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Remaining Useful Life Time of Gas Compressor in Kollness Field

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Reliability; Availability Maintainability, and Safety

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RELIABILITY, AVAILABILITY, MAINTAINABILITY, AND SAFETY

MASTER's THESIS

Department of Production and Quality Engineering
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Preface

This is a report for thesis in master program of RAMS (Reliability, Availability, Maintainability, and Safety) within the Department of Production and Quality Engineer at NTNU (Norwegian University of Science and Technology). The report is a continuation work from specialization project and is established in spring semester 2017.

The thesis discusses a topic that related to creation of Markov process models with various maintenance strategies to calculate the availability of gas compressors so that we can estimate residual lifetime or remaining useful lifetime (RUL) for the system in STATOIL's plant, Kollness.

This report is written for RAMS students who want to learn more about methods or tools that can be used to estimate RUL of a system with more than one phase.

Trondheim, 11 June 2017

Mariska Septiana Putri

Summary

This thesis contains information related to models that are established to calculate availability of a system using Markov process. The system that we study for this report is gas compressors that are operated by STATOIL and located in Kollness - Norway. STATOIL has six gas compressor trains that are made up from assembly unit of one variable speed drive, one unit of electrical motor, one unit of gear box, and one unit of gas compressor. The main goal of the project is to build models that are capable to represent the actual condition of the system with different possible maintenance strategies.

The models are developed start from a simple and basic condition until the involvement of degradation states. We will also discuss how an early treatment such as preventive maintenance toward degraded units will give big impact to system's performance.

Contents

Chapter 1

Introduction

1.1 Background

Gassco and STATOIL, as technical service provider, operate gas processing plant at Kollness. The gas is transported from Kvitebjørn and Visund [1] production site to England and France. Right now, six compressor systems are used to support the transportation process. Each compressor is made of one-unit electrical motor, one-unit gas compressor, one-unit gear box and one-unit Variable Speed Drives (VSD). The compressors are working throughout the year with two different production rates in summer and in winter. Full capacity production is applied during winter with all six trains of gas compressors are running. Meanwhile in summer, due to less number of gas demand, not all the trains are running for their full capacity and possible for some trains to be standby.

Five (5) out six (6) electrical motors in the system has been used since 1996. For each machine, there are number of year that it is expected to be available in supporting the production until finally the machines no longer can give the services. It is also an interest to estimate how long the machines can remain in service when we already know the current condition of the machines. The remaining useful lifetime of these machines can be a consideration for making decision such as when the company need to start preparing process to buy a new machine and what kind of maintenance strategies that can be implemented to prolong the machines' useful life time, etc.

Currently, maintenance for the gas compressor system is done periodically every summer. There is some consideration to change this maintenance strategy and there is also a consideration for applying continuous monitoring by online system so the company can have enough information to avoid system failure before it happens.

1.2 Objectives

The objectives of this thesis can be described as follow:

1. List all the possible maintenance programs.
2. Estimate mean availability of the system for the chosen scenario in point 1.
3. Compare all the models based on their mean availability.
4. Estimate remaining useful lifetime of the system with the implementation of the chosen scenario.
5. Find the proper maintenance program for gas compressor system in both season, winter and summer.

These outputs can be useful for STATOIL to consider whether they have to change current maintenance program and a apply continues online monitoring for the system.

1.3 Limitations and Assumption

For this report, there are several limitations that are put into consideration:

1. The values that are used for failure rates for every trains are based on data from OREDA, not on the actual numbers for the field.
2. For simplicity in modeling different scenarios, two trains of gas compressor are used instead of the actual total number of the gas compressor trains in which are six trains.

1.4 Approach

This thesis presents many possibilities on how maintenance program can be implemented in a system. A system is pictured by process diagram so called Markov process that shows different stages for each train. To compute numerical results of the process, MATLAB software is used.

Numerical results from MATLAB computation cover different condition between two periods of running time, winter and summer. Since during winter the requirement is higher, all of gas compressors are functioning in their full capacity. During summer, there are two schemes that are assumed. In some cases, the whole trains are running in varied capacity depend on demand, and in other case, some of the trains are treated as standby trains.

The results that we obtain are data regarding availability of the system in certain time horizon. We can also trace the possibility of the system in different state that will be useful to determine the remaining useful lifetime of gas compressor. This information can help the engineer to choose which maintenance programs that will give more benefit for the company.

1.5 Structure of the Report

The report will consist of four chapters. The first chapter shall cover introduction of the report, including the background, objectives, limitations, and approach that are used to establish the report. The second chapter will present some theory related to machines that compose the system as a whole and introduction theory about remaining useful lifetime and Markov process. In the third chapter, the report will contain information about several scenarios of the system with several options of maintenance programs and numerical results from MATLAB computation regarding availability for each possible option. In this chapter, we will also present availability comparison from different software to validate numerical results that we obtain from MATLAB. The last chapter, chapter 4, will cover the result, some discussion related to result to make sure all of the points in objectives have been answered. In this section, further study for the same topic will be discussed as well.

Chapter 2
Study Literatures

2.1 Gas Compressor System

Currently in Kollness field, there are six trains of gas compressors that are running. Each of train is installed with four different machines which consists one unit of Variable Speed Drive (VSD), one unit of electrical motor, one unit of gear box and one unit of gas compressor. Following figure is the assembly structure of the machines that compose each train of gas compressor.

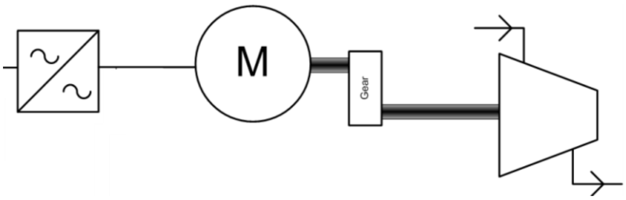


Figure 1. Compressor System

2.1.1 Definition

Electrical motor is an electrical machine that is used to convert form of energy, from electrical energy to magnetic energy and finally to mechanical energy [2]. Generally, electrical motor is formed by several parts such as rotor, stator, shaft, end bells, bearing and motor housing as showed in Figure 2.

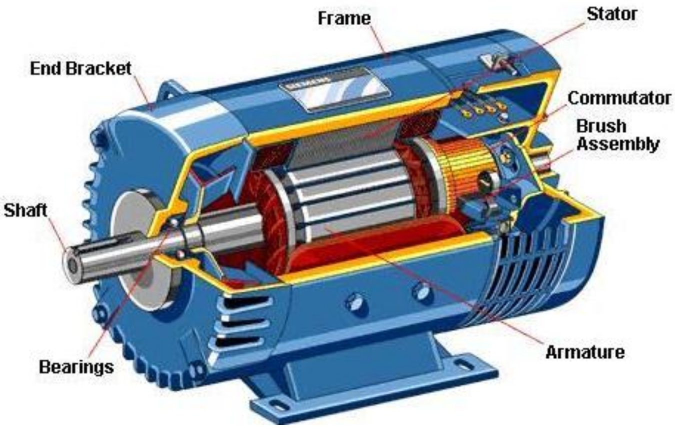


Figure 2. Electrical Motor Structure

Gear Gearbox is mechanical drives with step by step ratio change [2]. Mechanical drive is a unit set of mechanical power transmission that transfers power from prime mover to the actuator. Gearbox contains several gears. Gears are transmission mode with meshing or machines with toothed design. Gears have function to transmit or receive motion from another gear-tooth. When the gears are meshing with each other, they transmit torque moment, a force that has tendency to rotate around the axis [3].

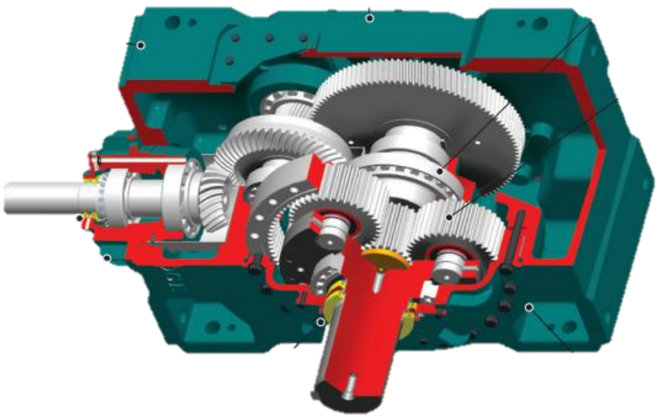
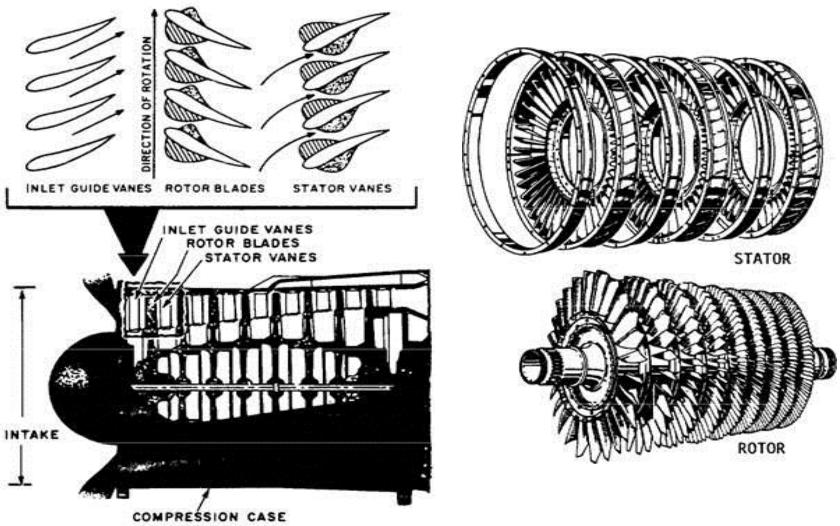


Figure 3. Example of Gearbox Design

Gas compressor is a method and devices for compressing gas. The gas is compressed by entering an inlet which is known as Inlet Guide Vanes (IGV) and accelerated by a row rotating airfoils (blades) called rotors and the diffused, to obtain a pressure increase, in a row stationary blades called stator[3]. A combination of a rotor and a stator makes up one stage and there are several stages in a compressor. Figure 4 is showing the operating principle



for the compressor.

Figure 4. Compressor Components and Operating Principle

2.1.2 Failure Mode

Degradation from each machine will give impact to system's performance. In the next section, we will present the summary of several degradation processes that can increase the failure rate for each component of gas compressor trains. In table 1 we can see the list of failures that can deteriorate performance of gas compressor system.

Table 1. Degradation Modes for Electrical Motor, Gearbox, and Gas Compressor

Unit Machine	Category	Faults
Electrical Motor	Electrical Faults	• Open or short circuit in winding • Wrong connection of windings • High resistance contact to conductor • Unstable ground • Partial discharge
	Mechanical Faults	• Broken rotor bars • Broken magnet • Cracked end-rings • Bent shaft • Bolt loosening • Bearing failure • Gearbox failure • Air-gap irregularity
	Outer System Failure	• Inverter system failure • Unstable current source • Shorted/ Opened supply line
Gear Box	Mechanical Faults	• Gear breakage • Flank damage
Gas Compressor	Mechanical Faults	• Fretting • Creep deformation • Hot corrosion

Electrical Motor has three different types of degradation which are electrical faults, mechanical faults and Outer system failure. Several faults that are common to happen in electrical motor are partial discharge, bearing failure, and broken rotor bars. Partial discharge (PD) is small electric sparks inside air bubbles that are formed due to non-uniform electrical distribution on insulation material [13]. This phenomenon usually happens in stator part of electrical motor. In excessive electrical stresses, PD can cause change in material properties to electrochemical reaction [14]. This changing causes material degradation that eventually will lead to the complete breakdown of the insulation [15]. Bearing of electrical motor can fail due to several causes such as misalignment and fatigue that can lead to excessive vibration and breakage, abrasion on the bearing due to improper lubrication, corrosion, and contamination.

Gear breakage and flank damage are the main reason for a gear-box to have decreasing performance. Gear breakage that represent statistically 60% of all gear damages can be caused due to fatigue in tooth root, unit overload, and inaccurate mounting that will lead to fracture of the gear. Another 40% of the cause is flank damage. Flanks damage can happen due to pitting or surface fatigue, loss of material, and high load that lead to plastic deformation.

Performance of gas compressor is mainly depending on performance of its turbine blades. The fractures that happen on turbine blades will be unfavorable for a gas compressor to maintain its performance. Fractures that happen on turbine blades can be caused by several reasons such as fretting, creep deformation and hot corrosion. Fretting is a wearing process between two surfaces that has oscillatory motion with small amplitude [4]. Creep deformation usually happens under operation condition where it is exposed to high temperature yet still below the melting point of material. It also is exposed with high stress level below the yield strength in long period of time [9]. Turbine blades that are experiencing long high temperature and high stress will stretch to the state that they will not be flexible anymore (plastic) or become permanently deformed. Hot corrosion is an accelerated corrosion process, causes by the existence of salt contaminants such as Natrium Sulfate ($Na2SO4$), Natrium Chloride (NaCl), and Vanadium Oxide ($V2O5$). These contaminants then are combined and create melted deposits and damage the protective surface [10].

2.2 Remaining Useful Lifetime

The interests in this report are to predict the future failure before it actually happens and estimate how much longer the machines can give the service before they reach the end of their functional lifetime. The result from prediction process or prognostic process can help the engineers to improve their maintenance policy. It can give a valuable information for engineers to decide and make plans for their maintenance strategies with better prediction of future failure, better preparation on spare part components, and better understanding of residual lifetime of the machines.

According to ISO 13381-1, prognostic is defined as "an estimation of time and risk for one or more existing and future failure modes. The capability to provide early detection of the precursor and/or incipient fault condition of a component, and to have the technology and means to manage and predict the progression of this fault condition to component failure." [5] said that "failure prognosis involves forecasting of system degradation based on observed system condition".

RUL as the result from prognostic process is defined as the length from the current time to the end of the useful life [6]. In general, RUL also can be formulated as follow [7] :

$$RUL(t) = inf\{h: Y(t+h) \in S_L \mid Y(t), Y(t) \notin S_L\} \quad (1)$$

Where $Y(t)$ is system condition at time t and S_L is set of failed states of the unit.

The method of prognostic technique in this report is model-based. Model-based prognostic methods mainly use the available mathematical or physical models to picture the progress of the system from the working state to its failure state. Model-based methods have the advantage to integrate physical understanding of the system to improve the knowledge for system degradation. The example of models that are using this approach are Markov and Semi Markov model, Hidden Markov, Bayesian Network, etc.

2.3 Markov Process

2.3.1 Introduction

To solve the existing problems, it will be better if we can translate them into models that can give description and represent the actual problems properly. By having models, it will be easier to understand the main focus where we can make limitations of contribution factors that will be included or not. The limitations that we set will make the models simpler and allow us to do experiments with possibility to change their parameters in order to seek the optimum solution.

Markov chain is one of stochastic process $\{X\ (t), t \geq 0\}$ to model a system by using states and transition between states [8]. Markov chain has Markov property which means that the future event depends on the current state, not its pass history. Variable $X\ (t)$ is a random variable that denotes the state of system at time t. Markov chain, based on time, is divided into discrete time Markov chain and continuous time Markov chain. When time is discrete, it may take value in $\{0,1,2,3,..\}$ or when we denote it by $\{X_n, n = 0, 1, 2, ..\}$. When time is continuous, we call it as continuous time Markov chain or Markov Process. Markov process can be categorized as homogenous and non-homogenous process. A model is called homogenous Markov process when transition from one state to another state does not depend on time. Otherwise, it will be called as non-homogenous Markov process.

We can start creating Markov process by defining several possible states and transition rates between states. The simplest state is a state with status as functioning state and not functioning or failed state. The transition from state i to state j can be denoted with $A(i, j)$. All of the transition rates in one process then will be organized into a matrix A.

To know the probability in which state we are at time t is always an interest in Markov process. This is called transient probability that will be denoted with μ_0 for initial state at time 0 and $\mu_t(i)$ denotes the probability that the system is at state i at time t. To calculate the value of μ_t, we can use the following formula

$$\mu_t = \mu_0 \, e^{tA} \tag{2}$$

2.3.2 Multiphase Markov Process

The models of gas compressor trains will have different characteristics during summer and winter period. In different periods, the system will have different parameters of failure rates and these parameters will continuously change from time to time between summer and winter. In order to depict the models close to reality, we will use multiphase Markov process.

One summer in the initial year will be denoted by T_1 which will represent time $t = 0$ until $t = 4380$. Winter time is from $t = 4381$ until $t = 8760$ and will be denoted as T_2. Next summer in second year will be denoted as T_3, and so on. In other word T_i is time at which system will have season change. Since the parameters of transition rates in summer and winter is different, transition matrix A for each phase will be different as well and will change at time T_i.

To calculate the probability for such process, we can use this following formula.

$$\mu_t = \mu_0 \, e^{tA_1} \text{ for } t \in [0, T_i] \text{ and } T_i = 4380 \tag{3}$$

Formula above is to calculate probability in operation process at time t where t starts from $t = 0$ until $t = 4380$, use transition matrix A_1 that contains transition rates that fit for summer period only. To continue the calculation for next period, which is winter, we need to change transition matrix A_1 to transition matrix A_2. Time t in winter starts from $t = 4381$ until $t = 8760$. The probability will be calculated as follow

$$\mu_t = \mu_{T_1} \, e^{(t-T_1)A_2} = \mu_0 \, . \, e^{T_1 A_1} \, . \, e^{(t-T_1)A_2}$$

for $t \in [4381, T_i]$ and $T_1 = 4380$; T_i for first winter which is $T_i = 8760$ (4)

For probability law at time t then we can use formula as follow

$$\mu_t = \mu_0 \left(\prod_{k=1}^{k=i} e^{(T_k - T_{k-1})A_k} \right) e^{(t - T_i)A_{i+1}} \tag{5}$$

k denotes the phases.

Chapter 3
Maintenance Models

3.1 Markov Process Model without Degradation

3.1.1 Model without Maintenance

First model starts with very simple scheme. As is mentioned in the assumption chapter 1, only two trains of gas compressor are used for the simplicity of the model. In the beginning, three stages are included to see how long the system will last from time $t = 0$ until $t = T$, where T is time when all of the trains are failed. In calculation with MATLAB, we use time horizon for 15 years or (131400 hours) for T to see the trend of the graphic that is created by numerical results. This duration is used so that the probability to have all the trains failed is close to 1. The initial state or state one of this Markov process model is a condition where all the machines are perfect, second state or state two is a condition where one machine is fail and one machine is still working. There will be different status for this state in different season. The third state or state 3 is a failure state where both of the machines fail. In this model, there is no maintenance is involved. For the first model or so called Model-1, is pictured by Figure 5.

In one year, the trains are treated differently depend on the season, summer and winter. During winter period, the trains is required to work in full capacity to fulfil the required demand. Any failure in any train will make the whole system fail since it will not be enough to cover the demand. Meanwhile in summer, demand decreases. Thus, the structure of the trains during summer can be varied. First option, all of the trains can be running yet not in full capacity. Second option, half of the trains are functioning to fulfil the order, and the rest are off for standby position in case there is a train that is failed during operation.

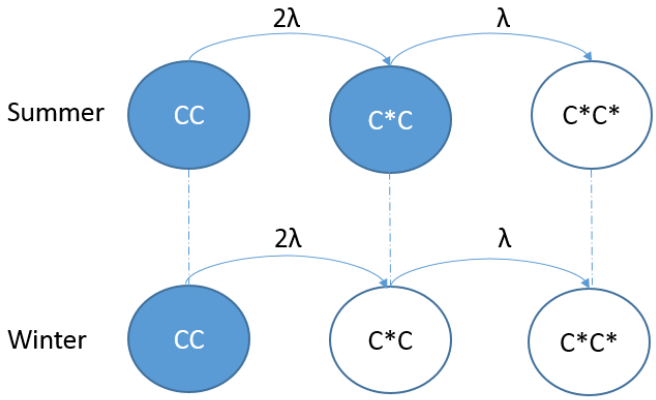


Figure 5. Model 1 – Markov Process Model of The System Without Any Maintenance Program

Due to different capacity requirements between summer and winter, second state of Markov model in both season has different status. It will be functioning state in summer phase because we can still have option to make the system work by manipulating the number of trains that need to be occupied or switching the failed train with standby train or changing the rate of trains' capacity to fulfil the required demand. Meanwhile during winter, the second state of Markov model will become a failure state since all of maximum capacity trains need to be functioning to reach the target. If we look at Model-1, we notice that there are different colors in second state between summer phase and winter phase to mark the status differences. First state in both phase is colored blue to indicate working state. Second state is blue for summer phase and white for winter. White circle indicates failure state.

To distinguish different availability between summer and winter, we make the model into multiphase Markov model. From figure 5, we can see that there are two phases of Markov model which are almost similar. First phase is named summer phase and the other is named winter phase.

In computation using MATLAB, we define different phases of Markov process with different transition matrix. A1 represents the transition between states in summer phase only and A2 represents the transition between states in winter phase only. Transition matrix A1 and A2 have three rows and three columns corresponding to number of states in each phase. When a_{ij} is the rate when we are leaving state i to go to state j, then transition matrix A can be defined as follow

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \tag{6}$$

For diagonal elements, the value $a_{ii} = -\sum_{\substack{j=0 \\ j\neq i}}^{r} a_{ij}$ where r is the last state of the model. Transition matrix for Model-1 then will be

$$A = \begin{bmatrix} -2\lambda & 2\lambda & 0 \\ 0 & -\lambda & \lambda \\ 0 & 0 & 0 \end{bmatrix}$$

Since there is a different in working status from winter and summer, the availability of the system in both period is calculated differently. Availability of the system for time t in period summer is accumulation of probability that the trains, for time 0 until time t, are in state 1 and state 2 or we can write as follow

$$Av(t)_{summer} = \mu_t(1,1) + \mu_t(1,2) \tag{7}$$
$$Av(t)_{winter} = \mu_t(1,1)$$

μ_t is probability of Markov process in each state. Thus, for initial probability of the system is $\mu_{(0)} = [1 \quad 0 \quad 0]$ which means all of the trains are in the first state. In equation (8), $\mu_t(1,1)$ referring probability in row 1 column 1.

From one state to another state, the transition rates that are used are following data from OREDA as the table 2 below. OREDA that is referred in this report is OREDA 6th Edition (2015) Volume 1 – Topside Equipment.

Table 2 – System Failure Rate from OREDA

Machine	Total Failure rate (Per 10^{-6} hours)	Degraded Failure rate (Per 10^{-6} hours)
Variable Speed Drive	10	3.5
Electrical Motor	114.91	38.3
Gear Box	15	5.25
Gas Compressor	524.46	193.89
Total	**664.37**	**240.94**

Thus, total failure rate for the system is total accumulation from four failure rates of composer machine units, which is 6.6437 x 10^{-4}/hours. Notice that the transition matrixes are the same for both phases, indicate that transition rates from state one to state two and from state two to state three is the same.

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summerwinter_final_Scene1.m

```
close all
clc

lambda = 0.000068251;
A1=[-2*lambda,2*lambda,0;0,-lambda,lambda;0,0,0];
A2=[-2*lambda,2*lambda,0;0,-lambda,lambda;0,0,0];
miu0=[1,0,0];
simulationyear=15;
timespan=0:simulationyear*8760;% in hour


for year=1:simulationyear
    for hour=1:4380 %summer
        if year ==1
            i=hour+1;
            miut(i,:)=miu0*expm(A1*timespan(hour));
        else
            i=hour+(year-1)*8760;
            miut(i,:)=miut((year-1)*8760,:)*expm(A1*timespan(hour));
        end
        prob(i,1)=miut(i,1)+miut(i,2);
    end
    for hour=1:4380 %winter
        i=4380+hour+(year-1)*8760;
        miut(i,:)=miut(4380+(year-1)*8760,:)*expm(A2*timespan(hour));
        prob(i,1)=miut(i,1);
    end
end

figure(1)
plot(prob);
```

Figure 6. MATLAB Code for Computing the Availability of Model -1

Using MATLAB program, we can calculate the availability of the system based on Markov process that we have built. In figure 6, we see MATLAB code to compute system's availability in each phase. Each phase or each season is designed to take place for six months' period or 4380 hours. The availability diagram from numerical result of Model-1 is showed in Figure 7.

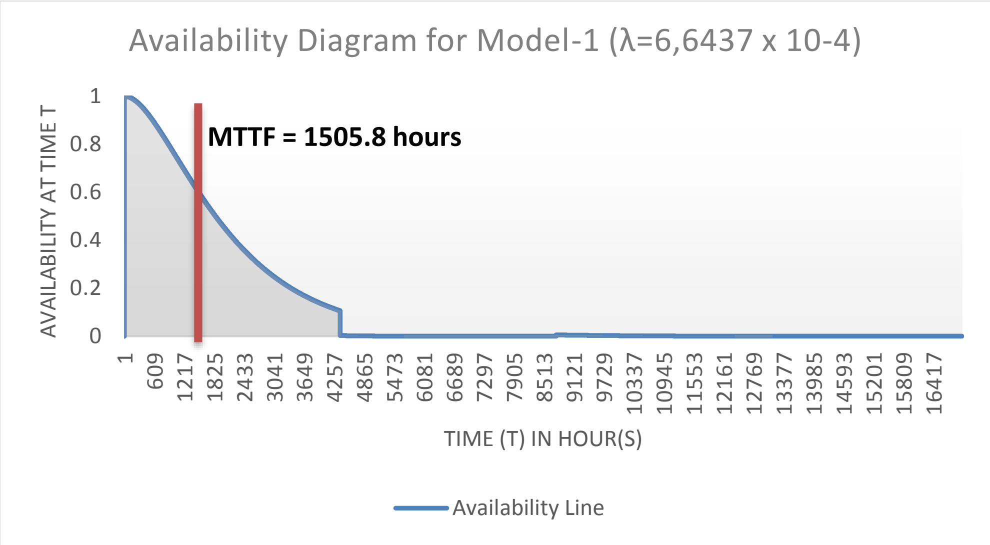


Figure 7. The Availability Graph for Model 1

From Table 2, we know that total failure rate is $\lambda = 6{,}6437 \times 10^{-4}\ /hours$, it means that the system has mean time to failure (MTTF) for 1505.18 hours. As we expect, the system will have total failure before it reaches second year of operation. To see the trend in longer period, the adjustment to failure rate is made. By using ten (10) time smaller λ value from OREDA, we can see the trend result in figure 8.

We start computing the model with summer phase first, then continue to winter phase, and go back to summer phase for the next year. From the graph in figure 8, we can see the dropping line for winter season is quite extreme. The gap between phases due to different condition for working state in each season. In fifteen years, the availability line for Model 1 is closed to 0.

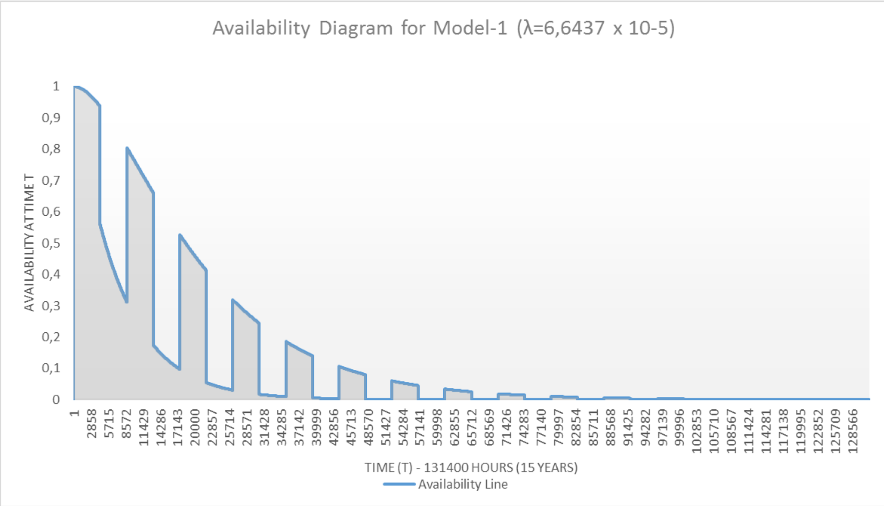


Figure 8 The Availability Graph for Model 1 Using Adjusted Failure Rate

3.1.2 Markov Process Model with Maintenance

Model 2

Model-1 above is very basic and does not consider any maintenance. Adjustment is needed to make the simulation can give a proper result to real case. Model-2 in figure 9 is a model that is created with involvement of maintenance when the system is failed. In this model, when the failure happened during winter at state 2, maintenance will be carried out. Yet, when the period of maintenance in this state start entering summer phase, the maintenance will be hold on or stopped because in summer phase we need fewer trains. In summer phase, we define second state as a working state where one failure train will keep the system goes on so the maintenance will be no longer needed.

Repair rate is simulated with two numbers of repair values i.e. maximum repair time (0.0027/hour) and mean repair time (0.04/hour) from OREDA. The result can be seen in Figure 10.

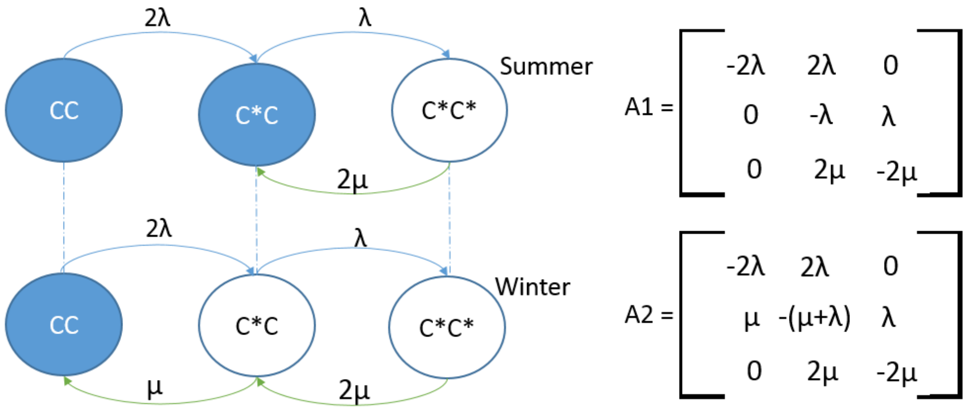
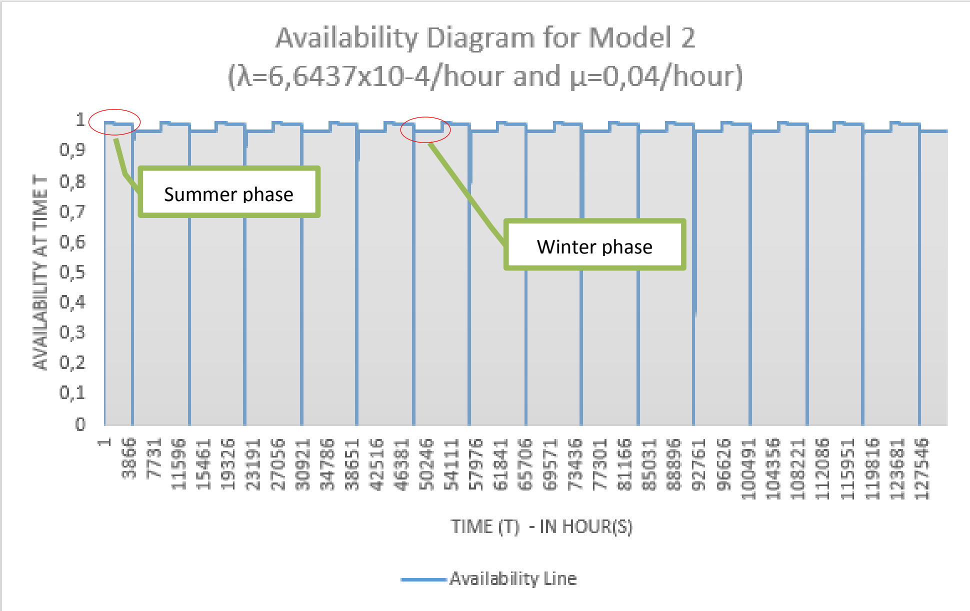


Figure 9. Model 2 – Markov Process With Maintenance

The graphs in Figure 10 are numerical result of Model-2 with different value of repair rates, maximum and average repair time. The total mean availability of each model in order is 75.426%, and 97.761%. The explanation about how to calculate mean availability value will be discussed in chapter 3 section 3.3.1 availability comparison. Despite of the result from Model-2 with average repair time is quite high, however in certain time when the system switches the phase to winter, the availability is close to 0. This is not the risk that a company will take because it can lead to failure for every winter phase. When we adjust the value of failure rate become ten (10) times smaller than the value from OREDA, we get result that is pictured on Figure 11.

In figure 10, we can see that the pattern of the graph gets steady in short period of time. We start the graph in summer phase at 1 of y axis. It goes down really slow for the first phase and suddenly drop with big gap when the system switches to winter phase at $t = 4381$. This happens since we calculate the availability from first state only during winter phase instead of first state and second state like we do in summer phase. The availability line in winter increases rapidly until it gets stable number. The increase happens since value of repair rate is bigger compare to failure rate. When the phase enters summer period in the following year, the availability line jumps higher since we come back to initial calculation, counting the availability from probability in the first and second state. The pattern goes on until in the end of time horizon used in this computation



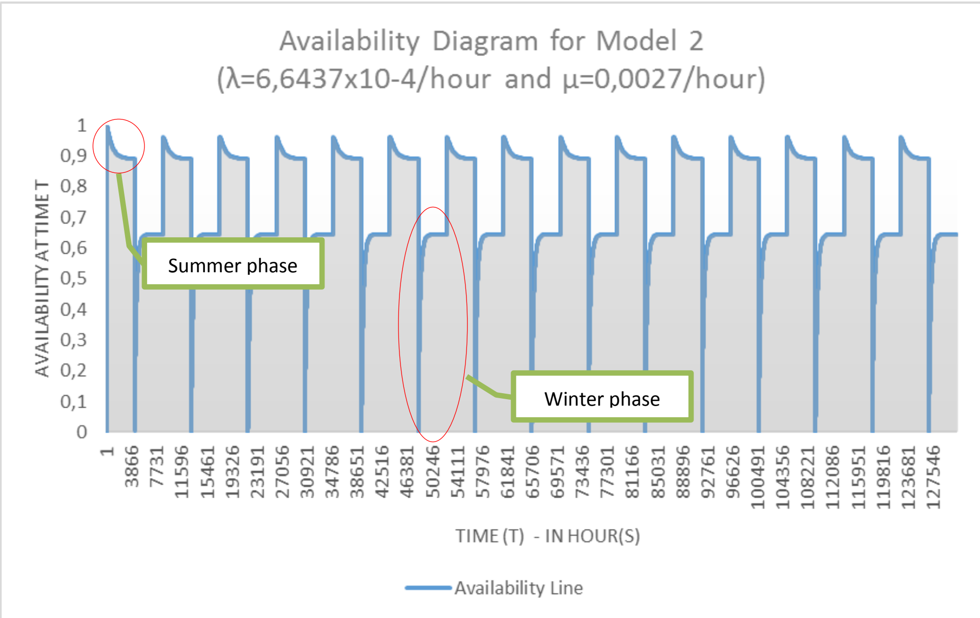


Figure 10. Numerical Result for Model 2 with Different values of Repair Rate

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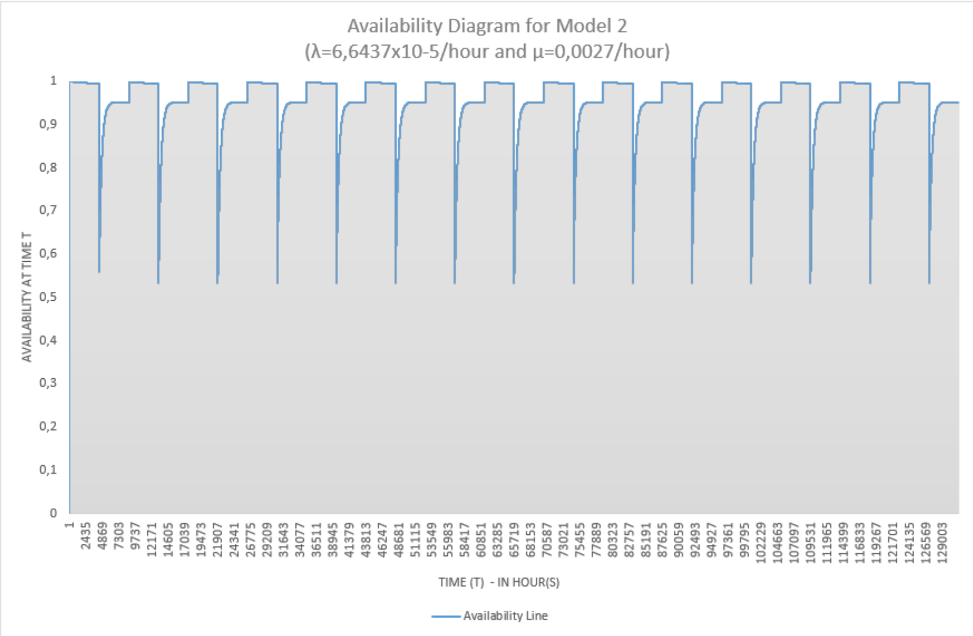
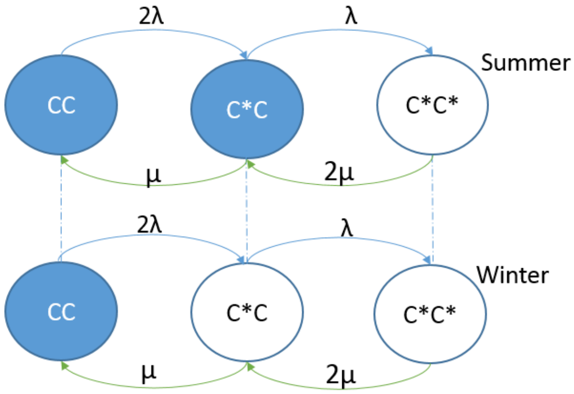


Figure 11 Availability Diagram for Model 2 with Maximum Repair Rate and Adjustment of Failure Rate

Total availability of the system in Model-2 with adjustment failure rate and maximum repair time is 95.751% and 99.696% for Model-2 with adjustment failure rate and average repair time. We can see that in every model, we can get steady state in short time, starting at year 2 or year 3. This fast formation of steady state occurs due to few number of phases which are only summer and winter and numerical result from the same phase is similar for every year.

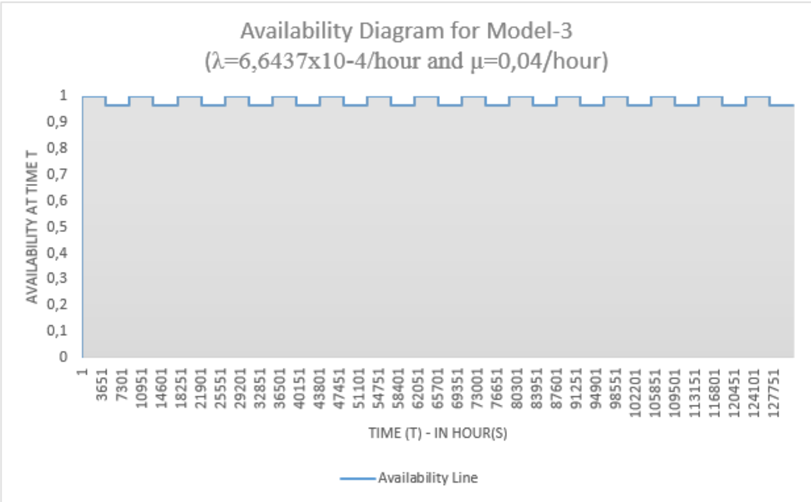
Model 3

In Model 3, we introduce maintenance program as soon as any failure happens to the running trains. In this case, we assume one maintenance crew is dedicated to each failed train and repair rates are the same for both phases. Model 3 is depicted on Figure 12.



$$A1 = \begin{bmatrix} -2\lambda & 2\lambda & 0 \\ \mu & -(\mu+\lambda) & \lambda \\ 0 & 2\mu & -2\mu \end{bmatrix}$$

$$A2 = \begin{bmatrix} -2\lambda & 2\lambda & 0 \\ \mu & -(\mu+\lambda) & \lambda \\ 0 & 2\mu & -2\mu \end{bmatrix}$$



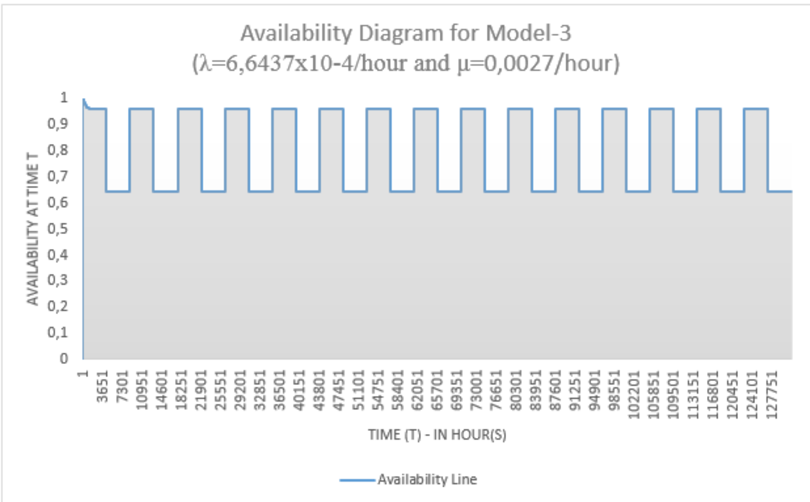


Figure 12 Markov Process Model 3, Availability Diagram for Model 3 in Average (Middle) and Maximum (Bottom) Repair time.

The availability for the system from Model-3 is quite high i.e. 80.265% with maximum repair rate value and 98.365% with mean repair rate. The availability diagram for each model is showed in Figure 13. The availability during summer and winter is plotted with straight line because the repair rate is higher than failure rate so the trains can maintain their constant condition almost as initial state. The dropping line in availability line during winter phase due to the number of state that is considered as working state which is only the first state.

Model 4

we change maintenance strategy into full maintenance which means that we repair the trains and turn them to new condition or we assume they turn as good as new after maintenance. The maintenance will be done when the whole system is failed. During summer, the system fails in the third state. Meanwhile in the winter, we define system failure in the second state and third state. Since in third state of winter phase all of the trains are failed, we need faster repair rate, thus we arrange value of $\mu 1$ is higher compare to $\mu 2$. The availability with this maintenance program is 84.234%.

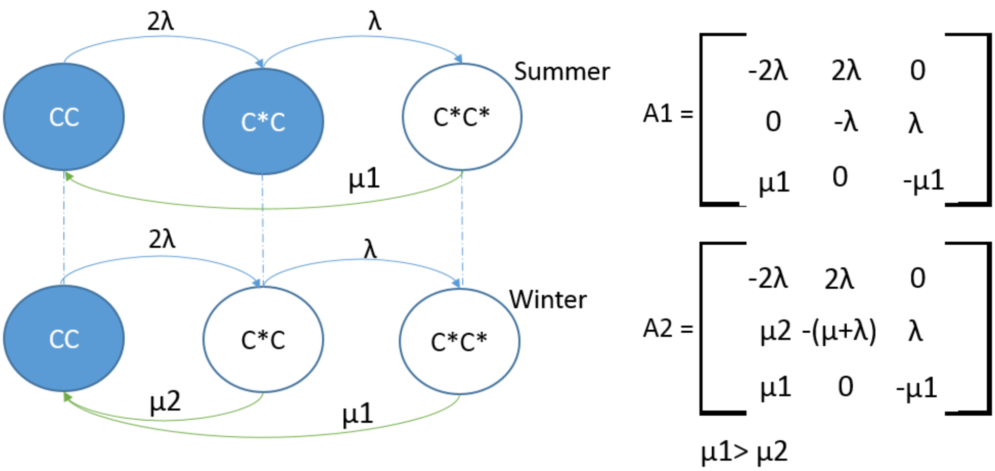


Figure 13. Markov Process - Model 4

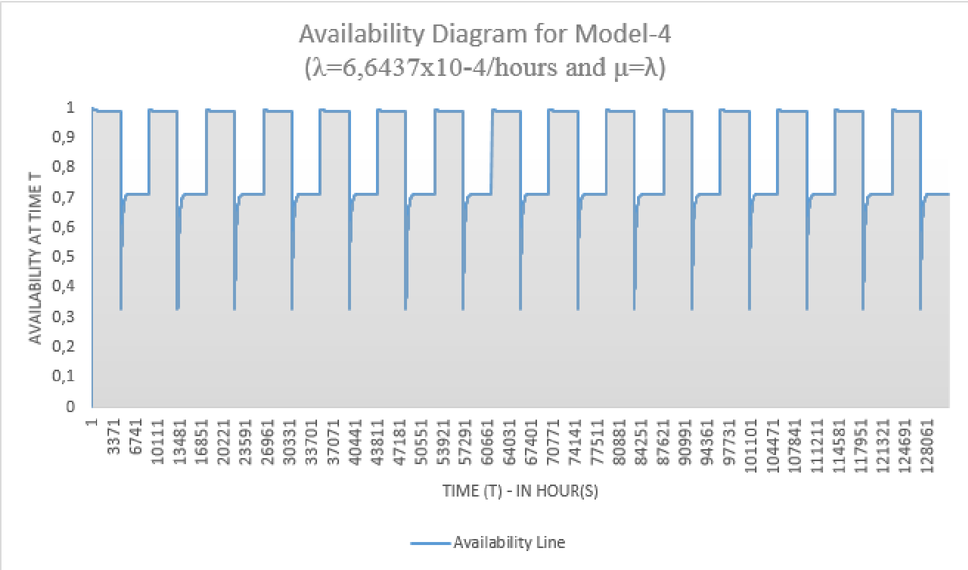
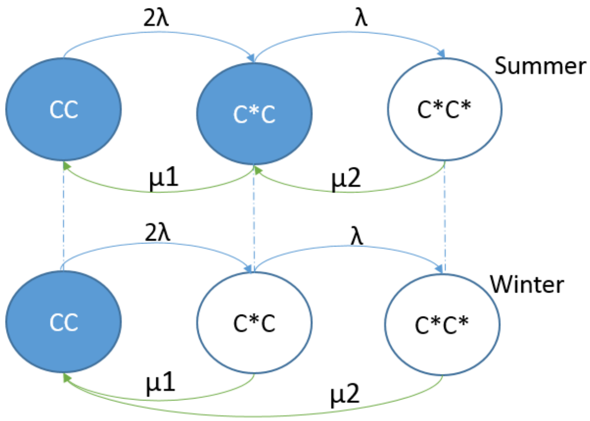


Figure 14. Model 4 and Availability Diagram for Model 4

Model 5

In this model, we conduct maintenance service as soon as any failure happens and return the trains to their last position when the system is in working state. With this program, we get better result compare to Model 4 result. The availability with this model is 97.696%



$$A1 = \begin{bmatrix} -2\lambda & 2\lambda & 0 \\ \mu1 & -(\mu1+\lambda) & \lambda \\ 0 & \mu2 & -\mu2 \end{bmatrix}$$

$$A2 = \begin{bmatrix} -2\lambda & 2\lambda & 0 \\ \mu1 & -(\mu1+\lambda) & \lambda \\ \mu2 & 0 & -\mu2 \end{bmatrix}$$

$\mu2 > \mu1$

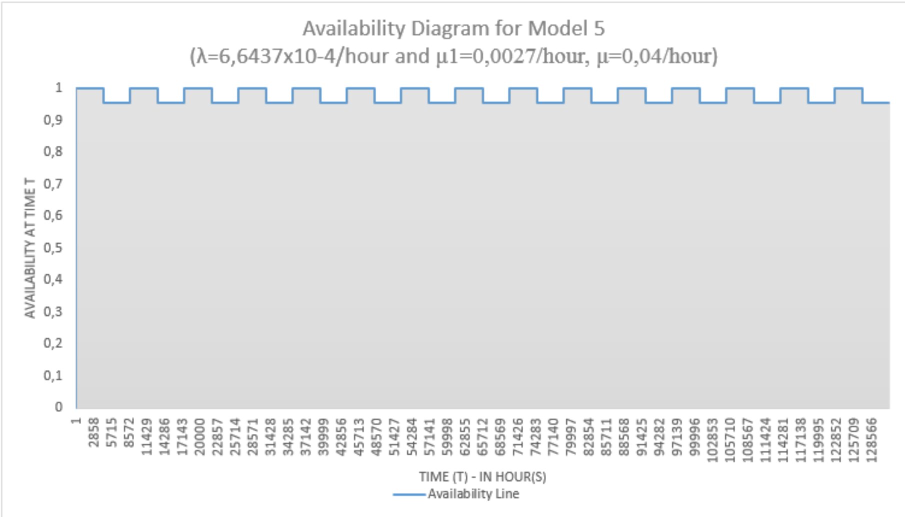
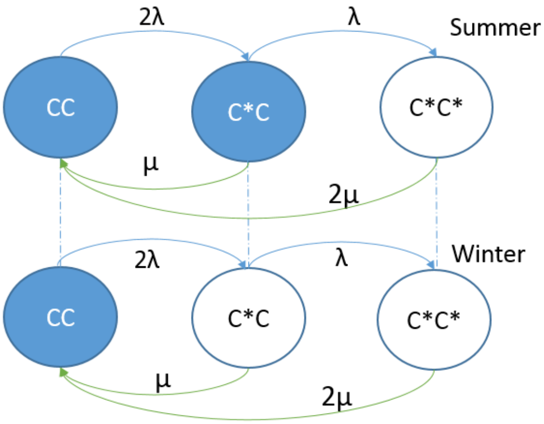


Figure 15. Model 5 and the Availability Diagram

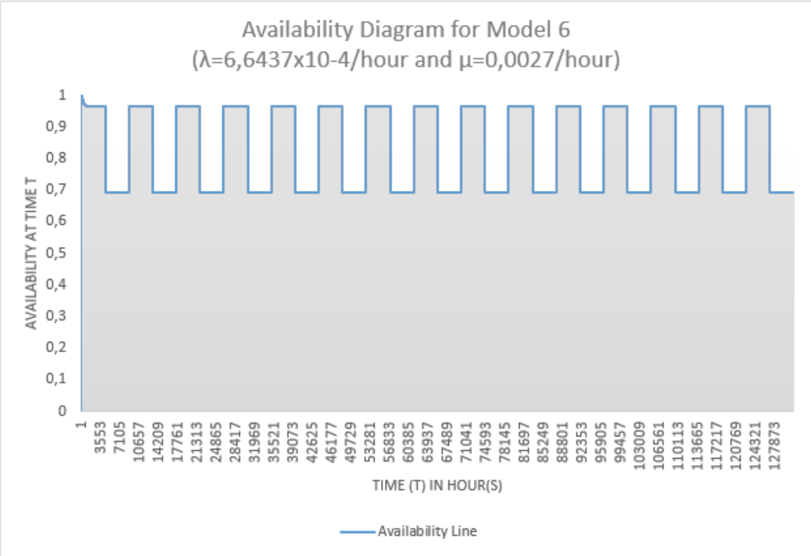
Model 6

In this model, we try to apply maintenance action as soon as any failure is happened. Slightly different compare to Model 5, instead of we repair the failed trains to the last position, in this model we return the trains as good a new like in the first state. This program gives the better result compare to the other model that has been described above. Using maximum repair time value, we can get availability of the system for 82,391% and when the mean repair time is used, the availability is 98,391%. The model and the numerical result diagram can be seen in figure 16.



$$A1 = \begin{bmatrix} -2\lambda & 2\lambda & 0 \\ \mu & -\lambda-\mu & \lambda \\ 2\mu & 0 & -2\mu \end{bmatrix}$$

$$A2 = \begin{bmatrix} -2\lambda & 2\lambda & 0 \\ \mu & -\lambda-\mu & \lambda \\ 2\mu & 0 & -2\mu \end{bmatrix}$$



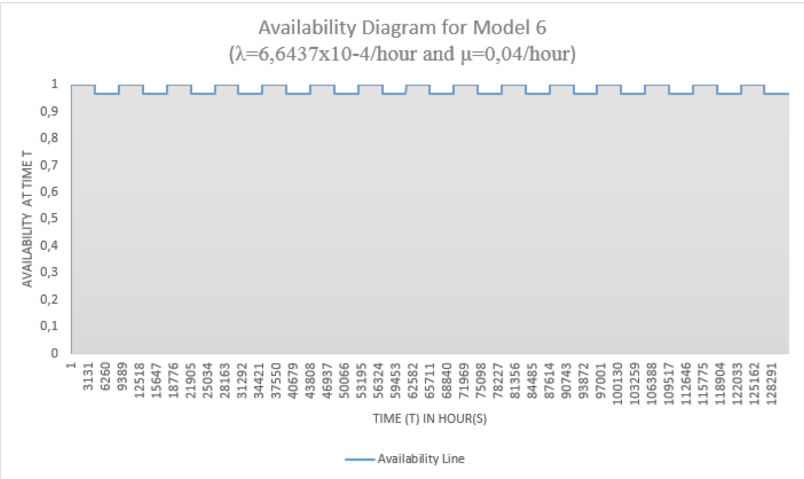


Figure 16. Model 6, Availability Diagram with Maximum Repair Time and Mean Repair Time

Model 7

The first six models above have the same scheme for winter phase. It has only one working state i.e. the first state. During winter phase the system is able to fulfil the order when all of the trains are in good condition and running in their full capacity. But more often in real case, one failure of the train will not make the rest of the trains stop operating. They will keep running. Speedy maintenance action however will be required in this situation to put the system back on track as soon as possible. While the failed train is under maintenance, the company will endure some loss since they cannot meet the target.

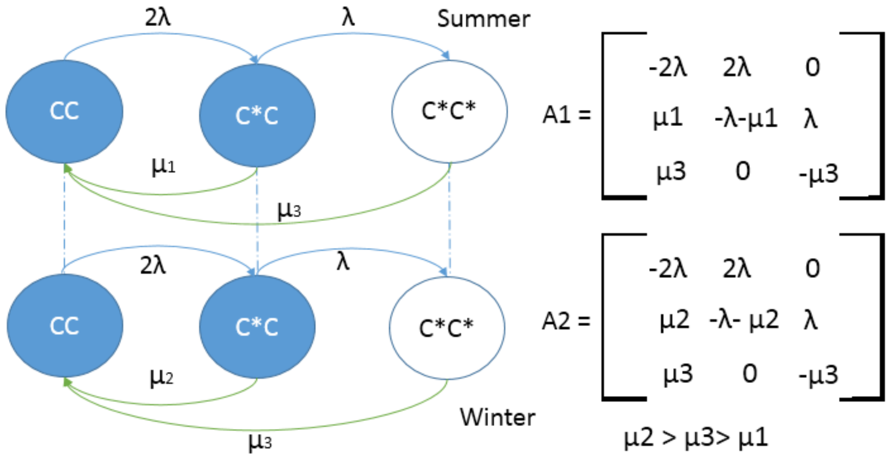
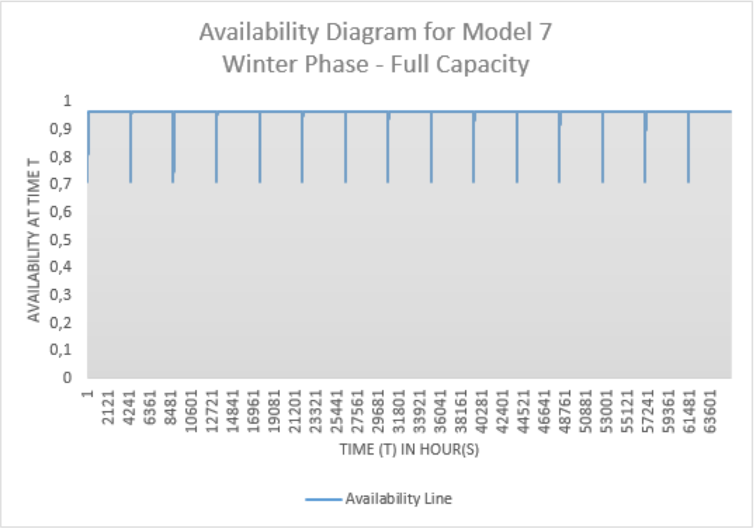


Figure 17. Model 7 - Markov Process Model

Model-7 is calculated to see how the difference in availability for the whole system when we make the second state of winter phase turn into working state. In Figure 17, the repair rate for $\mu_1$is smaller compare to μ_2. During winter phase, all the trains are required to be in place to fulfil the order. Thus, maintenance is more urgent and has to be done faster. In this case, the value of μ_2 and μ_3 are using mean repair time from OREDA and $\mu_1$is using maximum repair time value

Figure 18 displays two different availability diagrams for winter phase only. One diagram is showing the availability of the system when it is running with full capacity with average availability 96.63%, and the other one is showing the availability of the system when it is in the second state with system capacity is reduced. The average availability is 3.3% for reduced capacity. In total, the average availability of the system, including summer phase is increase to 99.75%.

When both of phases have the same working state, the gap between summer season and winter season is narrower and availability of the system is increased. But we need to consider that there is also cost for production. From this numerical result, we can estimate the approximation of production lost probability that company will face during winter operation. To get this estimation number, we calculate total availability of the system during winter phase when the system in state two and divided the number to total availability of the system. From this division, we get 1.6% from total availability as estimation number for production lost. Knowing this estimated production lost, the company can make planning earlier to cover the lost, for instance is by having buffer for the gas that need to be delivered to the customer.



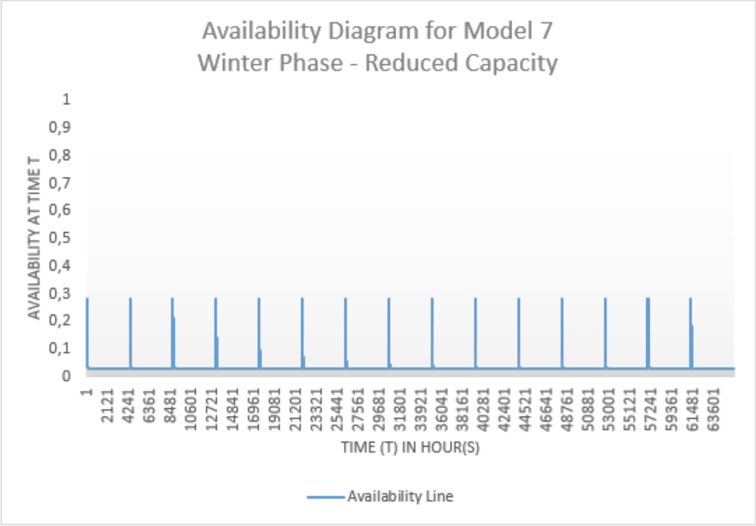


Figure 18. Availability Diagram for Model 7 (Winter Phase). Availability Diagram for state 1 (top) and state 2 (bottom)

3.1.3 Simulation with Standby Condition

Model 8

As was mentioned before, the treatment for the gas compressor trains during summer may vary. Another maintenance program that is adopted in this case is standby trains model. Standby model allows us to cut maintenance time by having trains exchange. The train that is failed will be replaced by good train as soon as the failure happens. With this planning, the repair time during summer can be smaller compare to winter time. In the model, we set $\mu1 > \mu2$. The mean availability for Model-8 is 85.348%.

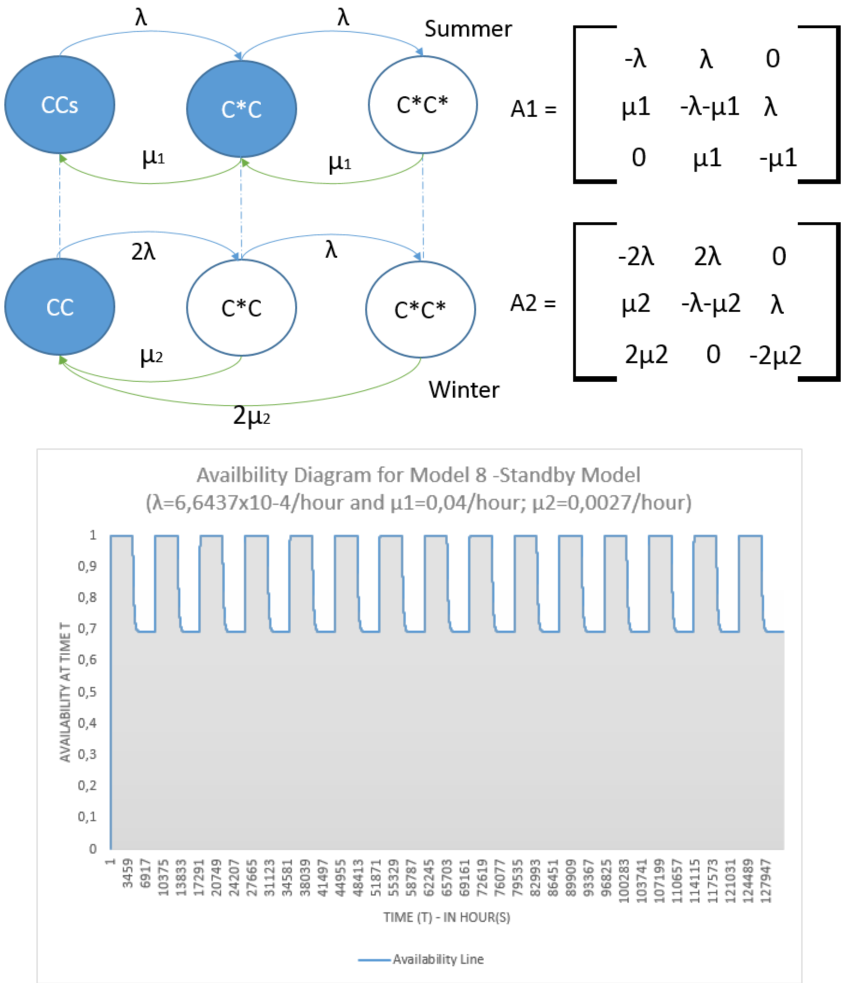


Figure 19. Model 8 - Markov Process Model and Availability Diagram

3.2 Markov Process Model with Degradation Process

Model 9

First section of this chapter presents system models without any degradation process. There is no observation or monitoring applied to the system before the system actually fails or breaks down. Monitoring activity towards degradation process in each machine can give advance warning to engineers that there will be digression in system performance. The engineers will be able to take preventive actions to avoid the unwanted event, system failure.

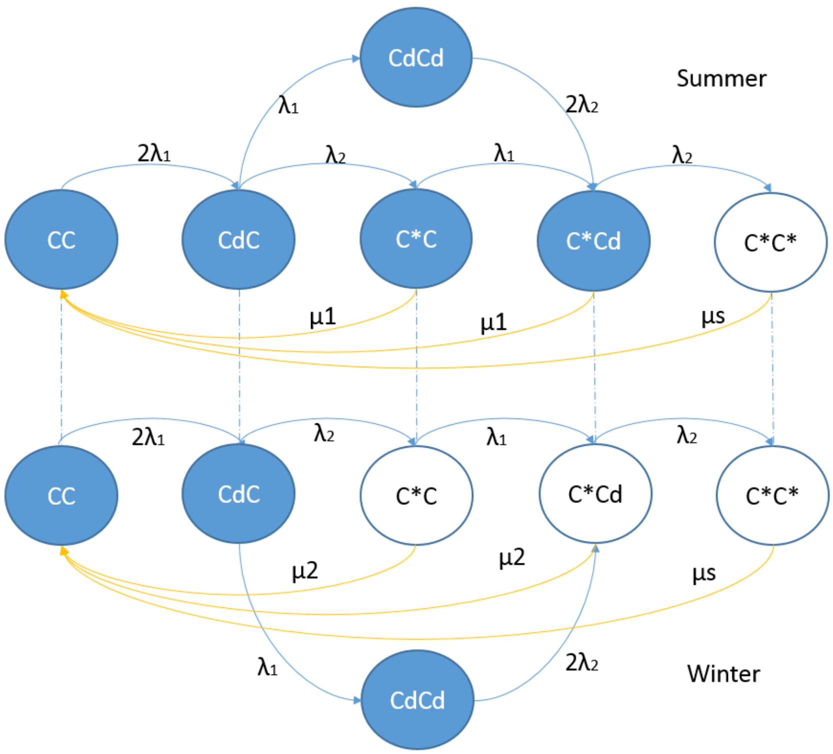


Figure 20. Model 9 – Markov Process Model with Degradation State

The models that are discussed in this section will give illustration on how the actions that are taken place to respond any degradation process will influence the availability number. Figure 20 shows the expansion of Markov process by having degradation states before the trains move to failure state. Performance of the machines will decrease rapidly after the machines experiencing degradation. Thus, the failure rate for λ_2 is higher compare to λ_1. By having the knowledge of trains' current state, we can have better planning for the maintenance such as advance planning for spare part supply, integrated maintenance schedule, proper number of required maintenance crew, and better coordination with another operation schedule.

In model 9, maintenance or repair activity is implemented as soon as the failure happens. Both phases have the same program maintenance. Yet, there is different rate for μ_1 and μ_2 since maintenance action during winter is more urgent and needs to be done faster.

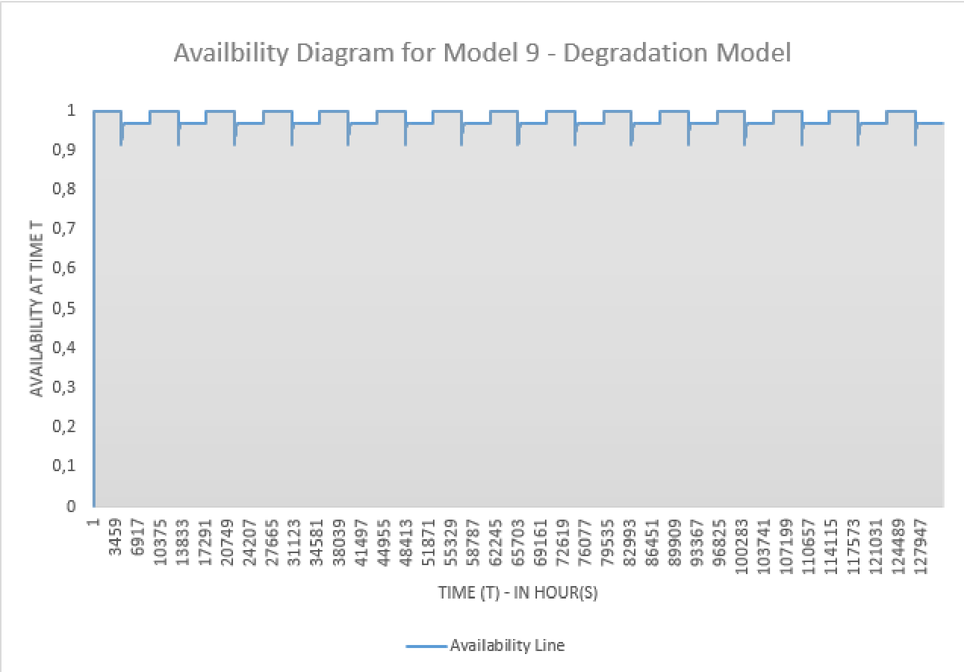


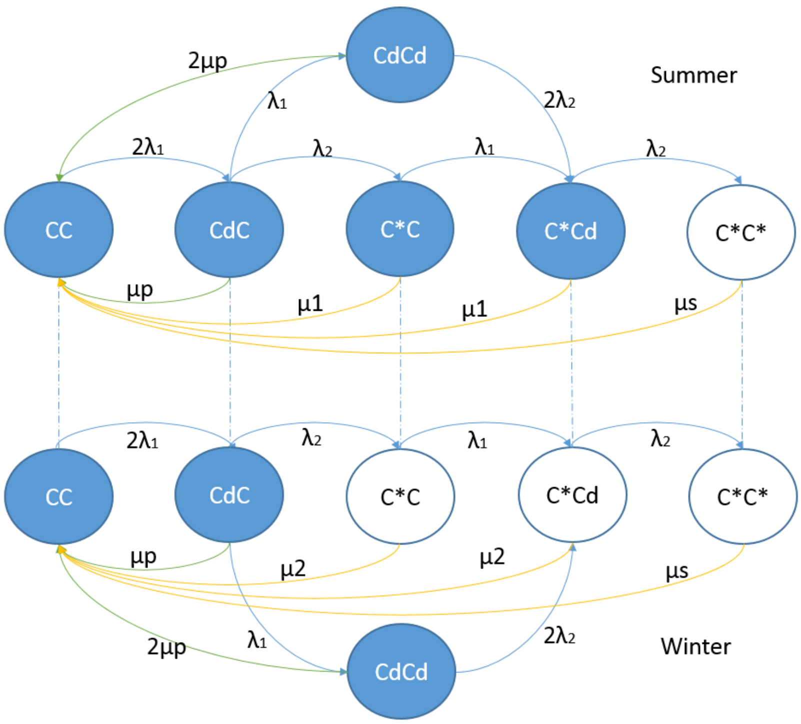
Figure 21. Avaialbility Diagram for Model 9

As expected, the mean availability for model 9 is quite high i.e. 98.30%. We calculate the availability from 5 states out of 6 states for summer phase where total failure will happen when both of the machines are failed in the same time. During winter, only 3 states out 6 states for winter phases that are considered as working states where all of the trains need to be in function.

System failure will less likely to happen in this model since monitoring actions of the machines are more frequent and the operators will have more attention to the machines once degradation symptoms start emerging.

Model 10

In the last model of this report, we will introduce preventive maintenance. Preventive maintenance will be done when the maintenance crews have identified that there is degradation happening in the trains. In Figure 22 we can recognize preventive maintenance for green arrow from state from state CdC or CdCd to initial state, CC. Since preventive maintenance is an early detection process to avoid further failure, maintenance action not necessarily to be done so fast. Thus, in this model, we set repair rate of preventive maintenance with same value of maximum maintenance time from OREDA ($\mu = 0{,}0027/hour$). Numerical result for this calculation, it gives average availability for 99.568%. It approves that by having preventive maintenance, we can keep our system always in working condition most of the time.



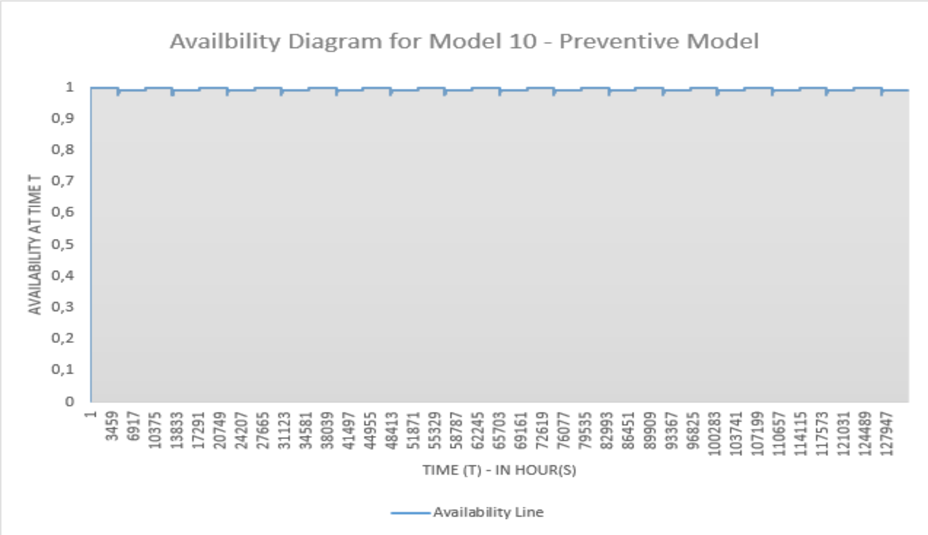


Figure 22. Model 10 - Markov Process Model with Preventive Maintenance

3.3 Model Recommendation from Availability Comparison

We have ten models that have been presented in this chapter to give the company information regarding availability for maintenance programs that can be implemented in the plant. Those models are considered possible to be applied in real technical condition on the existing gas compressor system even though the parameters value that are used need to be adjusted with the real number from the plant. Currently, there are no actual data that can be referred to, thus some of the parameters in this report are based on assumption and some of data are also referred to OREDA data base. To avoid unreasonable gap in comparing the availability between models, we will compare one model to another model that uses the same parameters assumption.

Table 3

Maintenance Program		***Mean Availability per unit time***
No Repair Time	Model 1-1	1.60 %
	Model 1-2	11.49 %
Maximum Repair Time (μ=0,0027/hour)	Model 2-1	75.43 %
	Model 3-1	80.27 %
	Model 6-1	82.96 %
Mean Repair Time (μ=0,04/hour)	Model 2-2	95.75 %
	Model 3-2	98.37 %
	Model 6-2	98.39 %
Combination of Repair Time	Model 4	84.23 %
	Model 5	83.73 %
Reduced-Capacity	Model 7	99.75%
Standby	Model 8	85.35%.
Degradation	Model 9	98.30%
	Model 10	99.57%

These average availability numbers are produced by following this formula:

$$Average\ Availability = \frac{\sum_{t=0}^{t=131400} \mu_t}{131400\ hours} \tag{8}$$

From MATLAB calculation, we will get 3 columns information of μ_t. Each column contains information for each state. Only μ_t in working state will be considered. During summer, information from state one and two will be added up together. Meanwhile for winter, μ_t for first state only that will be put into account. Total availability during winter will be summed with total availability of summer. Total number from this addition then will be divided by total time.

Model 2 and 3 share the same parameters assumption for failure rates and repair rates, both in summer and winter phase. Repairs in both models are done when failures happen and turn the trains back to previous condition. Model 6 is also almost similar with model 2 and 3 except we assume that reparation of the trains will turn the trains' condition as good as new. The models are calculated for two repair time, maximum repair time and average repair time that we get form OREDA.

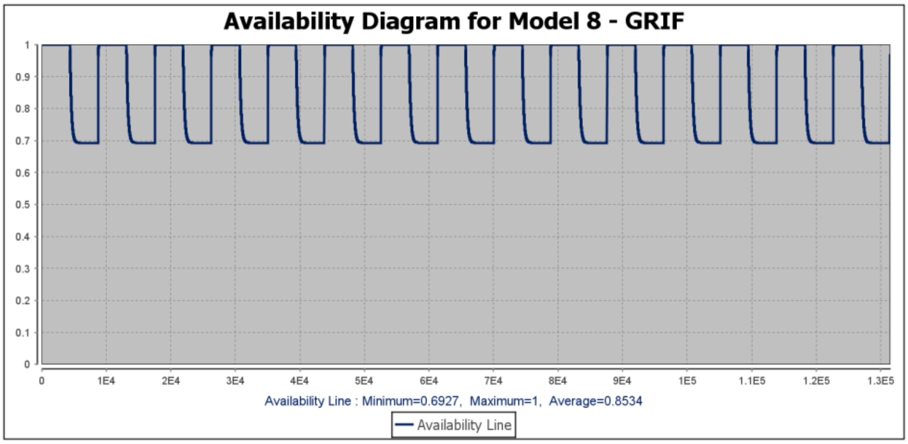
All of the models except model 7 have the same assumption for working state in winter phase. Gas compressor trains in winter season must not fail to fulfil the order. Thus, if one train fails then the system is considered fail as well. This assumption makes the availability in winter season only calculated from state one. Model-7 gives the highest average availability value, yet we have to consider the lost production that occurs.

For standby model, Model8, is similar with the condition that we have in Model-5. The difference is in summer. Instead of let all the machines are functioning, model in standby mode allows half of the trains to be in standby position so if any train fails during the operation, the operators can switch the train with standby train and repair the failed train in parallel. This model gives slightly higher availability in total. It also helps operators to more focus in repairing since they will have more time until the next failure.

Preventive model that is explained in Model 10 is showing the best availability number. It has been expected for having machine degradation monitoring. it will give better information for the operators to avoid the system failure. With this information, we can have better plan in maintenance and other strategies related to maintenance to make the operation optimum.

3.4 Model Validation

To be sure that models in this chapter are correct, we need to validate the models. One of the way to validate the models is by comparing the numerical results with results from another tool or software. Here, we will use another software called GRIF to check the numerical results from models that are processed by MATLAB. GRIF is one of many software that can be used to calculate Markov process. By inputting the Markov process graphs, we able to calculate the availability of the system. For an example, we will use model 8 to see whether the numerical results that we get from MATLAB and GRIF are the same or not. In previous section, it has been mentioned that average availability for Model 8 is 85.348%



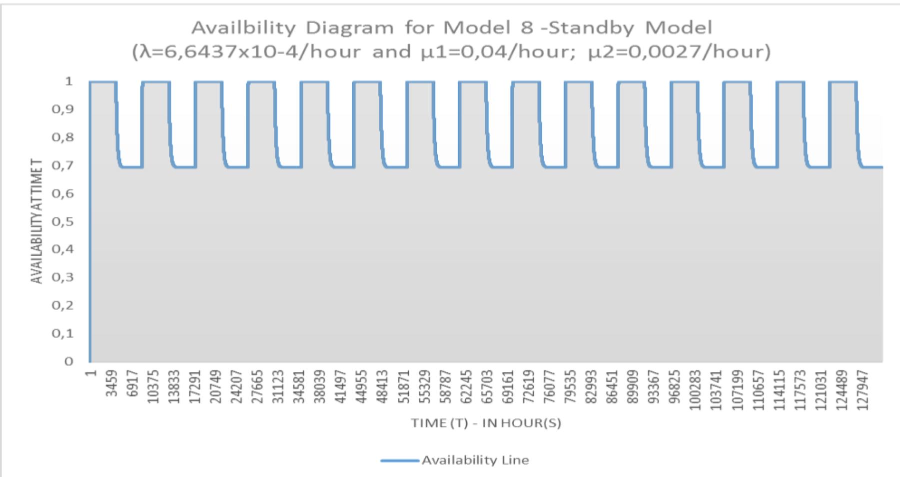


Figure 23. Diagram Comparison between GRIF (top) and MATLAB (bottom)

Figure 23 is showing graphs comparison that is produced by GRIF and MATLAB software. We can see that both programs give similar result. In GRIF's diagram, we can see the information related to average value of the availability which is 0.8534 or 85.34%.

We also compare the numerical result between GRIF and MATLAB per time (t) in figure 24. Error between two software in average is 0.073%. This number is small enough and acceptable to say that the result from both software is the same. In other word, the models that we create with MATLAB are valid. Comparison for other models will be presented in Attachment Chapter except for Model 9 and Model 10 due to graphics limitation in GRIF. Graphics limitation in GRIF means how much number of states and transition rates that we can calculate. GRIF has limitation for 25 graphics and Model 9 and Model 10 have more than the limitation allowed.

The spikes that are showed in figure 24 happen in the time when the phases are switching from summer to winter or winter to summer (T_i). To calculate the error, we use this following formula

$$\%\ Error = \left|\frac{\mu_t\ GRIF - \mu_t\ MATLAB}{\mu_t\ GRIF}\right| \times 100 \qquad (8)$$

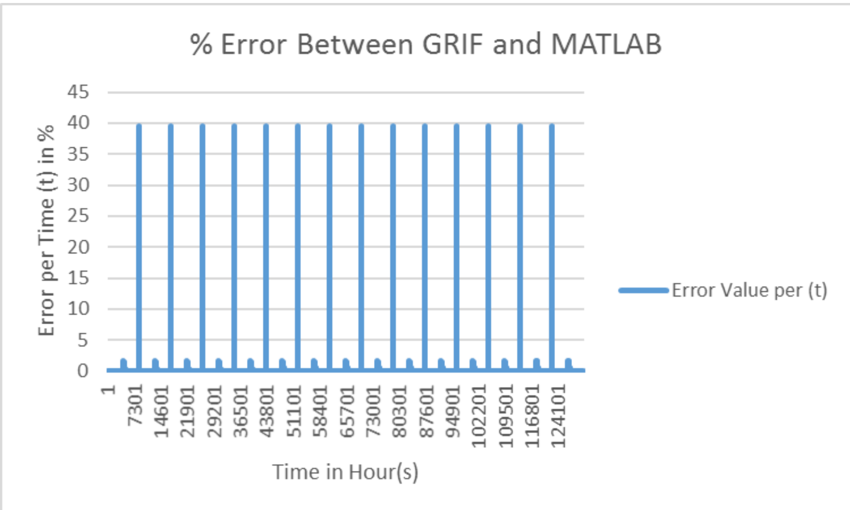


Figure 24 - Error Diagram Between GRIF and MATLAB

In summary, the comparisons between numerical results that are produced by GRIF and MATLAB are showed in table 4.

Table 4. Comparison of Availability Between GRIF and MATLAB

Model	% Error	Mean Availability per Time (t) in %		Description
		GRIF	MATLAB	
1	72.71823	1.6	1.6	
2	4.480605	78.24	75.43	μ=0,0027/hour
2	0.036443	97.79	95.75	μ=0,04/hour
3	0.000787	80.27	80.27	μ=0,0027/hour
3	2.03E-07	98.37	98.37	μ=0,04/hour
4	9.03E-06	84.23	84.23	
5	1.627436	85.29	83.73	
6	2.61E-05	82.96	82.96	μ=0,0027/hour
6	2E-07	98.39	98.39	μ=0,04/hour
7	0.014278	98.1	99.75	
8	0.073007	85.34	85.35	

To calculate the availability using GRIF is much simpler compare to MATLAB. GRIF has input interface that allows the user to create Markov process graph directly in the program.

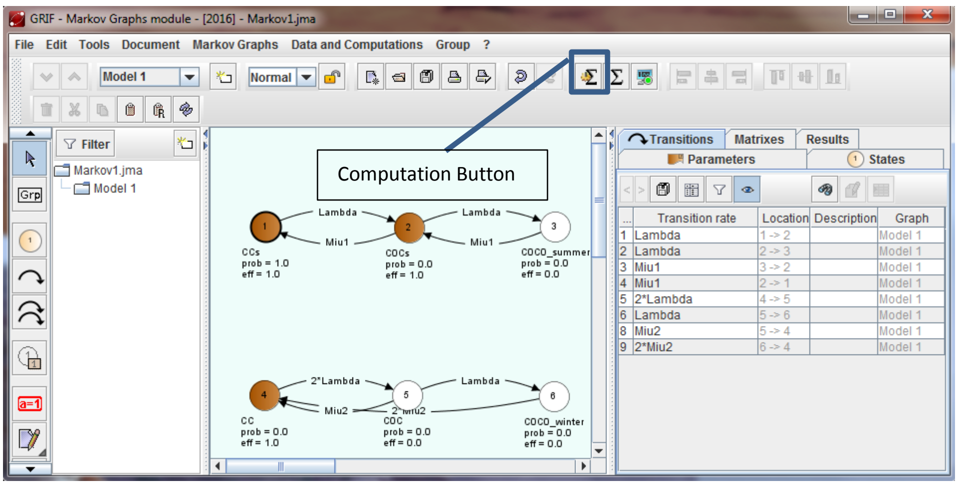


Figure 25.GRIF's User Interface

The brown circles identify the states that are available and white circles identify the failure states. The user can connect one state and another using the arrows for transition direction. It is possible to rename the state and change the efficiency of the state. For normal state, without degradation, usually the efficiency is 1.

To adjust the parameter, GRIF also has several columns that we can fill to set the duration of the simulation, single Markov Process or multiple process, etc. Using computation button, the program will start computing the availability of the process that has been input. The result can be a graph or set of number that shows the availability of the system in each t according to time setting.

Chapter 4
Conclusion

In this chapter, we will look back the objectives of this thesis and will discuss whether we have answered all the points which are mentioned in that section. In Objectives, we have five main points which are list of possible programs, availability estimation, availability comparison, remaining useful lifetime estimation, and maintenance program that will be recommended for the company.

4.1 Maintenance Models

We have discussed ten (10) models of Markov process with different number of parameters and different scenarios. MATLAB is used to help as calculator in producing numerical results for computing the probability of the system in each state at time t. The time period that is calculated is for fifteen (15) years.

Adjustment in each model is applied to make the model applicable for real condition. Since we do not proper information related to failure rates and maintenance time for real case, we use data from OREDA. There are several models that are calculated twice with different parameters to see how big the influence of a parameter to change system's availability.

4.2 System Availability

We define the model using Markov process by divided the physical conditions (working or fail) of the system into several possible states. Between each state, we set different parameters and assumptions such as value of transition rate, when maintenance action will be done, and the result of maintenance action toward the failure trains (as good as new or not). Different phases are applied to distinguish different conditions of states due to difference in demand requirement.

Using MATLAB as calculator, we can get numerical result on possibility of the system is exist in certain state, in this case we interest to know the possibility of the system exist in working state regardless in which phase. Different models share different trends on the graph. The highest availability is showed by model 10 where there is involvement of preventive maintenance and condition monitoring towards machine’s performance.

Condition monitoring let us to have better knowledge of the system that we have. It gives us earlier warning when the system start degrading so the crew can take action as soon as possible before further unwanted event occurs. With early information about what happen to gas compressors, the operators can decide what actions that need to be done in proper and timely manner.

The results that are produced from MATLAB are validated using GRIF. Another software that has capability in computing availability from Markov process. In chapter 3.4, we can see the that our calculation using MATLAB gives the same result if we use this software.

4.3 Remaining Useful Lifetime

Remaining useful lifetime is the remaining time that a system has until the end of useful life knowing the condition at current time. To estimate remaining useful lifetime with Markov process, we have to know the current state of the system.

Initial probability for every state at time t=0 is $\mu_0 = [1,0,0]$. When we compute Markov process model, we assume that the system starts with new machines so we can be sure that the system is 100% work. In real condition, the system may have run for several years, so we have to adjust the value of μ_0 and compute the model again. With the same procedure in the chapter 3.1.2, we can see the probability of the machine is being in working state for period of time that become our main interest.

Let's take Model-2 for example. When the system has run for 20 years, and we assume that in current condition, the probability of each state for the system is $\mu_0 = [0.3,0.65,0.05]$. Our interest is to know the availability of the system in the next 5 years. Using MATLAB, we can get estimation for 0.1539 or 15.4% that the system will be available for the next five years.

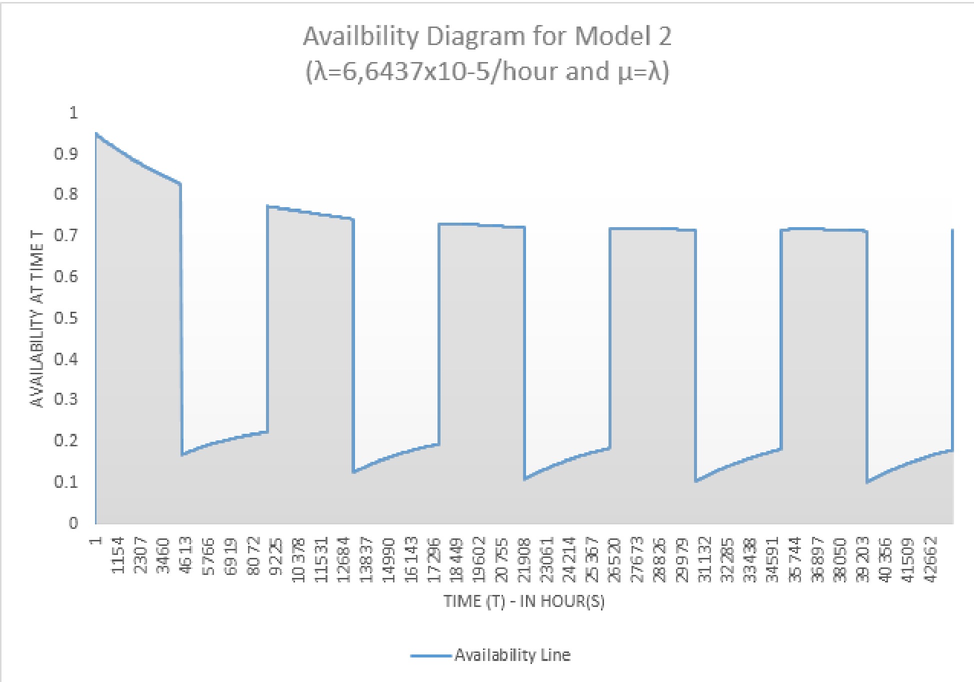


Figure 26. Availability Estimation for a System

4.4 Further Discussion

While writing this thesis, there are some points that become interest for the writer yet not have been covered or discussed. This interest can be input for the reader to explore more related to those topics. First, numerical results from all of the models show that they reach steady state in early time. It may be due to repair rate that is quite high, few number of phases which are only two, and also because the assumptions that are used for repaired condition. In this report, it is assumed that after repair or maintenance, the trains come back to new condition which may not be the case in real condition.

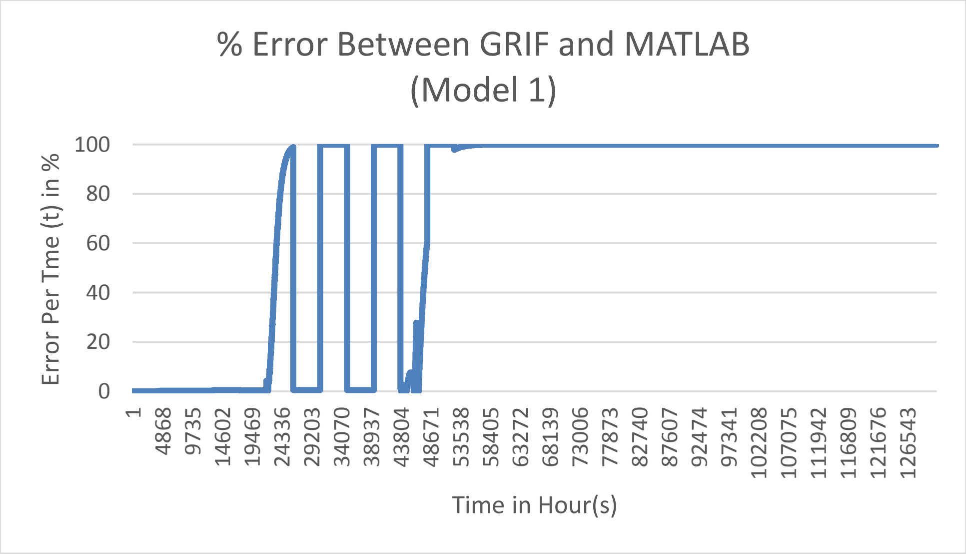
Second, condition monitoring is a good tool in supporting Model-10 as the recommended model that the writer proposed for this report. There are a lot of technics of condition monitoring that will be fit to be carried out for gas compressor system. This topic can be an option for another study in the future.

There are no data yet from the actual plant that can be useful for this report. Necessary adjustment need to be done when the required information will be available.

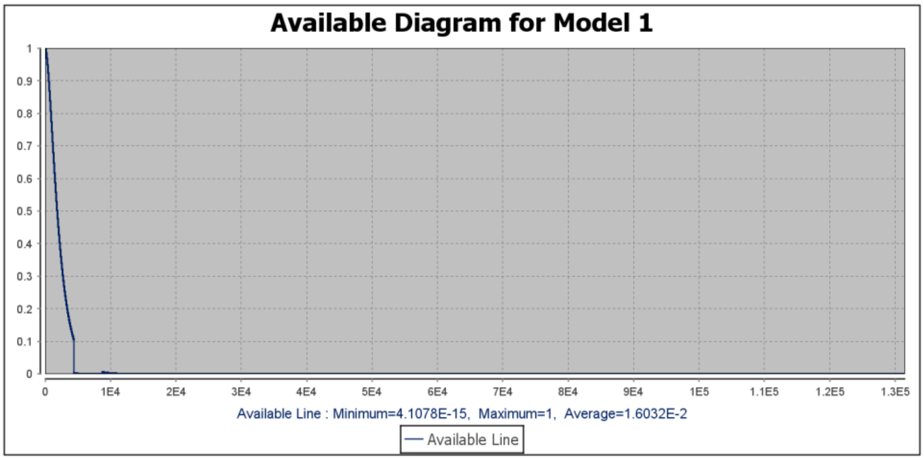
Attachment

In this section, we will present the comparison of Error computation from GRIF and MATLAB that have been explained in chapter 3.4.

Model 1

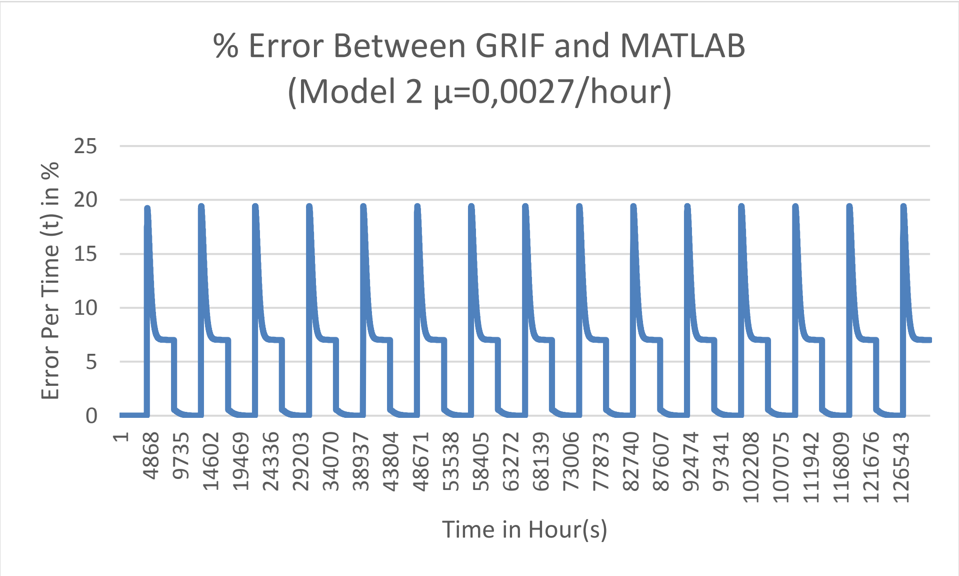


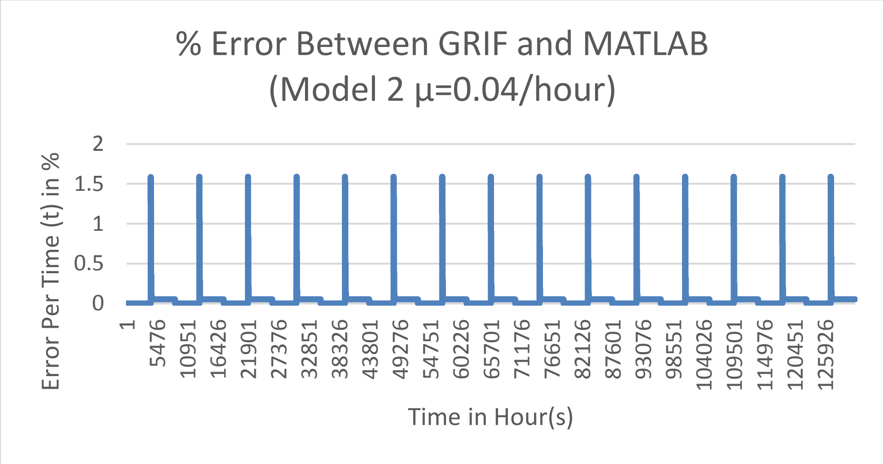
In the beginning of the graph, the errors are close to 0. After 2 years, the errors increase. This is because numerical results from MATLAB for μ_t keep decreasing into so small number ($\mu_{131400} = 1.555\ E - 76$). Meanwhile with computation using GRIF, the values of μ_t decrease only at T_i or when the season switches yet within each season the values remain constant. For example, the values from μ_{127021} until μ_{131400} are the same i.e. 6.5836 E-14. This different that make the error after two years decrease. The average of % error for Model 1 is 72,72%. Availability diagram for Model 1 by GRIF is presented in the next page.



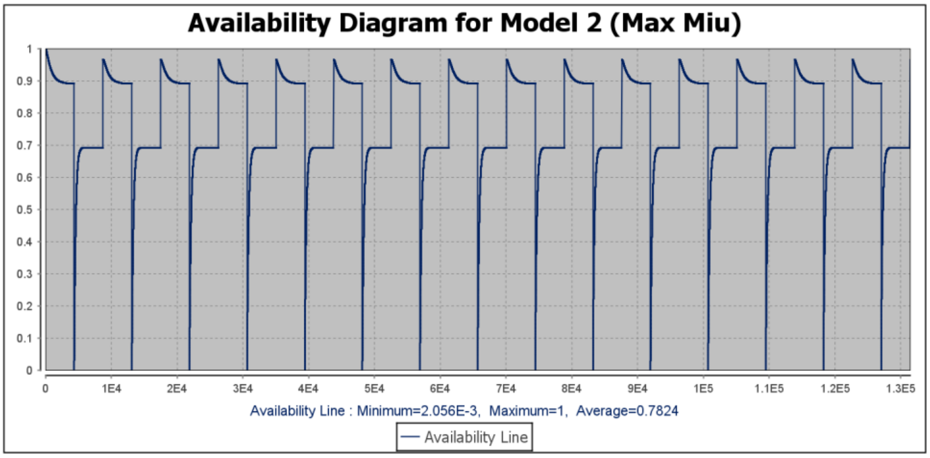
Model 2

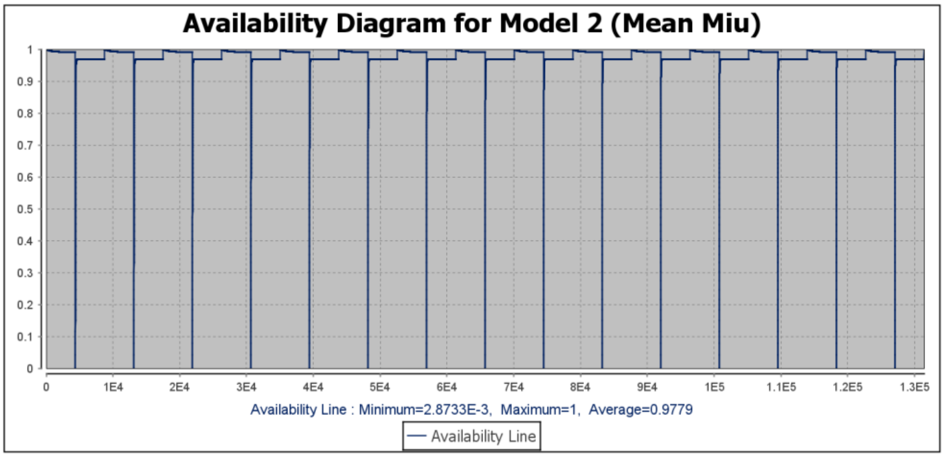
The average of error for Model 2 is 0,036% for Model 2 that use repair rate equal to 0,04/hour. And for Model 2 that uses maximum repair rate, the average of error is 4,48%. There is quite different results between GRIF and MATLAB even though the trend from availability diagram for both method are similar.





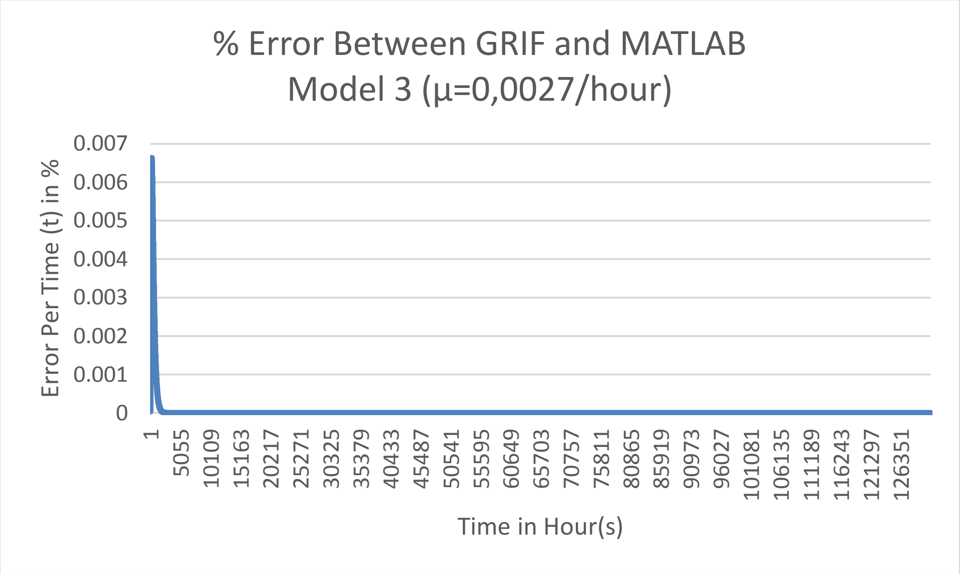
The spikes in both two diagrams above happen during phase changing.

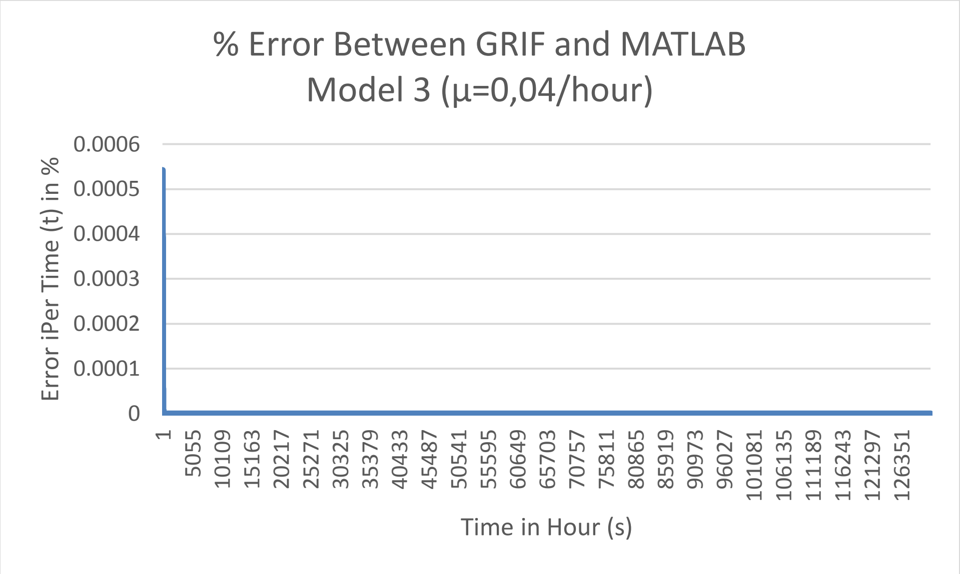


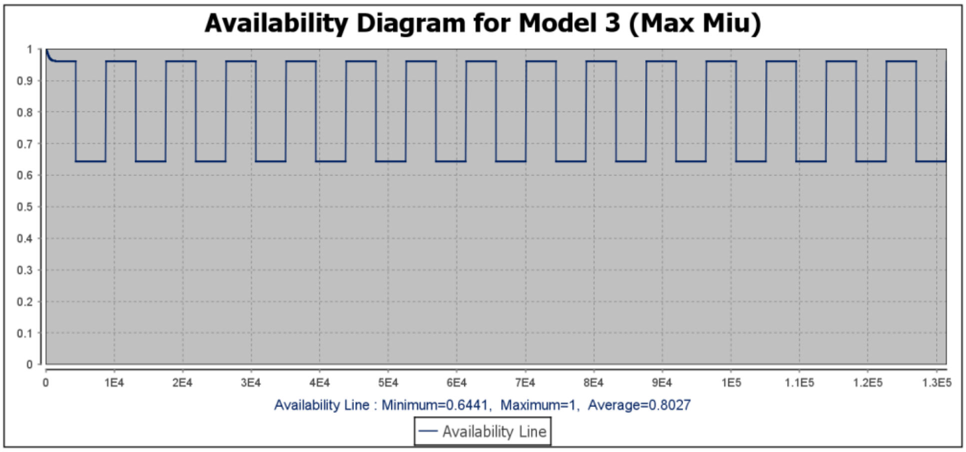


Model 3

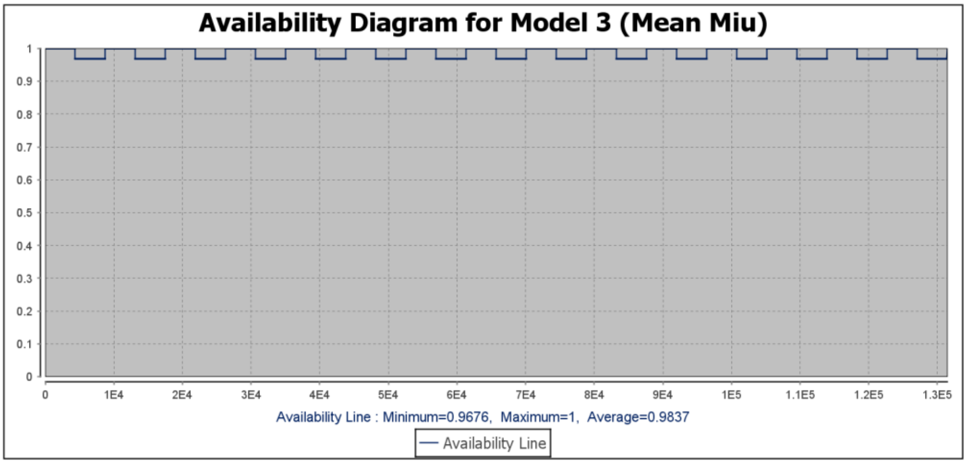
The trend for Model 3 between maximum repair time and average repair time shows the same pattern. The average error for Model 3 in consecutive order is 0.000787036 % and 2.03181E-07%. Different results between GRIF and MATLAB occur in the beginning of computation. While the model gives steady state result, the errors are close to 0.







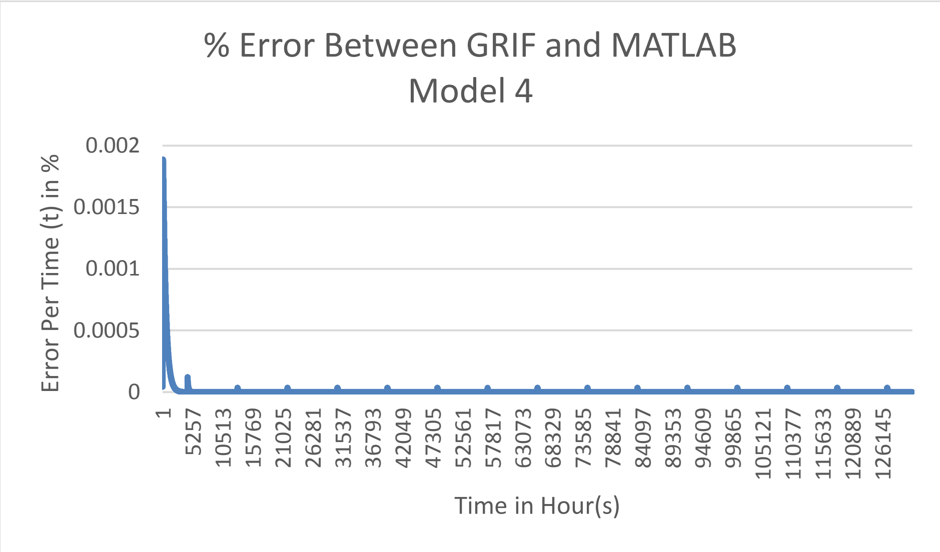
Model 3 with μ = 0,0027/hour

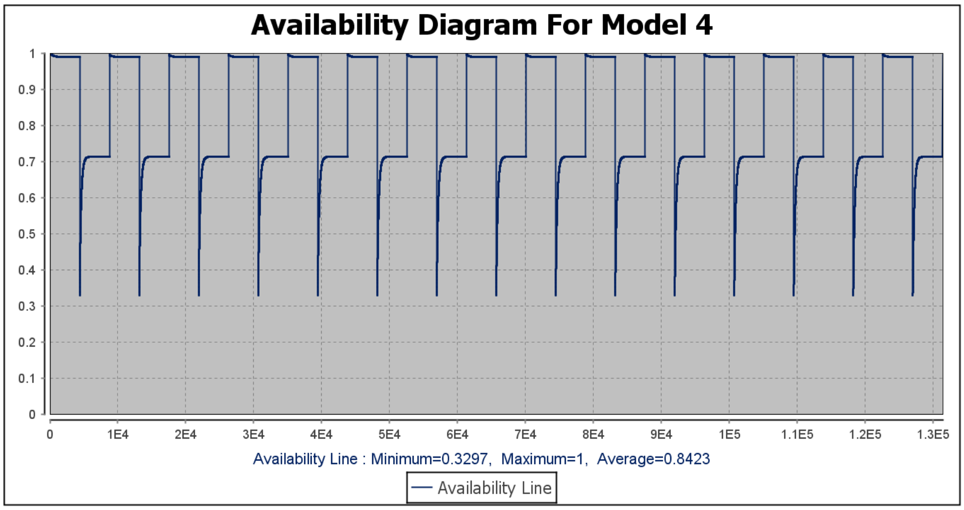


Model 3 with μ = 0,04/hour

Model 4

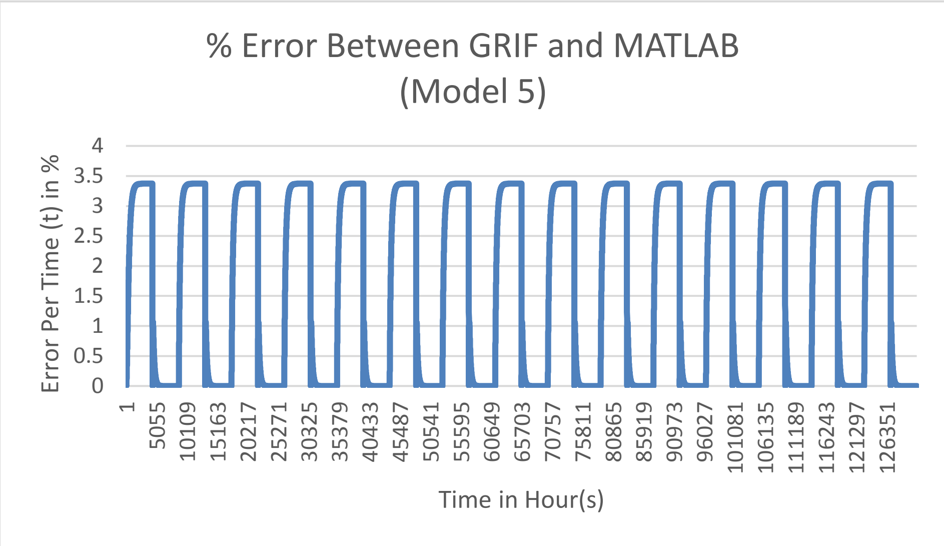
The average of error is 9.02595E-06%.

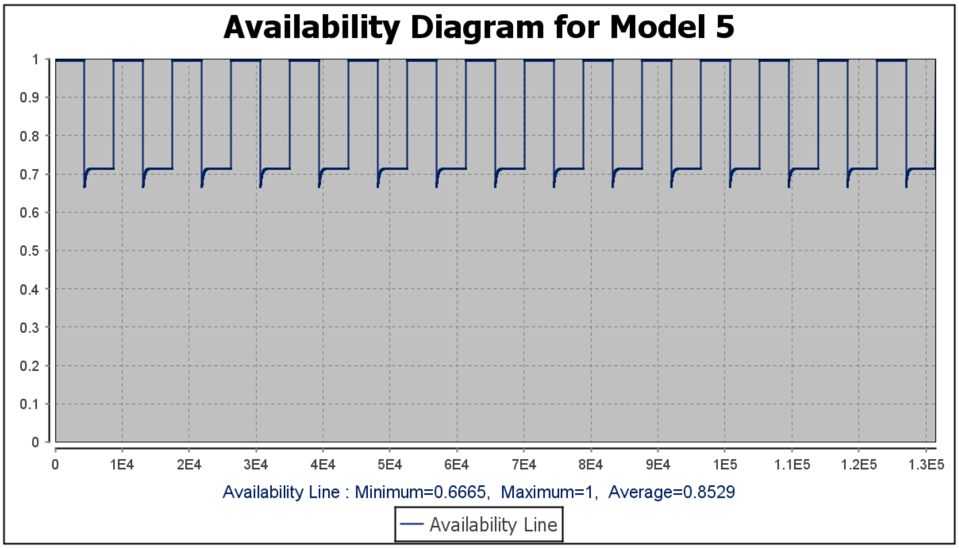




Model 5

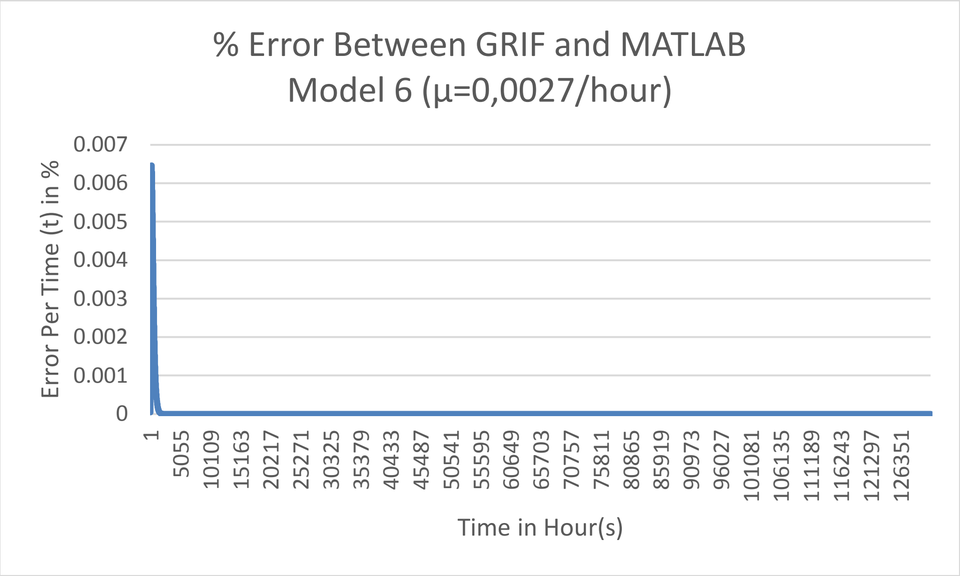
The average of error is 1.627435649%.

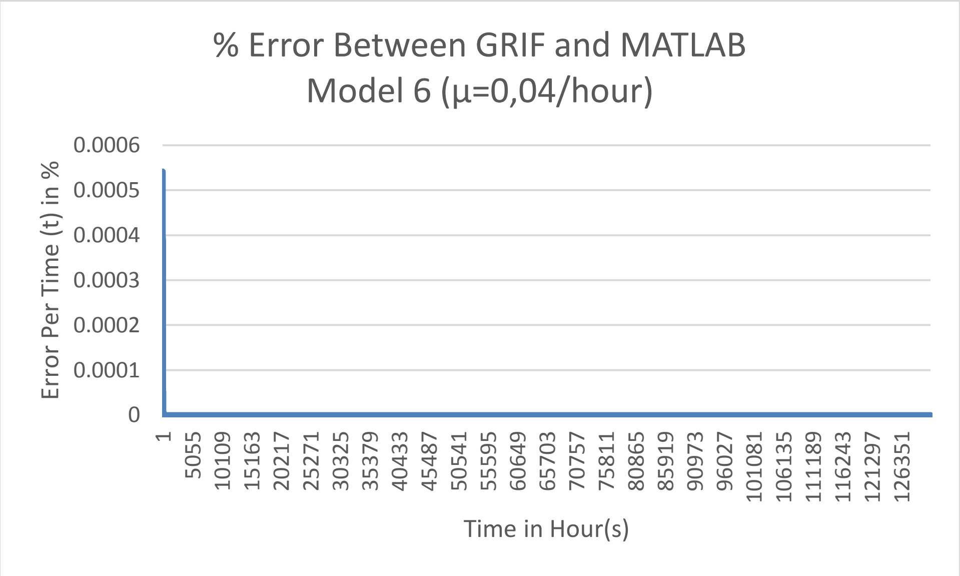


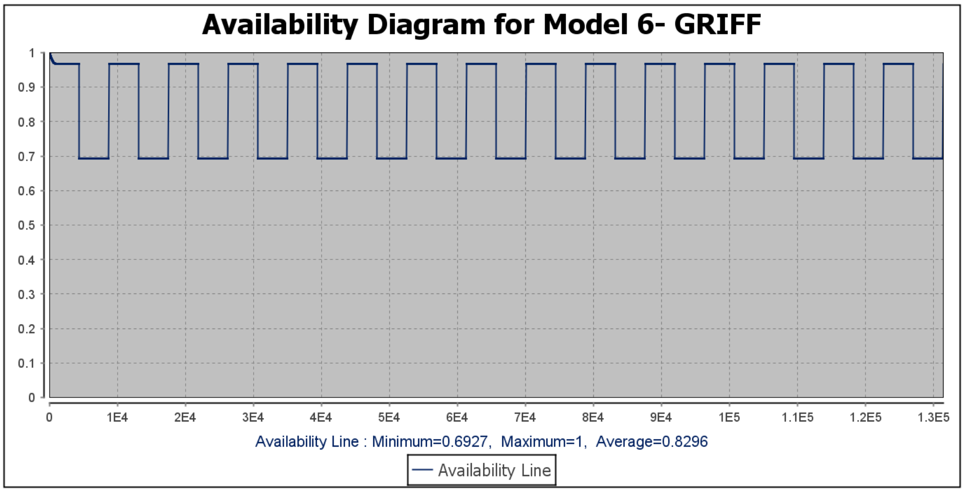


Model 6

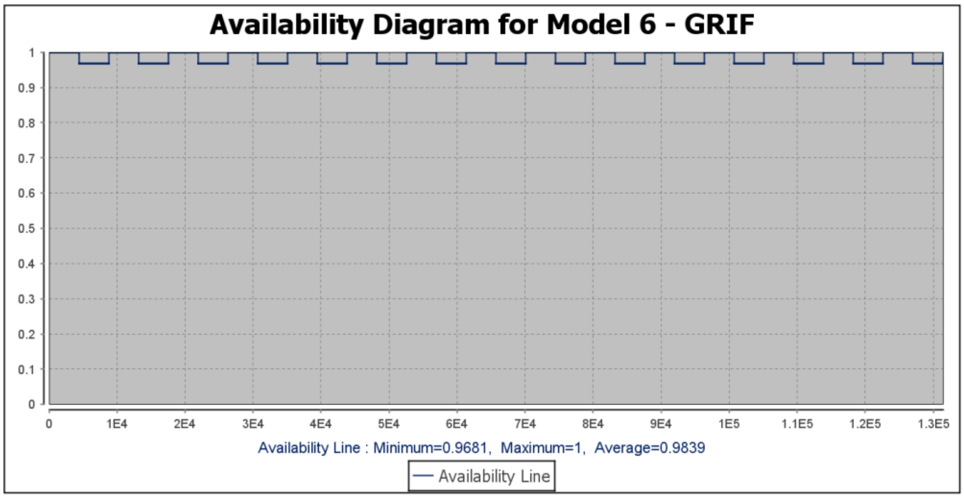
The average of error is 1.99989E-07% for μ = 0,0027/hour and 2.60589E-05% for μ = 0,04/hour







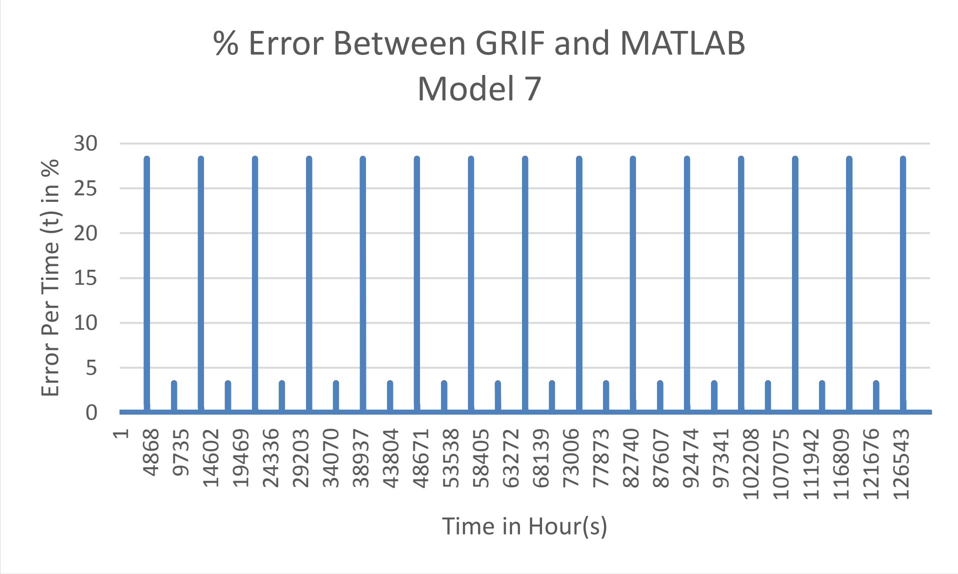
Model 6 with μ = 0,0027/hour

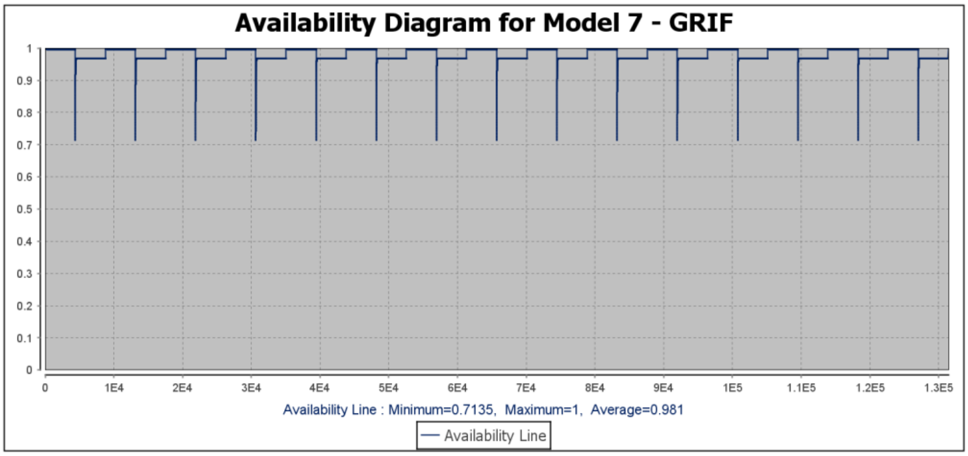


Model 6 with μ = 0,04/hour

Model 7

The average of error is 0.014277547%.





Bibliography

1. StatOil, *StatOil*. 2013.
2. Randall, R.B., *A New Method of Modeling Gear Faults.* Journal of Mechanical Design, 1982. **104**(2): p. 259-267.
3. Jelaska, D., *Introduction*, in *Gears and Gear Drives*. 2012, John Wiley & Sons, Ltd. p. 1-16.
4. Kermanpur, A., et al., *Failure analysis of Ti6Al4V gas turbine compressor blades.* Engineering Failure Analysis, 2008. **15**(8): p. 1052-1064.
5. Jianhui, L., et al. *Model-based prognostic techniques [maintenance applications]*. in *Proceedings AUTOTESTCON 2003. IEEE Systems Readiness Technology Conference.* 2003.
6. Kassner, M.E. and M.T. Pérez-Prado, *Five-power-law creep in single phase metals and alloys.* Progress in Materials Science, 2000. **45**(1): p. 1-102.
7. Barros, A.C.P., *Some notes about the Remaining Useful Lifetime*. 2016: NTNU. p. 2.
8. Rausand, M. and H. Arnljot, *System reliability theory: models, statistical methods, and applications*. Vol. 396. 2004: John Wiley & Sons.