Mechanical Process Control for Reducing Butter-Oil Defects in Industrial Production

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Abstract:

This research offers a numerical evaluation of the dependability and availability of a serial butter-oil production line from a mechanical engineering standpoint. The line consists of essential rotating and fluid-handling subsystems—raw-milk receiving pumps, cream separators, heat exchangers, mechanical agitators, homogenizers, gearboxes, and conveying components—whose mechanical integrity significantly influences throughput and quality. We describe the production train with continuous-time Markov chains (CTMCs) derived from a reliability block diagram (RBD) illustrating series dependencies and maintenance strategies. Component-level failure (λ) and repair (μ) rates, obtained from realistic duty cycles and mechanical failure modes (bearing wear, seal leakage, misalignment, lubrication starvation, cavitation, fouling, and thermo mechanical fatigue), are transmitted to system-level metrics through state-transition analysis. Numerical simulations provide mean time between failures (MTBF), mean time to repair (MTTR), and steady-state availability for the whole system and for mechanically critical subsystems (e.g., pump-valve trains and homogenization units). Sensitivity studies pinpoint availability constraints and prioritize mechanical parameters—bearing L10 life, seal MTBF, lubricant change interval, alignment tolerance, and cooling-water ΔT—based on their effect on throughput reduction. The findings indicate that modest enhancements in repair logistics for high-criticality assets (such as the installation of cartridge seals and quick-release couplings on feed pumps) may surpass significant MTBF reductions in low-criticality components. We further illustrate that the integration of mechanical condition monitoring (vibration and temperature trending) with SPC-based run charts and control limits stabilizes critical mechanical variables (overall vibration, RMS acceleration, and discharge pressure ripple), thereby diminishing special-cause variation and unplanned downtime. The study concludes with maintenance strategies designed for mechanical assets, including spares pooling for common failure categories, precision alignment, optimized lubrication practices, and threshold-based condition-directed overhauls, resulting in quantifiable improvements in line availability and energy efficiency while maintaining butter-oil quality standards.

Keywords: Reliability, Availability, Butter-oil Processing, Serial Process, Markov Analysis, Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR)

Introduction:

Despite the greatest efforts of academics and stakeholders, no system can be completely dependable. Therefore, two additional factors known as availability and maintainability have come into prominence due to the growing complexity of modern technology. In order to ensure ongoing and extended availability, maintenance is an essential preventative and corrective intervention. Maintainability is the likelihood that the system will function normally again within the allotted time frame following the completion of repairs in accordance with the stipulated condition. The idea of maintainability is linked to availability. The likelihood that the system will function within a specific time frame is referred to as availability. It refers to the percentage of time that the system is usable, excluding downtime (while undergoing maintenance).

If management wants their complex systems to be as reliable as possible, meeting worldwide standards and generating the predicted profit, they must detail the availability and cost of each component's reliability. More recently, a number of scholars have proposed availability allocation models as a means to minimize the system's total costs. The system's set availability, which is already attained after optimization according to another method, acts as a limitation. There are two main types of availability models: (a) those that aim to provide an accurate model of system availability, and (b) those that, in response to system needs, assign availability to specific components. The primary goal of this article is to save costs while achieving the minimal performance requirements of each component. This may be achieved by making sure that each component is designed to avoid failure or by allocating redundancy appropriately. Problems with reliability optimization have been the focus of a number of academic investigations. The impact of common cause shock failures and individual failures on the availability of a repairable system was highlighted by Verma and Chari [1], who also established related equations. When expanding distribution networks, Ramirez and Bernal [2] utilized Evolutionary Algorithm to optimize costs and ensure dependability. Using a Markov model and an exponential distribution, Upreti [3] suggested a stochastic study of a heating boiler system that is susceptible to preventative maintenance and repair.

In their research, Garg and Sharma [4] investigated the dependability, availability, and maintainability of the synthesis unit in the fertilizer plant. They also conducted an analysis of these factors. With the help of GWO, a variety of multi-objective and single-objective problems, both limited and unconstrained, have been effectively addressed, resulting in competitive outcomes. Using the GWO approach, Fouad et al. [5] discovered an extra number of nodal locations that were next to one another. The multi-layer perception neural networks were trained with GWO by Mosavi et al. [6], who used three different data sets to train them. These data sets included iris, lenses, and sonar. Gupta and Saxena [7] utilized GWO in order to discover the parameters that were necessary for the effective autonomous power dispatch in two locations that were linked. On the other hand, Jaya Bharati and colleagues [8] utilized crossover and mutation when working with GWO to answer the challenge of cheap power transmission. For the purpose of minimizing the fuel cost and avoiding the hazard zones in the (unmanned) ACV dilemma, Zhang et al. [9] utilized the GWO approach. Using binary and mutant GWO techniques, Manikandan et al. [10] performed gene selection on the micro array data with the intention of selecting genes. The non-convex economic load dispatch problem was addressed by Kamboj et al. [11], who presented the GWO algorithm. Mirjalili et al. [12] came up with the idea of Multi–Objective GWO, which involves incorporating an archive that defines the global optimum solution into the first GWO in order to ret ravel the Pareto Optimal solution. GA and fuzzy logic were presented by Kumar A [13] as a means of improving the dependability of industrial systems. Because of its very efficient findings, Kumar et al. [14] utilized GWO for the purpose of optimizing the dependability of complex systems. Specifically, they were able to optimize the cost and reliability of the life support system in a space capsule as well as a complicated bridge system. Additionally, Kumar et al. [15] suggested the use of GWO for the purpose of comparing and analyzing the availability and cost of engineering systems that are distributed in a series arrangement. In their subsequent work, Kumar et al. [16] advocated the utilization of GWO for the safety system of a nuclear power plant in order to maximize the cost-effectiveness of the residual heat removal system while maintaining its dependability. Negi et al. [17] provided an overview of the numerous forms and hybrids of GWO, as well as applications of various GWO applications. In their study, Uniyal et al. [18] provided a comprehensive review of the dependability applications of a few Nature-inspired optimization strategies. In order to tackle challenges involving the optimization of the dependability of complex systems, many types of GWO have been presented, and the results have been extremely competitive. WSNs are one example of this. The Modified Discrete GWO (MDGWO) algorithm was suggested by Li et al. [19] for the purpose of multi-level picture thresholding. This algorithm involves the use of the optimized function Kapur's entropy in conjunction with the discrete character of the threshold values. In their paper [20-22], Mirjalili and colleagues developed Multi-objective GWO (MOGWO), which is a method for tackling global engineering issues that makes use of Pareto-optimal solutions. The Chaotic GWO [23] and the Refraction Learning GWO [24] are two other examples of the diverse types. According to the there is no such thing as a free lunch theorem [25], there is no one meta-heuristic that can handle all of the difficult optimization issues. The technique of solution for a nonlinear system of equations that makes use of met heuristics was proposed by Pant et al. [26]. Additionally, Pant et al. [27] suggested a more sophisticated method of using the Particle Swarm optimization technique to the optimization of dependability. In addition to this, they [28] have suggested doing a review of the current state of the art on the development of the algorithm for flower pollination. The multi-objective particle swarm optimization (MOPSO) approach was also utilized by Pant et al. [29] in order to solve the reliability optimization challenge. Pant et al. [30] adapted PSO for nonlinear optimization. The decomposition approach was originally introduced by Li and Haimes [31] with the purpose of improving the dependability of big complex systems. Developed by Kennedy and Eberhart [32], PSO has been utilized to address a wide variety of engineering issues that are encountered in the real world, resulting in highly competitive outcomes. With further study, Coelho [33] addressed reliability-redundancy optimization utilizing an effective PSO technique for mixed integer programming. Using CSA, Kumar et al. [34] were able to overcome the difficulties of reliability optimization that were associated with complex systems. Baskan [35] suggested using CSA with L'evy Flights to optimize road network connection capacity additions. The CSA was proposed by Buaklee and Hongesombut [36] to optimize DG allocation in a smart distribution grid.

The ingredient commonly used in Nepalese cuisine, "butter-oil" is actually just melted butter that has been refined. It is one of the most essential components of traditional Nepalese cuisine, and eating it regularly helps maintain a healthy and fit physique. Aside from being a lubricant, it also gives the body heat and vitality. The most important byproduct of milk processing is butter-oil. Butter oil is produced by following a specific procedure that begins with milk as the basic ingredient. Quite a few facilities in India produce butter-oil. There are typically eight interconnected subsystems in a butter oil production facility. So, let's take a quick look at the several steps that go into making butter-oil.

1. Reception and Processing of Milk

Various contractors and milk collecting centers deliver milk to the plant dock using milk tankers pulled by a fleet of rented trucks. Unloading and grading are the main components of this task. Measurement, analysis, and evaluation of milk samples. Raw milk is kept in silos after being cooled to 4°C in milk chillers from the dump tank, which improves its storage quality. Afterwards, the raw milk is cooled and then put through the milk plate pasteurizer, an independent device that heats and cools the milk. After being heated to between 4 and 45 degrees Celsius, the milk is redirected to a cream separator, which strains out the cream. The skimmed milk is then returned to the milk pasteurizer, where it is heated to 80 degrees Celsius to ensure it is safe for human consumption. Finally, it is cooled to 4 degrees Celsius to further improve its storage quality.

2. Removing Fat from Milk

The milk that has been pasteurized at a temperature of 45 degrees Celsius is sent to the cream separator, where the fat is extracted from the milk in the form of cream that contains between 40 and 50 percent fat. The skimmed milk that is produced is then sent back to the milk pasteurizer.

3. The Process of Cold-Pressured Cream

To pasteurize cream, one must heat each individual particle to a temperature of at least 71°C. To prepare the pasteurized cream for subsequent processing into butter and butter-oil, it is held in a double-jacketed tank. To make churning feasible, cream is cooled and aged by reducing its temperature and kept for a few hours.

4. Production of Butter

The cream is transferred from the storage tank to the butter churner. The cream is processed in the machine to produce butter granules. Buttermilk is extracted individually and pumped back into the raw milk silos, while butter granules are processed further in the machine to produce a homogeneous mass of butter. The butter is extracted from the machine and sent to melting vats by butter carts.

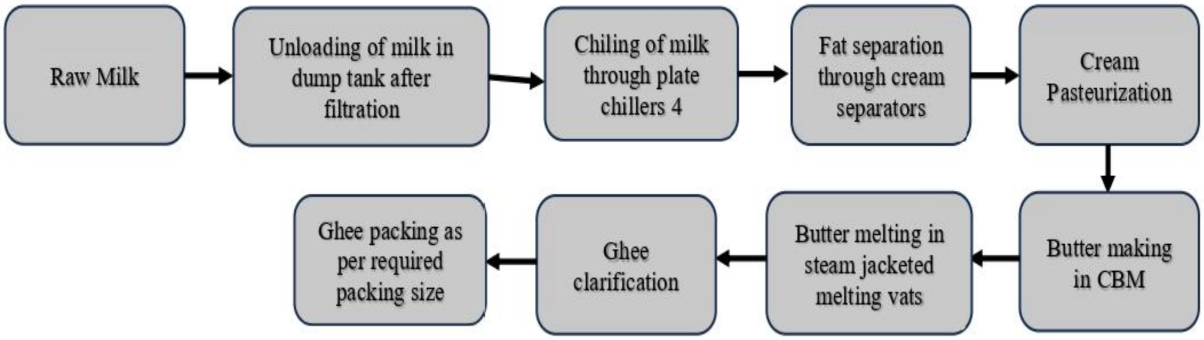
5. Producing Butter-Oil

After the butter has melted in the vats, it is transferred to the butter-oil boiler and gradually heated to 107° C to remove any water vapor. After that, it is left undisturbed for a few hours to finish melting. After being pumped out of the boiler, the butter-oil is sent to settling tanks to settle for a few hours. This process removes the tiny particles of residue from the butter-oil. Once clarified, the butter-oil is transferred to a storage tank and chilled to a temperature (between 28 and 30 degrees Celsius) that is ideal for filling.

6. Butter-oil Containers

The butter oil that is stored in the tank is tested by the team in charge of quality control for a variety of tests, and then it is packed into tins of varying sizes after the analysis.

An illustration of the flow chart that depicts the process of producing butter-oil may be seen in Figure 1.



Caption: figure 1: Flow diagram of butter-oil manufacturing plant

NOTATIONS AND THE SYSTEM

According to the information presented in this chapter, the production plant for butter oil is comprised of the following eight sub-systems.

1. **Sub-system 1 (Pumping):**

The most important component of the plant is the one that is responsible for unloading the milk that has been brought in from the numerous milk collection centers. A flawless switchover mechanism has been utilized in order to put two pumps in the plant, one of which is operational and the other of which is in standby mode. As a result, we have thought that this component of the system is completely reliable.

2. Sub-system 2 (Chiller):

A vital component of the plant, this is as well. We assume that the plant's backup chiller, which is always on standby, likewise never fails.

3. Sub-system S_1 (Separator):

Centrifugal force is the underlying mechanism that makes this plant component function. The milk is cooled in the chiller and then sent to the cream separator, where it becomes cream with 40-50% fat. The skimmed milk is then kept in milk silos to be made into milk powder. The motor, bearings, and high-speed gearbox are the three main parts that work together in sequence.

4. **Sub-system S_2 (Pasteurizer**):

This sub-system ensures that the cream from the separator is pasteurized. Pasteurization is the process of heating the cream to a temperature of at least 71°C for each individual particle. There is no holding period when it is heated to 80–82°C in practice. Its goals include the elimination of harmful microorganisms, the neutralization of unwanted taste compounds, the inactivation of enzymes, and the elimination of undesired pathogens. The tanning ingredients in the cream may also be extracted using this subsystem. For subsequent processing, the pasteurized cream is held in a double-jacketed cream storage tank. It has a motor and bearings connected in series and may function in a reduced condition.

5. Sub-system S_3 (Continuous Butter Making):

The CBM receives its cream supply from the cream storage tank and pumps it out. This equipment is used to get butter granules by churning the cream. The procedure ends with a homogenous mass of butter, which is achieved by further processing the butter granules in the machine after they have been pumped hack to raw milk silos. After the butter has been homogenized, it is transferred to the melting vats using butter carts. A gearbox, motor, and set of bearings form the CBM.

6. Sub-system S_4 (Melting Vats):

A storage tank with two jackets makes up this subsystem. Here, the butter is gradually heated to a temperature of around 107°C, allowing the water to evaporate. After that, the melted butter has to sit undisturbed for around 30 minutes. The components of this subsystem include motors, bearings, and monoblock pumps connected in series.

7. Sub-system S_5 (Butter-oil Clarifier):

After the butter-oil has melted in the vats, it is transferred to the settling tanks and left to settle for a few hours. The next step is to filter out any remaining little bits of butter-oil residue, and finally, the butter-oil is transferred to storage tanks. We may now store the butter-oil at a temperature between 28 and 30 degrees Celsius. In this subsystem, the motor and gearbox are connected in series.

8. Sub-system S_6 (Packaging):

This part of the system uses a pouch-filling machine to make the processed butter-oil packets. The machine knows how to fill, flow, and seal automatically. The pneumatic cylinder and printed circuit board are connected in series in this subsystem.
To keep things simple, we'll just look at the first two subsystems out of the total six.

Added Notes:

Alongside the designations for sub-systems, namely S_1, S_2, S_3, S_4, and S_5, we have employed the subsequent notations.
1.$\overline{S_2}$ Shows that sub-system S_2 is operating in a diminished condition.

2. λ_1, λ2, λ_3, λ_4, λ_5, λ_6, and λ_2 stands for the subsystems' respective constant failure rates

S_1, S3, S_4, S_5, S_6, $\overline{S_2}$ and S_2

3.μ_1, μ_2, μ_3, μ_4, μ_5 , and μ_6 indicate, respectively, the rates of repair that are constant for the subordinate system S_1,S_3, S_4, S_5, S_6, and S_2

4. $f_1(t)$, $f_2(t)$, … , $f_{13}(t)$ determined the probability that were associated with the systems at the moment t.

5.X_1,X_2, X_3, X_4, X_5, and X_6 represent the failed state of the sub-systems S_1,S_2, S_3,S_4, S_5, and S_6, respectively.

Presumptions:

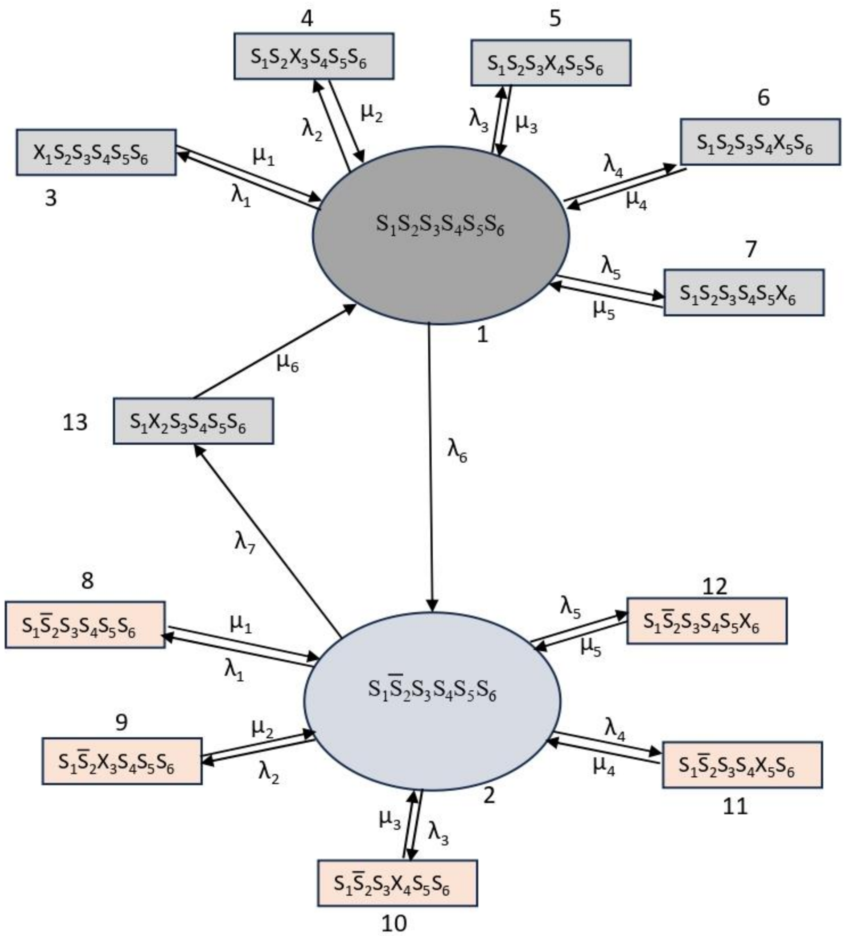
1. The rates of failure and repair are not dependent on one another, and the unit of measurement for both is per day.

II. It is not possible for any of the subsystems to experience failure at the same time.

III.Only through reduced state does the sub-system S_2 have a failure.

IV. In the same way that the new components work, the repaired ones do as well.

V. Standby systems' switchover devices are faultless.



Caption: figure 2: Butter oil production facility transition diagram

Mathematical Representation of the System:

Short-term state:

Based on probability, the following set of first-order differential equations and the system's transition map are linked.

$\frac{df_1(t)}{dt}+(\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_6)\,f_1(t)=\mu_1 f_3(t)+\mu_2 f_4(t)+\mu_3 f_5(t)+\mu_4 f_6(t)+\mu_5 f_7(t)+\mu_6 f_{13}(t)$ … (1)

$\frac{df_2(t)}{dt}+(\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_7)\,f_2(t)=\mu_1 f_8(t)+\mu_2 f_9(t)+\mu_3 f_{10}(t)+\mu_4 f_{11}(t)+\mu_5 f_{12}(t)+\lambda_6 f_1(t)$ … (2)

$\frac{df_3(t)}{dt}+\mu_1 f_3(t)=\lambda_1 f_1(t)$ … (3)

$\frac{df_4(t)}{dt}$ +μ_2 f_4(t)= λ_3 f_1(t) … (4)

$\frac{df_5(t)}{dt}$ +μ_3 f_5(t)= λ_3 f_1(t) … (5)

$\frac{df_6(t)}{dt}$ +μ_4 f_6(t)= λ_4 f_1(t) … (6)

$\frac{df_7(t)}{dt}$ +μ_5 f_7(t)= λ_5 f_1(t) … (7)

$\frac{df_8(t)}{dt}$ +μ_1 f_8(t)= λ_1 f_2(t) … (8)

$\frac{df_9(t)}{dt}$ +μ_2 f_9(t)= λ_2 f_2(t) … (9)

$\frac{df_{10}(t)}{dt}$ +μ_3 f_{10}(t)= λ_3 f_2(t) … (10)

$\frac{df_{11}(t)}{dt}$ +μ_4 f_{11}(t)= λ_4 f_2(t) … (11)

$\frac{df_{12}(t)}{dt}$ +μ_5 f_{12}(t)= λ_5 f_2(t) … (12)

$\frac{df_{13}(t)}{dt}$ +μ_6 f_{13}(t)= λ_7 f_2(t) … (13)

With the boundary condition

$f_m(0) = 1$ if m= 1

$f_m(0) = 0$ if $m \neq 1$

Equation (14) includes boundary conditions that have been solved using the Rk4 technique for the system of differential equations (1) to (13) with those conditions. For various subsystem failure rates and repair options, numerical companions have been run from time t=0 to t=360 days.
The system's dependability R(t) may be calculated by
R(t)= f_1(t)+f_2(t) … (15)

Permanent Condition:
Management is often concerned with the system's availability over the long term in sectors that include the processing of goods. It is necessary for us to have the probabilities of the system in its steady state in order to determine its availability over the long run. Obtaining the probability of the systems in their steady state may be accomplished by setting the following restrictions:
$\frac{d}{dt} \rightarrow 0$ as (t) $\rightarrow \infty$.

In this situation, equations (1) through (13) may be reduced to the equations that are presented below. Again, we made use of the symbols f_1, f_2, f_3,…, f_{13} as $t \rightarrow \infty$.
Then

$(\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_6)\ f_1= \mu_1 f_3 +\mu_2 f_4+\mu_3 f_5+\mu_4 f_6 +\mu_5 f_7+ \mu_6 f_{13}$ ... (16)

$(\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_7)\ f_2= \mu_1 f_8+\mu_2 f_9+\mu_3 f_{10}+\mu_4 f_{11} +\mu_5 f_{12}+ \lambda_6 f_1$ ... (17)

$\mu_1 f_3 = \lambda_1 f_1$ ... (18)

$\mu_2 f_4 = \lambda_2 f_1$ ... (19)

$\mu_3 f_5 = \lambda_3 f_1$ ... (20)

$\mu_4 f_6 = \lambda_4 f_1$ ... (21)

$\mu_5 f_7 = \lambda_5 f_1$ ... (22)

$\mu_1 f_8 = \lambda_1 f_2$ ... (23)

$\mu_2 f_9 = \lambda_2 f_2$ ... (24)

$\mu_3 f_{10} = \lambda_3 f_2$ ... (25)

$\mu_4 f_{11} = \lambda_4 f_2$ ... (26)

$\mu_4 f_{12} = \lambda_5 f_2$ ... (27)

$\mu_4 f_{13} = \lambda_7 f_2$ ... (28)

By recursively solving these equations, we obtain

$f_2= Gf_1$, where $G=\frac{\lambda_6}{\lambda_7}$ ... (29)

$f_3= \frac{\lambda_1}{\mu_1}f_1$ ... (30)

$f_4= \frac{\lambda_2}{\mu_2}f_1$ ... (31)

$f_5= \frac{\lambda_3}{\mu_3}f_1$ ... (32)

$f_6= \frac{\lambda_4}{\mu_4}f_1$ ... (33)

$f_7= \frac{\lambda_5}{\mu_5}f_1$ ... (34)

$f_8= \frac{\lambda_1}{\mu_1}Gf_1$ ... (35)

$f_9= \frac{\lambda_2}{\mu_2}Gf_1$ ... (36)

$f_{10}= \frac{\lambda_3}{\mu_3}Gf_1$ … (37)

$f_{11}= \frac{\lambda_4}{\mu_4}Gf_1$ … (38)

$f_{12}= \frac{\lambda_5}{\mu_5}Gf_1$ … (39)

$f_{13}= \frac{\lambda_6}{\mu_6}Gf_1$ … (40)

Presently, by use of the standardizing condition
$f_1+f_2+f_3+f_4+ … + f_{13}+= 1$ … (41),

We get

$f_1= [(1+\frac{\lambda_1}{\mu_1} + \frac{\lambda_2}{\mu_2} + \frac{\lambda_3}{\mu_3} + \frac{\lambda_4}{\mu_4} + \frac{\lambda_5}{\mu_5})(1+G)+ \frac{\lambda_6}{\mu_6}]$ … (42)

The long run availability of the system A (∞) can now be calculated by formula,

$A (\infty) = f_1+ f_2$

$= (1+G)f_1$ … (43)

A Study of Behavior

A STATE OF TRANSIENCE

The system's dependability, as delineated in equation (15), has been calculated for many combinations of repair and failure rates. It should be noted that these combinations are not comprehensive, since we have only examined the primary sub-systems in the numerical analysis. The system's dependability, determined by various combinations of failure and repair rates, is illustrated in Tables 1 through 6. The final row of the data presents the mean time before failure (MTBF) in days corresponding to the respective failure rates. The Mean Time between Failures (MTBF) has been calculated utilizing Simpson's one-third rule.

1. **Impact of separator failure rate on system dependability:**

The impact of the sub-system's failure rate on the overall system dependability is evaluated by adjusting its value to λ_1 = 0.006, 0.007, 0.008, 0.009, and 0.010. The failure and repair rates of further sub-systems are as follows: λ_2 = 0.0005, λ_3 = 0.00727, μ_1 = 0.41, μ_2 = 0.40, μ_3 = 0.67, μ_4 = 0.33, μ_5 = 0.67, and μ_6 = 6.00. The system's dependability is determined using these data, resulting in the system's reliability assessment. The values of α_1 have been examined during the span of days. The system's dependability diminishes by around 0.036% over time. Nonetheless, it diminishes by around 0.93% when the failure rate of the separator escalates from 0.0006 to 0.010, while MTBF declines by approximately 0.90%.

Table 1

Effect of Failure Rate of Separator on Reliability of the System

$\lambda_1 \rightarrow$ **Days ↓**	0.006	0.007	0.008	0.009	0.010
30	0.962089	0.959837	0.957596	0.955365	0.953144
60	0.961955	0.959704	0.957464	0.955233	0.953013
90	0.961872	0.959622	0.957381	0.955152	0.952932
120	0.961821	0.959571	0.957331	0.955101	0.952881
150	0.961790	0.959539	0.957299	0.955069	0.952850
180	0.961770	0.959519	0.957279	0.955049	0.952830
210	0.961758	0.959507	0.957267	0.955038	0.952818
240	0.961750	0.959500	0.957260	0.955030	0.952811
270	0.961745	0.959495	0.957255	0.955025	0.952806
300	0.961742	0.959492	0.957252	0.955022	0.952803
330	0.961741	0.959490	0.97250	0.955020	0.952801
360	0.961741	0.959489	0.957249	0.955019	0.952800
MTBF	**346.638**	**345.849**	**345.066**	**344.386**	**343.509**

2. Impact of the failure rate of Condition-Based Maintenance on system dependability:

As part of the investigation into the impact of the failure rate of sub-system C on the overall dependability of the system, the values of λ_2 are varied as follows: 0.005, 0.0052, 0.0054, 0.0056, and 0.0058. The calculated failure and repair rates for additional sub-systems are as follows: λ_1 equals 0.008, λ_3 equals 0.0027, λ_4 equals 0.0009, and λ_5 equals 0.0027, λ_6 equals 0.0055, and λ_7 equals 0.011. The values of μ_1 is 0.41, μ_2 is 0.4, μ_3 is 0.67, μ_4 is 0.33, μ_5 is 0.67, and μ_6 is 6.00. Table 5.1(b) displays the results of the calculation that was performed using these data to determine the system's level of dependability. This table illustrates how the failure rate of CBM affects the system's dependability for the purpose of discussion. Taking into account the number of days, the values of λ_2 have been taken into consideration. With an increase in time from 30 to 360 days, the system's reliability reduces by 0.036%. However, the system's reliability decreases by roughly 0.19% with an increase in the failure rate of CBM from 0.0052 to 0.0058, and the mean time between failures (MTBF) similarly decreases by approximately 0.19%.

Impact of CBM Failure Rate on System Reliability

Table 2

$\lambda_2 \rightarrow$	**0.0050**	**0.0052**	**0.0054**	**0.0056**	**0.0058**

DAYS↓					
30	0.958743	0.958284	0.957825	0.956366	0.956908
60	0.958610	0.958151	0.957692	0.957234	0.956777
90	0.958528	0.958069	0.957611	0.957152	0.956695
120	0.958477	0.958018	0.957560	0.957102	0.956643
150	0.958446	0.957986	0.957528	0.957070	0.956612
180	0.958426	0.957967	0.957508	0.957050	0.956592
210	0.958414	0.957955	0.957496	0.957038	0.956580
240	0.958406	0.957947	0.957489	0.957031	0.956573
270	0.958401	0.957943	0.957484	0.957026	0.956568
300	0.958399	0.957940	0.957481	0.957023	0.956565
330	0.958397	0.957938	0.957479	0.957021	0.956563
360	0.958396	0.957937	0.957478	0.957020	0.956562
MTBF	**345.468**	**345.306**	**345.147**	**344.985**	**344.826**

(iii) Dependability of the system as a function of melting vat failure rate

By changing its values to λ_3 = 0.0022, 0.0024, 0.0026, 0.0028, and 0.0030, the impact of sub-system D's failure rate on the system's dependability is investigated. The following values were used to calculate the failure and repair rates of the remaining subsystems: λ_1 = 0.008, λ_2 = 0.0055, λ_4 = 0.0009, λ_5 = 0.0027, λ_6 = 0.0055, λ_7 = 0.0111, μ_1 = 0.41, μ_2 = 0.40, μ_3 = 0.67, μ_4 = 0.33, μ_5 = 0.67, and μ_6 = 6.00. Table 3 displays the results of the reliability calculation performed on this data. The table below illustrates how the system's dependability is affected by the melting vat failure rate. We have taken the number of days into account while considering the λ_3 values. The table shows that the system's dependability drops by 0.0285% in the first quarter and stays the same in the remaining three months. As the melting vat failure rate increases from 0.0022 to 0.0030, the reliability and MTBF both fall by around 0.11%.

Table 3

Impact of Melting Vat Failure Rate on System Reliability

λ_3 → **DAYS ↓**	**0.0022**	**0.0024**	**0.0026**	**0.0028**	**0.0030**
30	0.958280	0.958006	0.957732	0.957459	0.957185
60	0.958148	0.957874	0.957600	0.957327	0.957053
90	0.958066	0.957792	0.957518	0.957245	0.956971
120	0.958015	0.957741	0.957467	0.957194	0.956920

15	0.957983	0.957707	0.957436	0.957162	0.956889
180	0.957964	0.957690	0.957416	0.957142	0.956869
210	0.957951	0.957678	0.957404	0.957131	0.956857
240	0.957944	0.957670	0.957396	0.957123	0.956850
270	0.957939	0.957665	0.957392	0.957118	0.956845
300	0.957936	0.957663	0.957389	0.957115	0.956842
330	0.957935	0.957661	0.957387	0.957113	0.956840
360	0.957933	0.957660	0.957386	0.957112	0.956839
MTBF	**345.306**	**345.210**	**345.314**	**344.018**	**344.922**

(iv) Dependability of the system as a function of separator repair rate

The impact of the sub-system separator's repair rate on system dependability is examined by adjusting its values to μ_1 = 0.30, 0.35, 0.40, 0.45, and 0.50. The failure and repair rates of the other subsystems are as follows: $\lambda_1 = 0.008$, $\lambda_2 = 0.0055$, $\lambda_3 = 0.0027$, $\lambda_4 = 0.0009$, $\lambda_5 = 0.0027$, $\lambda_6 = 0.0055$, $\lambda_7 = 0.0111$, $\mu_2 = 0.40$, $\mu_3 = 0.67$, $\mu_4 = 0.33$, $\mu_5 = 0.67$, and $\mu_6 = 6.00$. The system's dependability is determined using this data, with findings presented in Table 4. The table indicates that the system's dependability improves by 0.36% when the separator's repair rate (μ_1) is elevated from 0.3 to 0.35, with only minimal gains for μ_1 over 0.35. Moreover, dependability diminishes by around 0.036% as the duration extends from 30 to 360 days. MTBF rises by around 1.0% as the repair rate escalates from 0.30 to 0.50.

Table 4

System Reliability and the Separator Repair Rate

μ_1 → DAYS ↓	0.30	0.35	0.40	0.45	0.50
30	0.951082	0.954538	0.957149	0.959188	0.960827
60	0.950950	0.954407	0.957017	0.959056	0.960694
90	0.950870	0.954326	0.956935	0.958937	0.960611
120	0.950819	0.954275	0.956884	0.958922	0.960560
150	0.950788	0.954244	0.956852	0.958891	0.960528
180	0.950768	0.954224	0.956833	0.958871	0.960509
210	0.950756	0.954212	0.956820	0.958860	0.960496
240	0.950748	0.954204	0.956813	0.958852	0.960489
270	0.950744	0.954199	0.956808	0.958847	0.960484
300	0.950741	0.954197	0.956805	0.958844	0.960481

330	0.950739	0.954195	0.956803	0.958842	0.960479
360	0.950738	0.954194	0.956802	0.958841	0.960478
MTBF	**342.787**	**343.997**	**344.909**	**345.622**	**346.220**

(v) A system's dependability as a function of the CBM repair rate

By changing its values to μ_2 = 0.30, 0.35, 0.40, 0.45, and 0.50, the study examines the impact of the sub-system CBM repair rate on the system's dependability. The following values have been used for the failure and repair rates of various sub-systems: λ_1 = 0.008, λ_2 = 0.0055, λ_3 = 0.0027, λ_4 = 0.0009, λ_5= 0.0027, λ_6 = 0.0055, λ_7 = 0.0111, μ_1 = 0.41, μ_3 = 0.67, μ_4 = 0.33, μ_5 = 0.67, and μ_6 = 6.00. Table 5 displays the results of calculating the system's dependability using this data. The table shows that as the repair rate of CBM goes from 0.30 to 0.50, the system's dependability goes up about 0.66 percentage points. Concurrently, there is a 0.036 percentage point drop in dependability for every day that goes from 30 to 360. From a repair rate of 0.30 to 0.50, there is an increase of around 0.64% in MTBF.

Table 5

The Impact of CBM Repair Rate on System Reliability

μ_2 → DAYS ↓	0.30	0.35	0.40	0.45	0.50
30	0.953413	0.955798	0.957596	0.958998	0.959711
60	0.953281	0.955666	0.957464	0.958866	0.959578
90	0.953200	0.95585	0.957382	0.958784	0.959496
120	0.953149	0.955534	0.957331	0.958733	0.959445
150	0.953118	0.955503	0.957299	0.958701	0.959441
180	0.953098	0.955483	0.957279	0.958681	0.959393
210	0.953086	0.955471	0.957267	0.958669	0.959381
240	.953078	0.955463	0.957260	0.958661	0.959374
270	0.953074	0.955458	0.957255	0.958657	0.959369
300	0.953071	0.955456	0.957252	0.958654	0.959366
330	0.953069	0.955454	0.957250	0.958652	0.959364
360	0.953068	0.955453	0.957249	0.958651	0.959363
MTBF	343.603	344.437	345.066	345.556	345.807

(vi) Impact on system dependability of melting vat repair rate

As part of the investigation of the impact of the repair rate of sub-system melting vats on the dependability of the system, the following values of μ_3 are considered: 0.60, 0.65, 0.70, 0.75, and 0.80. It has been determined that the failure and repair rates of additional sub-systems are as follows: λ_1 = 0.008, λ_2 = 0.0055, λ_3 = 0.0027, λ_4= 0.0009, λ_5 = 0.0027, λ_6= 0.0055, λ_7 = 0.0111, μ_2 = 0.41, μ_3 = 0.40, μ_4 = 0.33, μ_5 = 0.67, and μ_6 = 6.00. The results of the calculation that determines the system's dependability are presented in Table 6, which may be found using these data. According to the data shown in this table, it is evident that the reliability and mean time between failures (MTBF) of the system experience a rise of roughly 0.1% when the repair rate of the separator (μ3) is increased from 0.60 to 0.80. The increase in time from thirty to three hundred and sixty days results in a drop in dependability of around 0.036 percent.

Table 6

Impact of Melting Vat Repair Rate on System Reliability

μ_3 → DAYS ↓	0.60	0.65	0.70	0.75	0.80
30	0.957165	0.957482	0.957554	0.957990	0.958196
60	0.957033	0.957350	0.957622	0.957858	0.958064
90	0.956951	0.957268	0.957540	0.957776	0.957982
120	0.956900	0.957217	0.957489	0.957725	0.957931
150	0.956868	0.957185	0.957457	0.957693	0.957899
180	0.956849	0.957166	0.957438	0.957673	0.957879
210	0.966837	0.957154	0.957426	0.957661	0.957867
240	0.956829	0.957146	0.957418	0.957654	0.957860
270	0.956824	0.957141	0.957413	0.957649	0.957855
300	0.956821	0.957138	0.957410	0.957646	0.957852
330	0.956820	0.957137	0.957408	0.957644	0.957850
360	0.956819	0.957135	0.957407	0.957643	0.957849
MTBF	**344.915**	**345.026**	**345.114**	**345.204**	**345.276**

PRESENT STATUS

The effect of change in failure and repair rates of some important sub-systems on the long run availability of the system is studied in this section.

(i) **The long-term availability impacted by separator and CBM failure rates**

In order to investigate the impact of failure rates on the long-term availability of the system, the values of the sub-systems S_1 and S_3 are varied. The values of λ_1 are as follows: 0.006, 0.007, 0.008, 0.009, and 0.010. The values of λ_2 are as follows: 0.0050, 0.0052, 0.0054, 0.0056, and 0.0058. The rates of failure and repair for other subsystems have been determined to be as follows: λ_3 = 0.0027, λ4 = 0.0009, λ_5 = 0.0027, λ_6 = 0.0055, λ_7 = 0.0111, μ_1 = 0.41, μ_2 = 0.40, μ_3 = 0.67, μ_4 = 0.33, μ_5 = 0.67, and μ_6 = 6.00. Utilizing this data, a calculation is performed to determine the system's availability over the long term, and the results are presented in Table 7. The data shown in this table demonstrates that an increase in the failure rate (λ_1) of the separator would have a negative impact of roughly 0.93% on the long-term availability of the system. This is in contrast to the failure rate of the CBM (λ_2), which would only have a negative impact of 0.19% on the availability.

Table 7

The consequences of the failure rates of the separator and the CBM on the system's availability over the long run

λ_1→	0.006	0.007	0.008	0.009	0.010

$\lambda_2\downarrow$					
0.0050	0.962963	0.960675	0.958429	0.956194	0.953969
0.0052	0.962499	0.960189	0.957981	0.955729	0.953514
0.0054	0.962036	0.959268	0.957522	0.955272	0.953060
0.0056	0.961574	0.959268	0.957064	0.954816	0.952606
0.0058	0.961112	0.958808	0.956606	0.954361	0.952153

(ii) Impact of failure rates of separators and melting vats on long-term availability

We have employed fixed failure and repair rates for all sub-systems, except the separator and melting vats, as follows: λ_2 = 0.0055, λ_4 = 0.0009, λ_5 = 0.0027, λ_6= 0.0055, λ_7 = 0.0111, and μ_1 = 0.41, μ_2 = 0.4, μ_3 = 0.67, μ_4 = 0.33, μ_5= 0.67, and μ_6 = 6.00. The failure rates for the separator and melting vats are as follows: λ_1 = 0.006, 0.007, 0.008, 0.009, 0.01 and λ_3 = 0.0024, 0.0026, 0.0028, 0.0030. The long-term availability of the system is estimated and displayed in Table 8. This table indicates that an increase in the failure rate of separators (λ_1) impacts the long-term availability of the system by roughly 0.93%, while an increase in the failure rate of melting vats (λ_3) affects it by around 0.12%.

Table 8

Impact of Separator and Melting Vat Failure Rates on System Long-Term Availability

$\lambda_1\rightarrow$ $\lambda_3\downarrow$	0.006	0.007	0.008	0.009	.010
0.0022	0.962527	0.960216	0.958009	0.955767	0.953542
0.0024	0.962249	0.959940	0.957733	0.955491	0.953269
0.0026	0.961971	0.959633	0.957458	0.955218	0.952996
0.0028	0.961694	0.959387	0.957183	0.954944	0.952724
0.0030	0.961417	0.958111	0.956909	0.954670	0.952452

(iii) Impact of separator failure and repair rates on long-term availability

We have also computed the system's long-term availability after adjusting for separator failure and repairs. The outcomes of using the following data are displayed in Table 9. The following five levels of separator failure and repair rates have been taken into consideration: λ_1 = 1006 0.007, 0.008, 0.009, 0.010 and μ_1 = 0.3, 0.35, 0.40, 0.45, and 0.50. λ_2 = 0.0055 μ_3 = 0.0027 λ_4 = 0.0009, λ_5 = 0.0027 λ_6 = 0.0055 λ_7 = 0.0111, and μ_2 = 0.4 μ_3 = 0.67 μ_4 = 0.33 μ_5 = 0.67, μ_6= 6.0 are the rates for the other sub-systems. Table 9 shows that a higher separator failure rate (λ_1) reduces the system's long-term availability, whereas a higher repair rate enhances it. When the separator's failure rate rises from 0.006 to 0.010, availability falls by 1.2% to 0.7%, and when the separator's repair rate rises from 0.30 to 0.50, availability rises by 0.7% to 1.2%.

Table 9

The Long-Term Availability of the System: The Impact of Separator Failure and Repair Rates

$\lambda_1\rightarrow$ $\mu_1\downarrow$	0.006	0.007	0.008	0.009	0.010
30	0.956881	0.953539	0.950816	0.947812	0.944827

35	0.959504	0.956881	0.954272	0.951677	0.949097
40	0.961481	0.959176	0.956881	0.954598	0.952325
45	0.963024	0.960969	0.958920	0.957432	0.954850
50	0.964262	0.962407	0.960558	0.958716	0.956881

iv) Impact of melting vats and CBM repair rates on long-term availability

In this area, we have adjusted the CBM and melting vat repair rates as follows: μ_2= 0.3, 0.35, 0.40, 0.45, 0.50 and μ_3 = 0.6, 0.65, 0.70, 0.75, 0.80. The following values have been used for the failure and repair rates of the sub-systems: λ_1= 0.008, λ_2 = 0.005, λ_3= 0.0027, λ_4 = 0.0009, λ_5= 0.0027, λ_6= 0.0057 λ_7, = 0.0111, μ_1= 0.4, μ_4= 0.33, μ_5= 0.67, and μ_6 = 6.00. Table 10 displays the results of the calculation of the system's long-term availability using these parameters. The long-term system availability is enhanced by both increasing the repair rate of CBM (μ_2) and the repair rate of melting vats, as shown in the table. However, while both rates have an impact on long-term system availability, the former has a greater impact of about 0.7% and the latter of only 0.1%.

Table 10

In the long run, the availability of the system is affected by the repair rates of both the CBM and the melting vats

$\mu_2\rightarrow$ $\mu_3\downarrow$	0.30	0.35	0.40	0.45	0.50
0.60	0.952715	0.955081	0.956817	0.958284	0.959387
0.65	0.953032	0.953032	0.957138	0.958605	0.959709
0.70	0.953351	0.955720	0.957458	0.988927	0.960032
0.75	0.953533	0.955902	0.955902	0.959111	0.960216
0.80	0.953714	0.956085	0.956085	0.959295	0.960400

Conclusion:

The separator, which is part of sub-system S_1, has the greatest impact on the overall system's dependability and long-term availability, according to an analysis of Tables 1 to 6 and 7–10. Graphs 1 and 2 further show how the repair and failure rates of sub-system S_1 affect the system's dependability. There are other subsystems that work almost as well [37-41]. Consequently, the butter-oil production plant's management should pay close attention to this sub-system if they want it to operate better overall.

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