Modeling opportunistic maintenance using discrete event simulation

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Abstract. This study aims to create a simulation model of Opportunistic Maintenance (OM). In continuous industries and with a large variety of equipment functions, options for maintenance are very small. Determination of the maintenance schedule is based on the time opportunity created by the inventory level conditions, are blocking by the next process or lack of material from the previous process. The research was conducted by using discrete event simulation to generate arrival time of equipment failure and opportunistic maintenance time from scheduled maintenance and arrival time for maintenance due to inventory conditions. The arrival time of failure and the arrival time of opportunistic maintenance will probably intersect. Such conditions will increase the availability of equipment. Then the replication process is carried out to compare the availability of equipment under real conditions and the expected value of availability from the simulation. Finally, scheduled maintenance can be a decision variable to choose the best maintenance time when faced with fluctuations in demand.

1. Introduction

Generally, maintenance can be categorized into two types, namely preventive and corrective maintenance. Preventive maintenance is a part replacement activity, oil change, and adjustments are made before a failure occurs. The purpose of preventive maintenance activities is to increase the reliability of the system from the effects of aging such as wear, corrosion, fatigue, and other related phenomena [1]. While corrective maintenance is an action taken after a failure occurs, it needs to be returned as soon as possible so that the production process can run again.

The application of preventive maintenance in different industries or environments has its uniqueness. In one particular industry has many options for conducting maintenance activities. This kind of industry is an industry that has a lot of equipment units where each equipment has a production capability. This industry is an industry that does not require large variations of equipment function. Every equipment unit that needs maintenance does not have much effect on the amount of production output. Because of these large options, such industries will tend to implement preventive maintenance based on time intervals. Maintenance time intervals depend on the threshold value and the quality of preventive maintenance. In the real world, the quality of preventive maintenance is difficult to be determined precisely. This uncertainty makes it problematic to optimize maintenance policy [2]. This paper discusses optimizing maintenance on different sides, which is related to the inventory.

The other one, implementation of preventive maintenance is more based on opportunistic time. As much as possible, the abnormalities that have founded in the field, will be postponed until there is a chance of time to repair. This opportunity can be obtained due to lack of raw material supply, low market demand or others. In the preventive maintenance analysis, the reliability value threshold may change every time because it follows the available time. The increasing of the reliability value after maintenance activity, is difficult to determine because maintenance work is not repetitive, as mentioned in other
typical preventive maintenance. In other words, industries that implement opportunistic maintenance strategies are those that have the following characteristics:

1. The continuous system, with a large variety of equipment functions, with a limited number of units for each function. Many machines are dedicated to certain functions only.
2. High machine setup costs, so it is necessary to avoid turning off the equipment at any time.

2. Literature Review

2.1 Opportunistic Maintenance

Chang and Banddyopadhyay [3], developed a systematic method for determining maintenance time, which is called maintenance opportunity. A simulation algorithm was developed by utilizing the buffer level to obtain maintenance opportunity time during the production process. The mathematical model of maintenance opportunity time is as follows:

$$\Delta T = \frac{(m_1 - m_2)T - (N_T - N_0)}{m_1}$$

$\Delta T$ is the maintenance time opportunity at T. $N_0, N_T$ is the buffer level at the start and T. $m_1, m_2$ is the production rate of input and output. With this model, it can be predicted that there is an opportunity for maintenance time. If the abnormality can be postponed, an estimated maintenance time $\Delta T$ is needed, then set the $N_0$ level, if necessary, set $m_2$ and Tc time, so that shortage can be avoided. Such a model is effective at predicting maintenance time opportunities if both the input and output have a deterministic production rate. But in most places, both input and output are stochastic processes.

Wu, et al. 2019, [4] design a two-phase opportunistic maintenance framework based on defect information and integrate it with the conditions of production waiting time into the decision-making process. The waiting time can occur due to low demand or a lack of production material. This model produces probability in three scenarios, namely Corrective replacement, Opportunity replacement and Preventive replacement. Corrective replacement scenario occurs if there is no Preventive maintenance plan, but there is a failure that needs immediate repair or replacement. While Opportunity replacement is an incident when maintenance opportunities come because of the production wait. The use of mathematical analysis is too complicated so it is necessary to assume the presence of the distribution of the arrival time of production. Also in the analysis, there are functions that may need further research to get it because of the limited data available, for example survival function. Besides that, the imperfect value of preventive maintenance activity is also needed, where this variable is varied and interdependent.

2.2 Complex Repairable System

It is important to discuss repairable systems. Real applications are often faced by complex systems that require assumptions so that the model can be derived. The Renewal Process Model (Maximum Repair) assumes that repairs are considered as new equipment. Process renewal is a recorded counting process in sequence. The assumptions underlying the NHPP (Minimal Repair) model imply that, when repairs are made, the latest system conditions are the same as those that occurred right before the failure. The non-homogeneous Poisson process (NHPP) differs from the homogeneous Poisson process only in that the failure rate varies with time rather than being constant. NHPP is the most appropriate model for the reliability of complex systems consisting of infinite components. However, for a limited number of components, this model can only function as an estimate, often poorly, because of the intensity function changes following each improvement [5]. Maintenance activities are often in the two extreme assumptions above.

It is clear that analytical and mathematical approaches are limited in solving complex treatments [6]. By developing analytic and simulation models to solve the same problem Rezg, Chelbi and Xie [7] find that complex analytic models with unrealistic assumptions compared to simulation models provide more flexibility and simpler estimates.
2.3 Optimization Maintenance Based on Simulation

The complexity of the maintenance system has significantly increased. This is partly due to the modern manufacturing system which involves many interactions and dependencies between components [8]. SL.Ho and M.Xie, [9] in their paper, discussing reliability forecasting with the ARIMA approach. The paper states that there is a rational matter if the time between failures (TBF-Time Between Failure) of an upcoming system is closely related to the latest TBF. Or even extends to past values. This is because future TBF depends on the level of success of the present and previous improvement. Here the simulation is presented to generate future behavior based on past behavior.

Even though research on maintenance optimization began a few decades ago [10], simulation-based maintenance became an emerging trend [11]. Roger [12] defines optimization based on simulation as an approach where the optimization engine provides factor input to a simulation program. The simulation will run and give the results of the optimization function objectives. This process will continue repeatedly between the simulation program and the optimization engine until it produces a satisfactory solution or termination due to the specified conditions. The application of simulation to maintenance does not only aim at optimization. Simulation application without optimization is used for comparison, evaluation, and validation purposes.

Simulation applications to optimize equipment availability with an inventory level approach have been demonstrated in a research conducted by Salsabila et al. This paper focuses on experimenting with buffer inventory levels and the capacity of a multi-state manufacturing network to increase production throughput on a company [13]. Increased equipment availability can be achieved through the availability of spare parts needed. Spare parts availability during downtime will reduce repair time (MTTR). Another study from Salsabila et al. develops a simulation model for failure and the whole system to find out the needs of critical parts. The development scenario is made by changing the ROP of the critical part. Availability of critical part when it is needed, will increase the equipment availability itself [14].

3. Research Methodology

Figure 1 shows the validation steps of the model that will be built. The opportunistic maintenance model for the simulation is made as explained in section 4. Reliability data from previous years were collected to predict the current operational condition of the year if it is met with current demand.

We already have performance data from kiln (one of the Cement industrial equipment) in 2019 and demand realization in the same year, from one of the cement companies in Indonesia. Failure data in 2019 is used as a real performance data of equipment. Data equipment failure 4 years earlier (in 2015 until 2018) are needed also. This failure and demand data, used for input simulation data to obtain the performance of equipment from the simulation. Results of the simulation output then compared with real equipment performance data in 2019. The verification and validation process will determine whether this model is suitable for predicting operational in the next years.

4. Proposed Opportunistic Maintenance Model

Kiln operates all the time except when overhaul. Overhaul is planned to conduct annual preventive maintenance activities. During operation there may be an unplanned failure that must be shutting down the kiln system.

For Kiln the conditions can be explained as follows, and can be seen in Figure 2:

1. Opportunity maintenance only during Overhaul, besides that it means corrective maintenance and read as downtime data.

2. Redundancy make increase equipment physical availability, but requires switching time so that it causes shutdown and is read as data downtime.
Build Model Opportunistic Maintenance (OM) for Simulation

Compare real performance data (year: 2019) with the result of simulation

Validated model (with α=5%)?

Verifying & Validating Model

Finished

Figure 1. Research methodology.

Figure 2. Preventive model for kiln.
In this Kiln model, up (kiln run time) and down (kiln off time) data have been suitable for data failure. We need to capture time horizon, as Figure 2, because sometimes maybe not all down data are carried out by maintenance activity. Down data may appear due to inventory limitations. Kiln, up and down operational data are needed on the model to be generated. These data use to determine the arrival of failure and how long repair finish in simulation. Thus, up data represent time to failure (TTF) and down data represent time to repair (TTR). Table 6 shows up and down data for kilns 1 from 2015 to 2018, the unit is in hours. For kiln 2, kiln 3 and kiln 4 are not shown here, but the results of distribution fittings for all equipment are displayed in Table 3.

Table 1. Equivalence generating TTF in montecarlo simulation and reliability.

| EVENT | CUMULATIVE FREQ. | RND(X) |
|-------|------------------|--------|
| $T_1$ | $F_1$            | $RND(X)$ |
| $T_2$ | $F_1 + F_2$      | $RND(X)$ |
| ...   | ...              | ...    |
| $T_n$ | $\sum_{1}^{n} F_n$ | $RND(X)$ |

R (t), reliability at time t is a cumulative function, this is equivalent to the process of generating time T from the TTF (Time To Failure) distribution in Monte Carlo simulations. This also implies that the value of the threshold is a random value based on past history. Another important assumption in this research is related to the increase in reliability after repair activity. After repair, the TTF distribution did not change. TTF distribution still follows the initial distribution that has been input to the simulation. Thus, this model is an NHPP (Non-Homogeneous Poisson Process) or minimal repair model.

Opportunity Maintenance (OM), presence under the following conditions,

\[ \text{Opportunity Maint. time} \]

\[ y \] is the arrival time for Opportunity time (schedule overhaul)
\[ z \] is the end of Opportunity time
\[ T \] is the threshold time for preventive maintenance

For analysis of the preventive maintenance (PM) model, there is an assumption that the repair time can be neglected. This is because repair time is much less than the total running time of the equipment. In this simulation, the duration of maintenance activities, both PM and CM, will be calculated. Thus, it will influence the amount of equipment availability. Preventive maintenance will occur if reliability threshold has not been achieved but repair activity has been taken before. The threshold in this simulation is the end time of each arrival of the TTF (Time To Failure) distribution.
Overhaul Schedule is carried out according to plan (both, duration and time begin), because overhaul schedule is a decision variable in this simulation. The assumption is, overhaul schedule is really well planned, so there is no delay in its execution. If the threshold has not been achieved but the arrival of overhaul has begun before PM, then repair time will be adjusted as long as the length of time for overhaul repair. This happens because the damage is not too severe and at this time it is very possible to control the duration of the repair.

Below, Table 2 is the possibility of the arrival of the failure and overhaul schedule so take effect to the duration of repair. Solid line represent time for overhaul and dash line represent failure time.

| No | Condition | Repair time | Explain |
|----|------------|-------------|---------|
| 1  | t(y) until t(z) and t(a) until t(b) | There is no intersection. Equipment off for two times, each according to the length of repair. |
| 2  | t(y) until t(z) | Failure arrival time is between of schedule overhaul. PM is occur. |
| 3  | t(a) until t(z) | Failure arrival time before overhaul schedule. CM is occur. Overhaul execution remain as planned. |
| 4  | t(y) until t(z) | Failure arrival time between overhaul. Overhaul execute as planned. |
| 5  | t(a) until t(b) | Failure arrive before overhaul begin execute. Although CM is occur, overhaul activities remain as planned. |

| No | Condition | Repair time | Explain |
|----|------------|-------------|---------|
| 1  | t(y) until t(z) and t(a) until t(b) | There is no intersection. Equipment off for two times, each according to the length of repair. |
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| 3  | t(a) until t(z) | Failure arrival time before overhaul schedule. CM is occur. Overhaul execution remain as planned. |
| 4  | t(y) until t(z) | Failure arrival time between overhaul. Overhaul execute as planned. |
| 5  | t(a) until t(b) | Failure arrive before overhaul begin execute. Although CM is occur, overhaul activities remain as planned. |

| Equipment | TTF       | TTR          |
|-----------|-----------|--------------|
| Kiln 1(K1)| 1+GAMM(349,0.793) | WEIB(12.2, 0.508) |
| Kiln 2(K2)| WEIB(193, 0.798) | WEIB(8.02, 0.517) |
| Kiln 3(K3)| EXPO(243)   | WEIB(14.4, 0.522) |
| Kiln 4(K4)| WEIB(176, 0.641) | WEIB(8.04, 0.478) |

The entity in the simulation is running time. The time each hour is given an attachment attribute status of the machine condition. 0 for status off and 1 for status running. For failure arrival time, interval of two entities arrival follow as the distribution of TTF, then entity is hold, duration of hold module
follow distribution of TTR. The arrival of overhaul also follows the same rule. When it is time for overhaul, the status attribute is set to 0.

Furthermore, the overhaul status and fail status are combined following the repair duration rules that have been defined in Table 2. Using the numerical algorithm in Table 4, we will get information of when the system starts and finish runs, how long it runs, how long it shutdown. Finally, performance of the equipment can be calculated based on simulations.

Table 4. Combination fail and overhaul status result system status.

| No | Fail status | Overhaul status | Additional condition | System status |
|----|-------------|----------------|---------------------|---------------|
| 1  | 0           | 0              |                     | 0             |
| 2  | 1           | 1              |                     | 1             |
| 3  | 1           | 0              |                     | 0             |
| 4  | 0           | 1              | t(y)\leq t(a)\leq t(z) | 1             |
|    |             |                | else               | 0             |

5. Result and Discussion

Below, Table 6 is the result of simulation with 10 replications. The response variable observed are MTBF, Availability, and Production. Table 4 is the t test from the simulation result in Table 6, according to the t test with confidence interval α=5%, we can conclude that the model is valid.

Table 5. Hypothesis testing.

| Hypothesis Testing | MTBF     | Availability | Production |
|--------------------|----------|--------------|------------|
|                    | REAL     | SIM          | REAL       | SIM        | REAL      | SIM        |
| Mean               | 272.4    | 248.9        | 7594.7     | 7897.7     | 2636409   | 2599029    |
| Std. deviation     | 32.2     | 68.2         | 205.7      | 299.7      | 123281    | 124459     |
| n                  | 4        | 40           | 4          | 40         | 4         | 40         |
| Sp                 | 66.2955  | 293.9932     | 124376     |
| t_{α/2=0.025,df=42} | 2.0181   | 2.0181       | 2.0181     |
| t                  | -1.2887  | 1.9648       | -0.5731    |
Table 6. Up and down time data for kiln 1, 2015 until 2018.

| No | UP  | DOWN | No | UP  | DOWN | No | UP  | DOWN | No | UP  | DOWN | No | UP  | DOWN | No | UP  | DOWN | No | UP  | DOWN | No | UP  | DOWN | No | UP  | DOWN |
|----|-----|------|----|-----|------|----|-----|------|----|-----|------|----|-----|------|----|-----|------|----|-----|------|----|-----|------|----|-----|------|----|-----|------|
| 1  | 43.8| 0.5  | 21 | 62.0| 415.2| 41 | 411.5| 4.9  | 61 | 319.7| 5.7  | 81  | 6.7  | 210.3| 101| 100.3| 163.2|
| 2  | 1.1 | 3.8  | 22 | 48.9| 0.1  | 42 | 389.7| 15.6 | 62 | 107.0| 1.2  | 82  | 73.5 | 9.5  | 102| 239.3| 7.5 |
| 3  | 79.6| 0.5  | 23 | 44.9| 1.7  | 43 | 40.0 | 119.6| 63 | 357.3| 20.2 | 83  | 129.7| 2.8  | 103| 617.2| 0.7 |
| 4  | 157.8| 0.6 | 24 | 514.5| 0.8  | 44 | 175.7| 9.3  | 64 | 660.7| 1.5  | 84  | 625.9| 1.1  | 104| 2.9  | 6.0 |
| 5  | 287.3| 2.4 | 25 | 75.8 | 4.0  | 45 | 295.1| 2.8  | 65 | 285.9| 0.9  | 85  | 63.4 | 48.7 | 105| 409.6| 31.1|
| 6  | 210.7| 0.4 | 26 | 769.8| 0.8  | 46 | 189.2| 37.1 | 66 | 163.9| 9.5  | 86  | 566.6| 2.2  | 106| 3.4  | 53.6|
| 7  | 271.8| 1.1 | 27 | 523.7| 22.6| 47 | 321.7| 0.3  | 67 | 616.5| 0.9  | 87  | 1354.8| 1.0 | 107| 44.1 | 0.5 |
| 8  | 574.6| 0.9 | 28 | 119.0| 3.4  | 48 | 160.7| 0.7  | 68 | 36.8 | 26.6| 88  | 263.9| 1.5  | 108| 430.1| 20.3|
| 9  | 427.6| 0.5 | 29 | 699.5| 0.3  | 49 | 59.9 | 1.3  | 69 | 39.9 | 6.2  | 89  | 344.4| 9.2  | 109| 425.3| 0.8 |
| 10 | 142.1| 1.0 | 30 | 150.7| 0.6  | 50 | 1110.1| 13.7 | 70 | 436.4| 9.4  | 90  | 343.6| 17.3 | 110| 2.3  | 24.0|
| 11 | 153.4| 15.1| 31 | 27.9 | 4.5  | 51 | 132.5| 38.0 | 71 | 184.1| 0.9  | 91  | 58.8 | 616.7| 111| 44.0 | 2.8 |
| 12 | 366.2| 0.9 | 32 | 98.4 | 25.0| 52 | 2.9  | 16.4| 72 | 1533.7| 53.3| 92  | 18.0 | 131.4| 112| 715.1| 7.5 |
| 13 | 457.9| 4.3 | 33 | 369.9| 15.3| 53 | 118.8| 0.3  | 73 | 74.7 | 1.1  | 93  | 5.1  | 6.0  | 113| 34.3 | 0.8 |
| 14 | 186.7| 7.4 | 34 | 344.9| 1.0  | 54 | 648.3| 410.9| 74 | 252.4| 111.0| 94  | 155.4| 13.9 | 15 |
| 15 | 85.3 | 9.7  | 35 | 89.9 | 1.9  | 55 | 11.3 | 1.9  | 75 | 105.9| 2.1  | 95  | 23.3 | 0.8  | 16 |
| 16 | 24.8 | 0.5  | 36 | 223.2| 0.9  | 56 | 366.0| 3.1  | 76 | 47.8 | 1.3  | 96  | 89.4 | 6.4  | 17 |
| 17 | 152.0| 2.3 | 37 | 179.6| 9.1  | 57 | 392.6| 2.9  | 77 | 423.0| 5.0  | 97  | 1113.2| 10.8 | 18 |
| 18 | 558.3| 2.1 | 38 | 339.8| 215.8| 58 | 25.4 | 120.4| 78 | 50.8 | 15.9 | 98  | 1160.1| 1.0  | 19 |
| 19 | 218.1| 1.1 | 39 | 185.5| 6.0  | 59 | 298.1| 1.4  | 79 | 81.3 | 0.5  | 99  | 3.0  | 38.5 | 20 |
| 20 | 432.2| 0.9 | 40 | 227.6| 14.1| 60 | 811.0| 15.9| 80 | 122.4| 2.3  | 100 | 155.9| 39.9 |
| MTBF      | REAL (Year : 2019) | SIMULATION (n=10 replication) |
|-----------|--------------------|--------------------------------|
|           | 1                  | 2                | 3                | 4                | 5                | 6                | 7                | 8                | 9                | 10                |
| KILN 1    | 284.87             | 235.7            | 387.3            | 264.03           | 190.84           | 335.04           | 395.31           | 259.95           | 401.57           | 297.91           | 309.38           |
| KILN 2    | 272.92             | 172.1            | 322.08           | 313.53           | 182.92           | 186.83           | 213.33           | 273.04           | 197.43           | 231.03           | 234.18           |
| KILN 3    | 303.90             | 185.75           | 275.32           | 341.59           | 151.92           | 268.12           | 210.82           | 317.83           | 231.18           | 223.96           | 282.37           |
| KILN 4    | 228.00             | 160.81           | 246.95           | 217.96           | 195.3            | 166.41           | 226.13           | 305              | 137.37           | 174.75           | 234.1            |

| Availability | REAL (Year : 2019) | SIMULATION (n=10 replication) |
|--------------|--------------------|--------------------------------|
|              | 1                  | 2                | 3                | 4                | 5                | 6                | 7                | 8                | 9                | 10                |
| Total Run Hours K1 | 7691.42          | 7365             | 7909             | 7996             | 7885             | 7882             | 7819             | 8008             | 7697             | 7885             | 7702             |
| Total Run Hours K2 | 7641.90          | 8010             | 8443             | 8235             | 8399             | 8474             | 8055             | 8442             | 8238             | 8229             | 8485             |
| Total Run Hours K3 | 7293.60          | 7727             | 7951             | 7621             | 7573             | 7976             | 7431             | 7870             | 7659             | 7797             | 7824             |
| Total Run Hours K4 | 7752.02          | 7812             | 8083             | 7504             | 7852             | 7413             | 7749             | 8006             | 7530             | 7618             | 7752             |

| Production | REAL (Year : 2019) | SIMULATION (n=10 replication) |
|------------|--------------------|--------------------------------|
|            | 1                  | 2                | 3                | 4                | 5                | 6                | 7                | 8                | 9                | 10                |
| Total Prod K1 | 2472548           | 2451977          | 2630726          | 2658854          | 2621861          | 2620879          | 2601447          | 2662069          | 2557852          | 2621573          | 2559685          |
| Total Prod K2 | 2689274           | 2665484          | 2810152          | 2736581          | 2791391          | 2816472          | 2680428          | 2804833          | 2738498          | 2733910          | 2819735          |
| Total Prod K3 | 2621946           | 2577470          | 2651705          | 2540984          | 2527119          | 2659580          | 2479083          | 2624690          | 2554519          | 2601076          | 2608725          |
| Total Prod K4 | 2761869           | 2476982          | 2564775          | 2382286          | 2491053          | 2354124          | 2463317          | 2543504          | 2394529          | 2419626          | 2461603          |
I = I + (Prod-Dem)

**INVENTORY LEVEL**

Optimization

Opportunistic Time (Reduce Inventory)

Simulation OM Model

Prod(tovh,tidle)

I = I - RP.(tovh+tidle)

**Figure 4.** Optimizing inventory level and production.

The simulation results show the OM model that was built is valid. It fit with the real conditions of the 2019 data. In 2019, the opportunity for maintenance time occurs because of the overhaul time interval. Production output is absorbed by the market and does not cause significant problems with the number of inventories. At the present time where demand can be low, it is necessary to pay attention to inventory so that production costs are not high. Inventory reduction is done by equipment shutdown (idle). Idle equipment condition is opportunistic time for maintenance. Equipment shutdown means that the setup costs are higher. Thus, there is a pay off between inventory costs and setup costs that must be minimized. Our proposed model combines the OM model simulation with a minimizing inventory level so that the overall cost of production can be minimized, as can be seen in Figure 4.

Under certain conditions, idle time is held in series with overhauls to reduce setup frequency. The optimization is to minimize existing inventory by regarding the amount of demand only. Other conditions that may occur are low set up costs but limited inventory by certain capacities. This happens as in equipment finish mill (other equipment systems in the cement industry). The optimization model is replaced with inventory limits according to inventory capacity. Thus, the idle time can be determined as opportunistic maintenance time.

A factory that has several production lines, if there is a shortage in a production line, it can be supplied from another line. However, this will drive transportation costs. If the buy option is made for reducing shortage, a purchase cost will appear. In low demand conditions, several lines must be turned off so that inventory is not too much. This means there is idle time. So, there are several optimization models that follow simulation OM model, as can be seen in Figure 4.

**6. Conclusion**

OM Simulation Model has been proven valid as a model that can be used. In very simple conditions, the opportunistic time is the equipment overhaul time interval only. With this situation, we can localize the validity of this model. However, in a real system, complexity increases when the opportunistic time does not only come from overhaul time but may appear due to minimization of inventory costs. Inventory is closely related to the production scheme. Production scheme strategies can be easily attached to simulations as compare to mathematical analysis. Figure 4 is an alternative combination of simulation and production scheme optimization models that produce low production costs. This model is not carried out in this paper because, as in the original goal, it only focused on Opportunistic Maintenance.
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