIGINATOR | ACTIVITY | TIME | COST | DETAILS |
|---|---|---|---|---|---|
| 4691694 | CUSTOMER | Document_ entry | 3/24/2016 20:05 | 48379.739321638 | Dry;Green Line |
| 4691694 | TPS | Vessel_ berthing | 3/24/2016 22:10 | 690.90816831999 | Dry;Green Line |

The case_id on the event log represents the container processed in the port container terminal. Thus, the number of container per day can be defined by the number of case_id each day. The number of container per day is the main data for the forecast methods.

The traces we get from the event log is a vital element in this research. As we have the activities occurred on the port container terminal, we can determine the start activity to the last activity of each case. Thus, we can determine which trace each case of the generated event log is. The traces and each of the trace occurrence frequency that we found on the existing event log are shown in Table 3.

Table 3 Frequencies of traces

| Trace | Frequency Percentages |
|---|---|
| Quarantine, Dry, Green Line | 18.15% |
| Quarantine, Dry, Red Line | 0.81% |
| Quarantine, Reefer, Green Line | 3.81% |
| Quarantine, Reefer, Red Line | 0.13% |
| Quarantine, Uncontainer, Green Line | 0.02% |
| Quarantine, Uncontainer, Red Line | 0.00% |
| Dry, Green Line | 70.68% |
| Dry, Red Line | 2.53% |
| Reefer, Green Line | 3.45% |
| Reefer, Red Line | 0.15% |
| Uncontainer, Green Line | 0.24% |
| Uncontainer, Red Line | 0.01% |

Since we already know the number of container each day, the data necessary for the forecast methods is complete. Therefore, the forecast methods are then used on the data of container each day. The error result for each of the forecast methods are shown on Table 4.

Table 4 Error results of forecasts

| No | Forecast Methods | MSE |
|---|---|---|
| 1 | Simple Exponential Smoothing | 406618.9 |
| 2 | Brown's Double Exponential Smoothing | 338701 |
| 3 | Holt's Double Exponential Smoothing | 360086.2 |
| 4 | Moving Average | 228243.2 |
| 5 | Linear Regression | 395147 |

Table 4 shows that moving average have the minimal error result. Therefore, we use moving average to forecast the number of container for the next month which is April 2016.

After we have got the number of container from the forecast results, we can generate the future log using the traces and the number of container. The standard deviation and the average occurrences of each trace we got from the existing log is needed to generate random normal distribution of each trace.

The generated log has the activities respective to each trace. But, time and cost for each activities have not been generated yet. Thus, we used random normal distribution to generate the time and cost for each activities. The generated event log is then structured similar to the existing event log shown on Table 2.

Both the generated event log and the existing event log now can be simulated. We simulate both of the log using Anylogic 8. The results of the existing event log are shown on Table 5 and Table 6, while the generated log simulation results are shown in Table 7 and Table 8.

Table 5 Existing log average time and cost (ABS)

| Trace | Sojourn Time (seconds) | Execution Time (seconds) | Cost (USD) |
|---|---|---|---|
| Quarantine, Dry, Green Line | 378328.5366 | 184717.9393 | 59391.03314 |
| Quarantine, Dry, Red Line | 1469578.268 | 1083532.142 | 84800.73246 |
| Quarantine, Reefer, Green Line | 375544.1463 | 141857.3045 | 59410.76177 |
| Quarantine, Reefer, Red Line | 1470039.171 | 1074825.677 | 84820.46109 |
| Quarantine, Uncontainer, Green Line | 366324.1455 | 145015.7797 | 59445.58008 |
| Quarantine, Uncontainer, Red Line | 0 | 0 | 0 |
| Dry, Green Line | 273182.7805 | 110998.0819 | 57701.49272 |
| Dry, Red Line | 789132.6829 | 474756.5338 | 83111.19204 |
| Reefer, Green Line | 285735.2439 | 127159.7882 | 57721.22135 |
| Reefer, Red Line | 789593.5854 | 471745.6637 | 83130.92067 |
| Uncontainer, Green Line | 285735.2439 | 132776.1129 | 57756.03966 |
| Uncontainer, Red Line | 789593.5854 | 630221.0811 | 83165.73898 |

Table 6 Existing log average time and cost (DES)

| Trace | Sojourn Time (seconds) | Execution Time (seconds) | Cost (USD) |
|---|---|---|---|
| Quarantine, Dry, Green Line | 149400.0976 | 83544.75192 | 59365.58036 |
| Quarantine, Dry, Red Line | 268526.2195 | 175122.91 | 84775.27968 |
| Quarantine, Reefer, Green Line | 161906.9512 | 82446.68892 | 59385.30898 |
| Quarantine, Reefer, Red Line | 268987.122 | 174555.3679 | 84795.0083 |
| Quarantine, Uncontainer, Green Line | 152886.753 | 83028.81618 | 59420.12729 |
| Quarantine, Uncontainer, Red Line | 0 | 0 | 0 |

| | | | |
|---|---|---|---|
| Dry, Green Line | 135006.7073 | 73905.27836 | 57699.64759 |
| Dry, Red Line | 255795.9268 | 186768.8031 | 83109.34691 |
| Reefer, Green Line | 151483.2439 | 76464.80412 | 57719.37621 |
| Reefer, Red Line | 256256.8293 | 158744.8661 | 83129.07553 |
| Uncontainer, Green Line | 151483.2439 | 77734.97578 | 57754.19452 |
| Uncontainer, Red Line | 256256.8293 | 153827.5339 | 83163.89384 |

Table 7 Generated Log average time and cost (ABS)

| Trace | Sojourn Time (seconds) | Execution Time (seconds) | Cost (USD) |
|---|---|---|---|
| Quarantine, Dry, Green Line | 354058.4716 | 186923.6258 | 58168.41797 |
| Quarantine, Dry, Red Line | 1563333.792 | 1270345.183 | 84929.88415 |
| Quarantine, Reefer, Green Line | 374874.5098 | 167832.0137 | 58190.51081 |
| Quarantine, Reefer, Red Line | 1555556.384 | 1324027.998 | 84951.97699 |
| Quarantine, Uncontainer, Green Line | 373712.4817 | 165290.8434 | 58247.8042 |
| Quarantine, Uncontainer, Red Line | 0 | 0 | 0 |
| Dry, Green Line | 268329.7569 | 113646.1323 | 56464.01456 |
| Dry, Red Line | 981225.8175 | 511376.3825 | 83225.48074 |
| Reefer, Green Line | 278979.9779 | 135061.4391 | 56486.1074 |
| Reefer, Red Line | 1091736.731 | 610911.2967 | 83247.57358 |
| Uncontainer, Green Line | 300956.9839 | 134633.1249 | 56543.40079 |
| Uncontainer, Red Line | 940686.6293 | 641956.7142 | 83304.86697 |

Table 8 Generated log average time and cost (DES)

| Trace | Sojourn Time (seconds) | Execution Time (seconds) | Cost (USD) |
|---|---|---|---|
| Quarantine, Dry, Green Line | 154049.6789 | 84049.92475 | 58143.11277 |
| Quarantine, Dry, Red Line | 330899.3487 | 188229.1493 | 84904.57895 |
| Quarantine, Reefer, Green Line | 159565.8873 | 93357.37835 | 58165.20561 |
| Quarantine, Reefer, Red Line | 299609.208 | 172130.6301 | 84926.67179 |
| Quarantine, Uncontainer, Green Line | 164423.0528 | 105980.6363 | 58222.499 |
| Quarantine, Uncontainer, Red Line | 0 | 0 | 0 |
| Dry, Green Line | 137087.1612 | 76513.6836 | 56462.18242 |
| Dry, Red Line | 290214.8894 | 186471.3188 | 83223.6486 |
| Reefer, Green Line | 159475.3002 | 77573.34265 | 56484.27526 |
| Reefer, Red Line | 283700.6807 | 158651.518 | 83245.74144 |
| Uncontainer, Green Line | 160120.9508 | 81839.32822 | 56541.56865 |
| Uncontainer, Red Line | 287108.4498 | 158414.2491 | 83303.03483 |

The results of the simulations also show the difference of agent based simulation and discrete event simulation. This is shown in the form of Gantt chart for both of the simulation methods.

For agent based simulation, the Gantt chart shows the activities grouped according to the agent who did the activity. Therefore, each agent has its own start activity and end activity.

Since the Gantt chart for agent based simulation is constructed by grouping activity respective to each agent who did the activity, we can see the communication process in the form of messages happening when the agents are still completing other activities (asynchronous). The activities which the agent are working on when the messages arrive are typically the activities of other cases.

In contrary with agent based simulation, discrete event simulation only has one start activity and end activity for all traces which happen on the port container terminal. Discrete event simulation does not take messages and agents into consideration. Therefore, the Gantt chart of discrete event simulation results will not show any communication process since it only shows the process sequentially.

The Gantt chart for agent based simulation and discrete event simulation results are shown on Figure 1 and Figure 2 respectively.

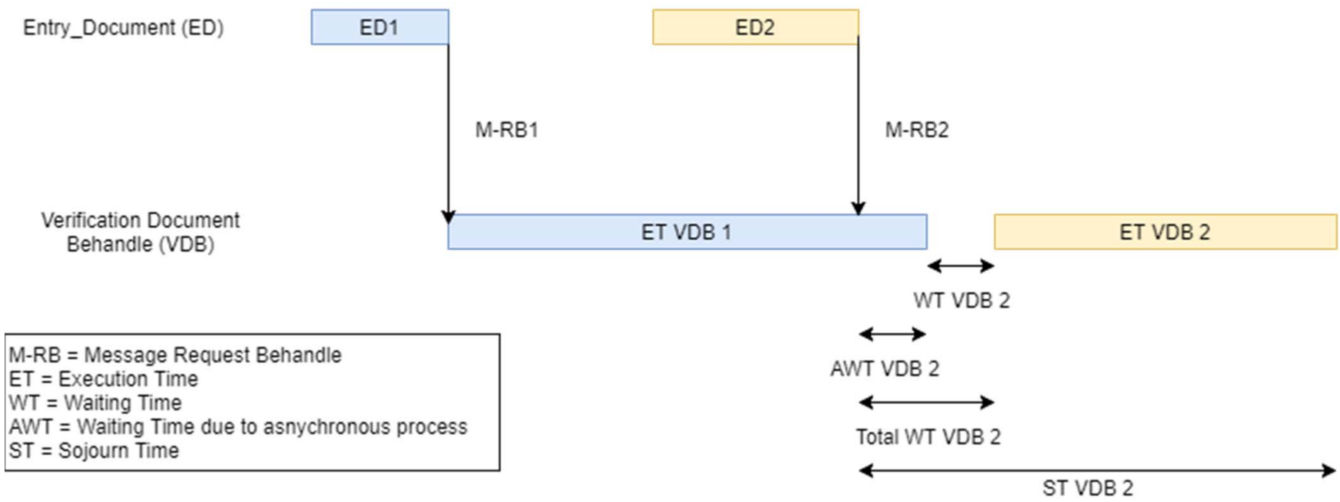

Figure 1 Gantt chart of agent based simulation

Figure 2 Gantt chart of discrete event simulation

## V. CONCLUSION

In this paper we generate the event log for April 2016 by forecasting the number of container from January 2016 to March 2016. Moving average results have the lowest MSE compared to simple exponential smoothing, Brown's double exponential smoothing, Holt's double exponential smoothing, and linear regression on this data. The existing log and the generated log are then simulated using discrete event simulation and agent based simulation. The results show that discrete event simulation always outperform agent based simulation as discrete event simulation does not take messages into account. While agent based simulation outperformed by discrete event simulation, agent based simulation shows better results as it is closer to the real world situation.

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