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Modelling, Sensitivity Analysis and Optimization of System Parameters of Edible Oil Refinery

Navpreet Kaur[1*], Karanvir Singh[1] and Vanita Garg[2]

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[1]Department of Mathematics, Maharaja Ranjit Singh Punjab Technical University Bathinda, India;
[2]Department of Mathematics, Galgotias University, Noida, India

E-mail/Orcid Id:

NK, navpreet008@gmail.com, https://orcid.org/0000-0002-1967-5839; *KS,* karanvirs786@gmail.com;
VG, vanitagarg16@gmail.com, https://orcid.org/ 0000-0002-7599-5351

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Abstract: This research paper models the system parameters of Edible Oil Refinery applying the Regenerative Point Graphical Technique (RPGT) and illustrations aimed at sensitivity analysis of the parameters, further, an attempt has been made to optimize the parameters with the use of machine learning. The edible oil refinery's components are arranged into four separate subsystems. Subsystem A, which is in charge of cleaning, has parallel subcomponents that enable it to function at a reduced capacity in case one or more subunits fail. As a result, the system's overall performance is diminished. The subsystems Shelling B, Crushing D, and Expeller E are connected in series to Subsystem A in case of Subsystem A failure, which would result in a total system failure. Given their interdependence, it is implied that the collapse of any one of these subsystems will result in an overall failure of the organization. A single repairman who is presented 24x7 carries all types of repairs and replacements upon failure of subsystem(s). The failure and repair time distributions are distinct and constant for each unit. A state transition diagram of the system is drawn using the Markov process. Illustrations taking subsystem's failure/repair rates fixed and increasing the repair/failure rates of units, system behavior for different repair and failure rates is discussed graphically and in tabular form, followed by analysis. Comparison of the performance of system parameters is carried out using Machine Learning Linear Classifier and Logistic Regression. From illustrations for sensitivity analysis, it is concluded that for an efficient and cost-effective system, the repair rates of subsystems should be the minimum possible, and the best quality subsystem should be employed with minimum failure rates. From the comparative analysis of Machine Learning models, it is concluded that the linear classifier gives better results than the logistic regression for system parameters.

Introduction

Edible oil refineries play an important role in the oil industry. There exist several parameters that control the performance of the system of the refinery plants. The edible oil refinery units are divided into four subsystems, with subsystem 'A- Cleaning ' comprising parallel subcomponents, in the event of component failure within subsystem 'A', the subsystem can continue operating at reduced capacity, which results in the system functioning in a reduced state. However, if unit A fails, the entire system experiences a total shutdown. The subsystems B-Shelling, D- Crushing, and E- Expeller are arranged in series for the effective working of the whole system so that if any one of these subsystems fails, the entire system will cease to function. Fuzzy logic can be used to declare that a particular subsystem or whole of the subsystem has failed and there is a single server that is 24x7 available. Shakuntla et al. (2011) conducted a behavior analysis of polytube using a supplemental adaptive technique. They discussed relative analysis of the subsystems that failed

*Corresponding Author: navpreet008@gmail.com

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simultaneously. Similarly, Kumar et al. (2018) analyzed the performance of a bread plant. In their study, Kumar et al. (2019) employed the Regenerative Point Graphical Technique (RPGT) methodology to conduct a sensitivity analysis on a cold standby framework consisting of two identical units; the system considered server failure and prioritized preventative maintenance. The analysis is carried out into two parts, with one part focusing on the operational unit and the other part on the unit in cold standby mode. In a paper mill washing unit, Kumar et al. (2019) investigated mathematical formulation and behavior study. The particle Swarm Optimization algorithm was used by Kumari et al. (2021) to research limited situations. Using a heuristic approach, Rajbala et al. (2022) investigated the redundancy allocation problem in the cylinder manufacturing plant. Following the notations, abbreviations & assumptions system elements, and process parameters are modeled. Behavior shown by system parameters is discussed aimed at different repair and disappointment rates graphically and in tabular form. Overall, the availability analysis is an important tool for identifying the factors that impact the production and profitability of a plant (Zhu, 2013; Shamshirband et al., 2013; Taphade et al., 2021). By understanding these factors, plant managers can make informed decisions about investments in equipment, raw materials, and labor that can improve production efficiency and profitability (Shalev and Pasternak, 1989; Mosavi et al., 2019; Sharangi, 2013).

Machine learning algorithms further assist in identifying patterns and inclinations in large datasets that cannot be immediately apparent to human analysts (Sarkar et al., 2019; Sarkar et al., 2020; Sarkar et al., 2018; Sarkar et al., 2018a). This can assist in improving the accuracy of the availability analysis and enable plant managers to make more informed decisions about how to improve production efficiency and profitability. For example, machine learning algorithms can be trained on historical data from the plant to predict future demand for inputs for optimum output (Sarkar et al., 2017; Pramanik et al., 2021; Sarkar et al., 2021). This can help managers adjust production levels and raw material orders to match expected demand, reducing waste and improving profitability. Similarly, machine learning can be used to identify patterns in raw material availability and price fluctuations, enabling managers to optimize purchasing decisions and reduce costs. Another potential application of machine learning in availability analysis is predictive maintenance. By analyzing statistics from machine sensors and additional foundations, machine learning algorithms can identify patterns that might indicate an impending breakdown or maintenance issue.

This study's main goals center on using a multifaceted approach to improve our understanding of edible oil refinery systems. To provide a thorough picture of the dynamics of the system, the study first attempts to simulate the complex system parameters using the Regenerative Point Graphical Technique (RPGT). Sensitivity analysis is the second method used in the research to examine the effects of fixed subsystem failure/repair rates while gradually raising the associated repair/disappointment rates. This methodology illuminates the system's robustness in many scenarios, providing valuable perspectives for well-designed systems. Finally, using machine learning approaches to improve decision-making processes, the study explores the optimization of system parameters. Finding the ideal values for subsystem failure/repair rates is the main reason for doing this study.

The primary motivation for this research is to find the best values for subsystem failure/repair rates, which will help optimize system parameters. In addressing this requirement, the research has practical implications for industry experts looking to improve the efficiency and dependability of their operations, in addition to making a theoretical contribution to the understanding of edible oil refinery systems.

Assumptions and Notations

1) There is a single repairman who is always present.
2) Failures/repairs of units are distinct and statistically independent.
3) Repair of subsystems is perfect.
4) Failure and repair distributions are statistically independent.

$R_i(t)$: Reliability of system at period t, assumed that organization is in the un-failed regenerative state.

$A_i(t)/B_i(t)/V_i(t)$: Availability /busy period of server/ expected number of server's visits for time 't', specified that the organization entered the reformative state 'i' at t = 0.'

MTSF: Mean time to system Failure (T_0)

AOS: Availability of system (A_0)

BPOS: Busy period of the system (B_0)

EFNIR: Expected Fractional Number of Inspection by Repairman (V_0)

$\left(i \xrightarrow{s_r} j\right)$: *r*-th directed simple path since *i*-state to j-state; r takes optimistic integral values for diverse paths since *i*-state to j-state.

$\left(\xi \xrightarrow{sff} i\right)$: A directed simple disappointment-free path since base state ξ to i-state.

v_{ij}: path probability in moving from state i to state j,

'‘’': denotes derivative.

S_r: r-th simple path,

$s_r(sff)$: simple failure-free path,

$pr\left(0 \xrightarrow{s_r(sff)} x\right)$:
$probability\ in\ transiting\ from\ initial\ state\ to\ state\ x,$

$\mu_i = \int_0^{\infty} R_i(t)dt$: mean sojourn time in state i

$q_{i,j}(t)$/ p_{ij}: transition/steady probability in moving from state i to state j

* : Denotes Laplace transform

○ : Working State,

⬭ : Ellipse denoted reduced capacity working.

□ : Failed State

A/a: Full capacity functioning / unsuccessful state, similarly for other units B, D, E.

w_i/ λ_i $(0 \le i \le 5)$: Denote repair failure rates of units.

(i, j, k): 3-D cycle through states i, j, k.

Methodology

The formulae for four system parameters using RPGT are as below

MTSF:

$$T_0 = \left[\sum_{x,s_r}\left\{\frac{\left\{pr\left(0\xrightarrow{s_r(sff)}x\right)\right\}.\mu_x}{\prod_{m_1\neq 0}\{1-V_{\overline{m_1,m_1}}\}}\right\}\right] \div \left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(0\xrightarrow{s_r(sff)}0\right)\right\}}{\prod_{m_2\neq 0}\{1-V_{\overline{m_2,m_2}}\}}\right\}\right]$$

AOS:

$$A_0 = \left[\sum_{y,s_r}\left\{\frac{\left\{pr\left(0\xrightarrow{s_r}y\right)\right\}f_y.\mu_y}{\prod_{m_1\neq 0}\{1-V_{\overline{m_1,m_1}}\}}\right\}\right] \div \left[\sum_{x,s_r}\left\{\frac{\left\{pr\left(0\xrightarrow{s_r}x\right)\right\}.\mu_x^1}{\prod_{m_2\neq 0}\{1-V_{\overline{m_2,m_2}}\}}\right\}\right]$$

BPOS:

$$B_0 = \left[\sum_{j,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r}j\right)\right\}.\eta_j}{\prod_{k_1\neq \xi}\{1-V_{\overline{k_1,k_1}}\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r}i\right)\right\}.\mu_i^1}{\prod_{k_2\neq \xi}\{1-V_{\overline{k_2,k_2}}\}}\right\}\right]$$

EFNIR:

$$V_0 = \left[\sum_{j,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r}j\right)\right\}}{\prod_{k_1\neq \xi}\{1-V_{\overline{k_1,k_1}}\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r}i\right)\right\}.\mu_i^1}{\prod_{k_2\neq \xi}\{1-V_{\overline{k_2,k_2}}\}}\right\}\right]$$

Where,

i: a reformative un-failed state to which the organization can transit previously entering any failed state while arriving at the initial state- ‘0’ at period t= 0.

k_1 : a reformative state beside the path $\left(0 \xrightarrow{s_r(sff)} x\right)$, at which a $k_1 - \overline{cycle}$ is formed through reformative un-failed states.

k_2: a regenerative state beside the path at which a is shaped through reformative un-failed states.

Base state ξ: It is a state in which primary cycles are maximum and secondary cycles are minimum.

Transition Diagram:

Following the upstairs assumptions and notations, a state transition diagram using the Markov Process is drawn in Figure 1 below.

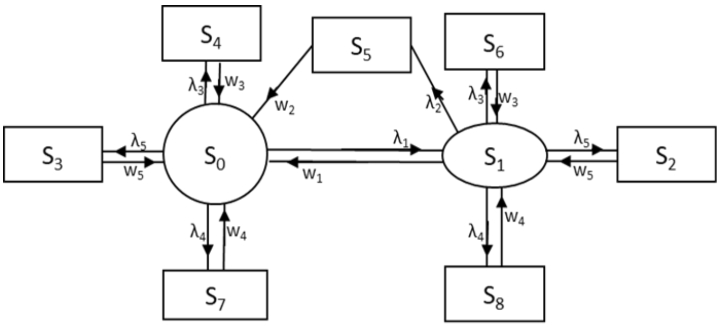

Figure 1. State Transition Diagram of System

S_0 = ABDE, S_1 = $\bar{A}$BDE, S_2 = $\bar{A}$BDe, S_3 = ABDe, S_4 = AbDE, S_5 = aBDE, S_6 = $\bar{A}$bDE,

S_7 = ABdE, S_8 = $\bar{A}$BdE.

Transition Probabilities p_{ij} and Mean Sojourn Times μ_i:

Using RPGT, transition probabilities are derived in Table 1.

Table 1. Transition Probabilities Using RPGT

$q_{i,j}(t)$	$p_{ij} = q^*_{i,j}(t)$
$q_{0,1} = \lambda_1 e^{-(\lambda_1+\lambda_3+\lambda_5+\lambda_4)t}$ $q_{0,3} = \lambda_5 e^{-(\lambda_1+\lambda_3+\lambda_5+\lambda_4)t}$ $q_{0,4} = \lambda_3 e^{-(\lambda_1+\lambda_3+\lambda_5+\lambda_4)t}$ $q_{0,7} = \lambda_4 e^{-(\lambda_1+\lambda_3+\lambda_5+\lambda_4)t}$	$p_{0,1} = \lambda_1/\{\lambda_4+\lambda_3+\lambda_5+\lambda_1\}$ $p_{0,3} = \lambda_5/\{\lambda_4+\lambda_3+\lambda_5+\lambda_1\}$ $p_{0,4} = \lambda_3/(\lambda_4+\lambda_3+\lambda_5+\lambda_1)$ $p_{0,7} = \lambda_4/(\lambda_4+\lambda_3+\lambda_5+\lambda_1)$
$q_{1,0} = w_1 e^{-(w_1+\lambda_2+\lambda_3+\lambda_5+\lambda_4)t}$ $q_{1,5} = \lambda_2 e^{-(w_1+\lambda_2+\lambda_3+\lambda_5+\lambda_4)t}$ $q_{1,6} = \lambda_3 e^{-(w_1+\lambda_2+\lambda_3+\lambda_5+\lambda_4)t}$ $q_{1,2} = \lambda_5 e^{-(w_1+\lambda_2+\lambda_3+\lambda_5+\lambda_4)t}$ $q_{1,8} = \lambda_4 e^{-(w_1+\lambda_2+\lambda_3+\lambda_5+\lambda_4)t}$	$p_{1,0} = w_1/\{w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3\}$ $p_{1,5} = \lambda_2/\{w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3\}$ $p_{1,6} = \lambda_3/\{w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3\}$ $p_{1,2} = \lambda_5/\{w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_4\}$ $p_{1,8} = \lambda_4/\{w_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5\}$
$q_{2,1} = w_5 e^{-w_5 t}$	$p_{2,1} = 1$
$q_{3+i,0} = w_5 e^{-w_5 t}$	$p_{3+i,0} = 1, 0 \le i \le 5$

Mean Sojourn Times μ:

Using RPGT Mean Sojoun Times μ_i for various states is derived below in table 2.

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Table 2. Mean Sojourn Times Using RPGT

$R_i(t)$	$\mu_i=R_i^*(0)$
$R_0^{(t)}= e^{-(\lambda_1+\lambda_3+\lambda_5+\lambda_4)t}$	$\mu_0 = 1/(\lambda_4+\lambda_3+\lambda_5+\lambda_1)$
$R_1^{(t)}= e^{-(\lambda_5+\lambda_3+\lambda_2+\lambda_4+w_1)t}$	$\mu_1 = 1/(w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3)$
$R_2^{(t)}=R_3^{(t)}= e^{-w_5 t}$	$\mu_2 = \mu_3 = 1/w_5$
$R_4^{(t)}= R_6^{(t)} = e^{-w_3 t}$	$\mu_4 = \mu_6 =1/w_3$
$R_5^{(t)}= e^{-w_2 t}$	$\mu_5 = 1/w_2$
$R_8^{(t)}= R_7^{(t)} = e^{-w_4 t}$	$\mu_8 = \mu_7 = 1/w_4$

Path Probabilities $V_{i,j}$:

The path probabilities since the initial state '0' to further states are,

$V_{0,0} = 1$

$V_{0,1} = \lambda_1(w_1+\lambda_5+\lambda_3+\lambda_2)\ (w_1+\lambda_4+\lambda_2+\lambda_3)\ (w_1+\lambda_5+\lambda_2+\lambda_4)/(\lambda_1+\lambda_4+\lambda_5+\lambda_3)\ (w_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5)^3$

$V_{0,2} = \lambda_1\lambda_5(w_1+\lambda_5+\lambda_3+\lambda_2)\ (w_1+\lambda_2+\lambda_4+\lambda_3)\ (w_1+\lambda_5+\lambda_4+\lambda_2)/(\lambda_1+\lambda_4+\lambda_3+\lambda_5)\ (w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3)^4$

$V_{0,3}$ = …….., so on.

Evaluation of System Parameters

The system parameters using RPGT with initial and base state as '0' are evaluated under

MTSF (T0): The un-failed regenerative states to which the organization moves before failure since the initial state '0' is given by,

$\text{MTSF}\ (T_0) = (V_{0,0}\mu_0+V_{0,1}\mu_1)/1-(1, 0, 1)$

AOS (A0): The states where the system is working in reduced or full capacity working are S_0 S_1 and regenerative states are S_0 to S_8 taking base state 'ξ' = '0' availability of the system is

$A_0 = [1/(\lambda_1+\lambda_4+\lambda_3+\lambda_5) + \lambda_1(w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3)/(\lambda_1+\lambda_3+\lambda_5+\lambda_4)\ (w_1+\lambda_5+\lambda_3+\lambda_2)\ (w_1+\lambda_4+\lambda_3+\lambda_2)\ (w_1+\lambda_2+\lambda_4+\lambda_5)]/1/(\lambda_1+\lambda_3+\lambda_4+\lambda_5) +\{1+(\lambda_5/w_5) +(\lambda_3/w_3) +(\lambda_4/w_4)\} +\{k+(\lambda_4/w_4) +(\lambda_5/w_5) +(\lambda_2/w_2) +(\lambda_3/w_3)$

BPOS (B0): The states where the BPOS are S_1 to S_8, with base and initial state ξ = '0', is given as

$B_0= 1-V_{0,0}\mu_0/1/(\lambda_1+\lambda_3+\lambda_5+\lambda_4) +\{1+(\lambda_5/w_5) +(\lambda_3/w_3) +(\lambda_4/w_4)\} +\{\lambda_1(w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3) /(\lambda_1+\lambda_5+\lambda_4+\lambda_3)\ (w_1+\lambda_5+\lambda_3+\lambda_2)\ (w_1+\lambda_4+\lambda_3+\lambda_2)\ (w_1+\lambda_5+\lambda_4+\lambda_2) + (\lambda_4/w_4) + (\lambda_5/w_5)+(\lambda_2/w_2) +(\lambda_3/w_3)$

EFNIR (V0): Reformative states where server visits afresh for repair taking base state 'ξ' = '0', is

$V_0 = \lambda_1(w_1+\lambda_2+\lambda_5+\lambda_4+\lambda_3)/\ (\lambda_1+\lambda_5+\lambda_4+\lambda_3)\ (w_1+\lambda_2+\lambda_5+\lambda_3)\ (w_1+\lambda_2+\lambda_4+\lambda_3)\ (w_1+\lambda_5+\lambda_4+\lambda_2)\ (w_1+2\lambda_2+2\lambda_4+2\lambda_3+\lambda_5) + [(\lambda_5+\lambda_3+\lambda_4)/(\lambda_1+\lambda_5+\lambda_4+\lambda_3)]$

Sensitivity Analysis

In the context of the edible oil refinery, sensitivity analysis can be used to evaluate the impact of changes in input variables on the system parameters. Sensitivity analysis is carried out by passing parameter values to system parameters manually for two illustrations described below and, sensitivity analysis is carried out using a machine learning technique to evaluate the robustness of a model's performance to changes in its input variables or parameters i.e., values of disappointment/repair rates.

Dataset:

Table 3. Table of Systems Parameters of the refinery

W (w1, w2, --------, wn)	$\lambda(\lambda 1, \lambda 2, \dots\dots, \lambda n)$	S (s1, s2, - ------, sn)	p
(0-20, 21-100)	(0-30, 31-100)	(0-100)	(0-80)

To perform a sensitivity analysis of a dataset related to the edible oil refinery using machine learning in Table 3, the following steps are followed:

1. Preprocess and clean the dataset: Before performing any analysis, it's important to ensure that the dataset is cleaned, preprocessed, and formatted correctly. This may involve removing misplaced values, converting categorical variables into arithmetical ones, and scaling or regularizing the statistics.
2. Split the data into exercise and difficult sets: To appraise the recital of the model, it's important to split the dataset into exercise and difficult sets. The training set resolve is cast to train the classical, while the testing set resolve is used to gauge its recital.
3. Train a machine learning model: one could choose to train a regression model to predict the output variable i.e., system parameters, based on the input variables.
4. Perform sensitivity analysis: Once the model has been trained, one can perform sensitivity analysis to determine the impact of changes in input variables on the output variable. This can be done by varying the input variables within a certain range and observing the resulting changes in the output variable. One can use tools such as partial dependence plots or sensitivity indices to quantify the impact of changes in each input variable on the output variable.
5. Evaluate the presentation of the model: Finally, one should appraise the performance of the model by associating the foretold values with the definite values in the testing set. One could use metrics such as mean-shaped error or R-squared to assess the accuracy of the model's predictions.

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Overall, sensitivity analysis helps to identify which input variables are most important for predicting the output variables i.e., system parameters in the edible oil refinery. This information can be used to optimize processing parameters, improve the disappointment/repair rates of subsystems, and ultimately increase the efficiency and profitability of the industry.

Sensitivity analysis depicts the increasing and decreasing trend of system parameters through the rise in repair rates increasing and fixing the failure rates of all units, and vice-versa. It is analyzed in the following illustrations.

Illustration 1: Taking failure rates of all units fixed at 0.10 and varying w_i $(1 \leq i \leq 5)$ for each unit one by one respectively as 0.80, 0.85, 0.90, 0.95, 1.

Values of various system parameters are derived in the following tables.

MTSF (T_0):

Table 4. MTSF values for different w

w_i	w_1	w_2	w_3	w_4	w_5
0.8	2.9	2.9	2.9	2.9	2.9
0.85	29	2.9	2.9	2.9	2.9
0.9	2.9	2.9	2.9	2.9	2.9
0.95	2.9	2.9	2.9	2.9	2.9
1	2.9	2.9	2.9	2.9	2.9

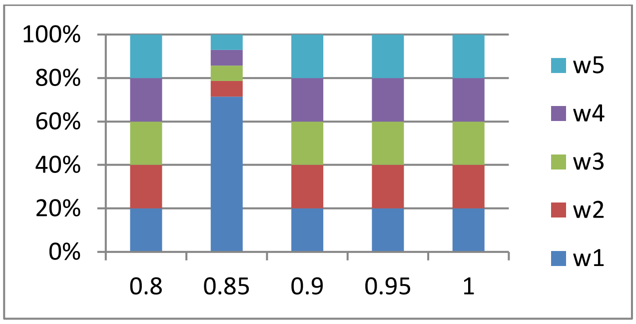

Figure 2. MTSF

According to Table 4 and Figure 2, it is observed that the value of MTSF is constant, which implies that MTSF is independent of the repair of units.

AOS (A_0):

Table 5. AOS values for different w

w_i	w_1	w_2	w_3	w_4	w_5
0.8	0.656	0.643	0.623	0.611	0.603
0.85	0.659	0.656	0.641	0.629	0.617
0.9	0.673	0.664	0.656	0.645	0.632
0.95	0.676	0.669	0.678	0.656	0.647
1	0.678	0.681	**0.694**	0.681	0.656

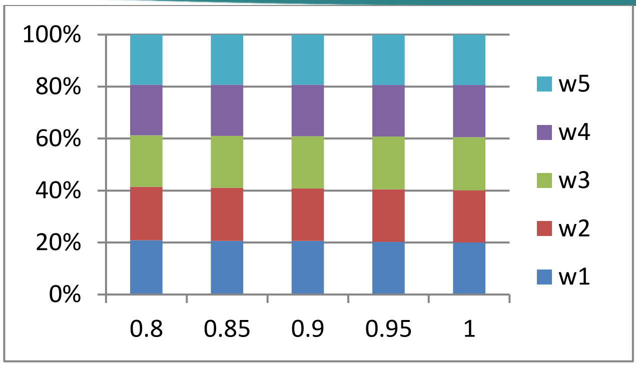

Figure 3. AOS

From Table 5 and Figure 3, while moving down the columns, it is concluded that an increase in repair rates of subsystems increases availability but does not significantly rise. However, the repair rate of unit "D" should be kept at its highest level for maximum availability, as highlighted in the table.

BPOS (B_0):

Table 6. BPOS values for different w

w_i	w_1	w_2	w_3	w_4	w_5
0.8	0.323	0.328	0.345	0.368	0.397
0.85	0.317	0.323	0.332	0.352	0.3375
0.9	0.313	0.318	0.323	0.341	0.354
0.95	0.306	0.311	0.315	0.323	0.337
1	**0.301**	0.308	0.304	0.311	0.323

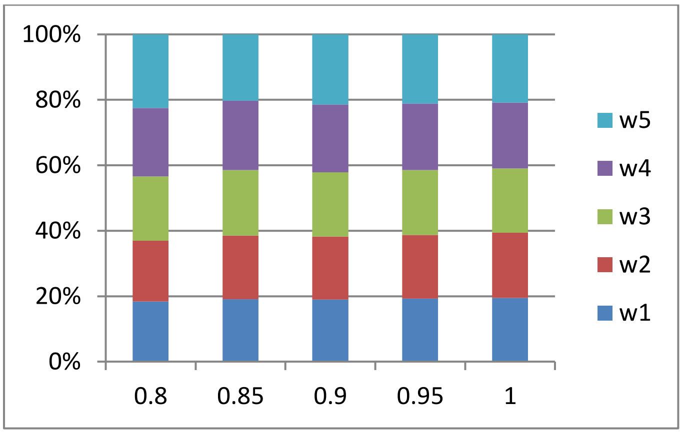

Figure 4. BPOS

It is realized from Table 6 and Figure 4 that the value of BPOS minimum when the repair rate of unit 'E' was at its highest level relative to other units. As a result, the repairman should be effective in fixing unit 'A' to minimize the BPOS. The minimum value of BPOS is **0.301** as highlighted in Table 6.

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EFNIR (V_0):

Table 7. EFNIR values for different w

w_i	w_1	w_2	w_3	w_4	w_5
0.8	0.232	0.227	0.212	0.203	**0.196**
0.85	0.236	0.232	0.224	0.210	0.202
0.9	0.239	0.236	0.232	0.218	0.211
0.95	0.242	0.240	0.238	0.232	0.219
1	0.245	0.247	0.243	0.238	0.232

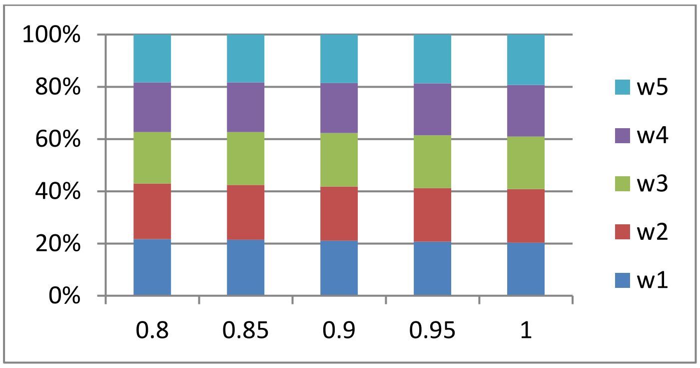

Figure 5. EFNIR

As per Fig. 5 and Table 7, for the cost-effective system, the number of calls for the server should be kept to a minimum, whereas it increases while observing in segments from top to bottom. It is a minimum of **0.196,** as highlighted in the table.

Illustration 2: Taking repair rates of all subsystems fixed as, $w_i = 0.80$ ($1 \leq i \leq 5$) and increasing failure rates λ_i, one by one respectively as 0.10, 0.15, 0.20, 0.25, 0.30.

MTSF (T0):

Table 8. MTSF values for different λ

λ_i	λ_1	λ_2	λ_3	λ_4	λ_5
0.10	2.41	249	2.54	2.69	**2.91**
0.15	2.37	2.41	2.48	2.57	2.78
0.20	2.33	2.37	2.41	2.48	2.64
0.25	2.27	2.23	2.36	2.41	2.49
0.30	2.22	2.18	2.27	2.34	2.41

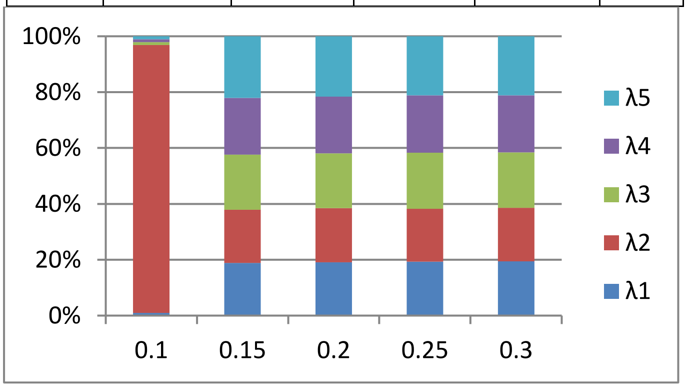

Figure 6. MTSF

Table 8 and Figure 6 demonstrate that as the value of T_0 decreases in moving from top to bottom in all columns, which corresponds to the practical trend, and is maximum as highlighted in the table at **2.91,** which should be tried to be kept largest for the efficient and cost-effective working of the system**.**

AOS (A0):

Table 9. AOS values for different λ

λ_i	λ_1	λ_2	λ_3	λ_4	λ_5
0.10	0.523	0.534	0.546	0.553	**0.572**
0.15	0.509	0.523	0.538	0.546	0.560
0.20	0.502	0.512	0.523	0.537	0.551
0.25	0.498	0.504	0.513	0.523	0.543
0.30	0.492	0.495	0.504	0.515	0.523

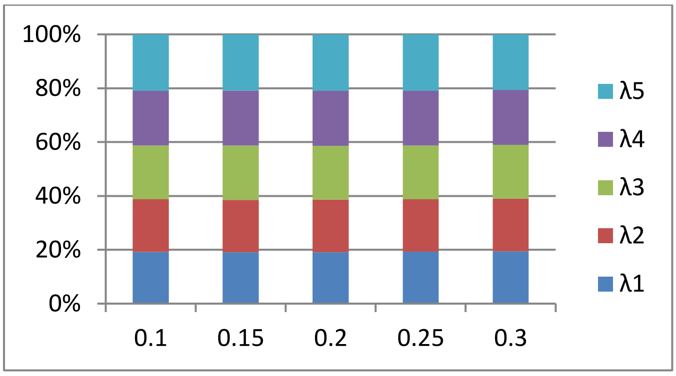

Figure 7. AOS

According to Table 9 and Fig. 7, as seen from columns from top to bottom availability decreases with the rise in disappointment rates of subsystems, which is a practical trend and is maximum as **0.572** which is highlighted in the table.

BPOS (B_0):

Table 10. BPOS values for different λ

λ_i	λ_1	λ_2	λ_3	λ_4	λ_5
0.10	0.520	0.512	0.505	0.485	**0.474**
0.15	0.534	0.520	0.513	0.498	0.485
0.20	0.545	0.533	0.520	0.507	0.499
0.25	0.558	0.547	0.528	0.520	0.514
0.30	0.568	0.558	0.537	0.534	0.520

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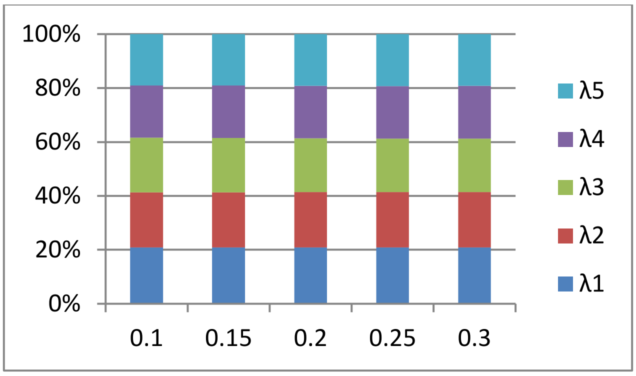

Figure 8. BPOS

From Figure 8 and Table 10, it is seen that the value of B_0 increases in going from top to bottom as the failure rates of subsystems increase, hence for an efficient and cost-effective system disappointment rate of subsystems would be maintained to the lowest possible level, which is practical too, its optimum is **0.474** as highlighted in the table.

EFNIR (V_0)

Table 11. EFNIR values for different λ

λ_i	λ_1	λ_2	λ_3	λ_4	λ_5
0.10	0.38367	0.38262	0.35236	0.33979	**0.32763**
0.15	0.38471	0.38367	0.37081	0.35515	0.34386
0.20	0.38560	0.38464	0.38367	0.36963	0.35693
0.25	0.38664	0.38556	0.39666	0.38367	0.37031
0.30	0.38702	0.38646	0.40947	0.39555	0.38367

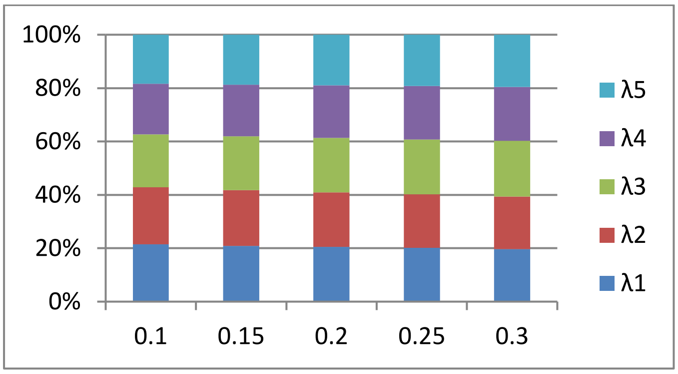

Figure 9. EFNIR

From Table 11 and Figure 9, for efficient and cost-effective system value of $\mathbf{V_0}$ should be minimum, which is **0.32763** as highlighted in the table. Also value of $\mathbf{V_0}$ increases with the rise in disappointment rates of subsystems, so it is recommended that failure rates of subsystems should be kept at a bare minimum

Performance Measure using Machine Learning:

Here system parameters are evaluated using Linear SVC Classifier (LC) and Logistic Regression (LR**)**

Table 12. Performances of machine learning models

Model	MTSF T_0	Expected proportional Number of Visits by the repair man V_0	Busy Period B_0	Availability A_0
Linear SVC Classifier (LC)	**0.9523**	0.9703	**0.9512**	**0.9823**
Logistic Regression (LR**)**	0.9402	**0.9502**	0.9623	0.9745

The results of the sensitivity analysis of a dataset related to the edible oil refinery provide valuable insights into the impact of changes in input variables on the output parameters. From the upstairs table, it is realized that the best values of T_0, B_0, and A_0 are provided by the Linear SVC Classifier and that the value of V_0 is given by Logistic Regression (LR**)**. As optimum values of T_0, B_0, and A_0 values are preferred over the value of $V_{0,}$ hence, Linear SVC Classifier (LC) provides the better values of input parameters from the data set.

A system operation is best if MTSF's availability is large, whereas proportional server visits and BPOS are small, so, according to Table 12 comparative analysis of models in Linear Classifier gives better results than Logistic Regression.

Future Scope

The future researchers can expand their research in this domain in the following ways:

1) The study can be extended to analyze the similarly situated industries.
2) Future researchers can calculate the profit of the system for a given period.
3) The study can be carried out by different failure and repair distributions observed by subsystems.

Limitations

The study is limited to a finite number of subsystems in an industry.

Recommendations

This can help to advance the efficacy, and reputation, and optimize processing parameters and profitability of the industry.

Conclusion

In the framework of an edible oil refinery, this study explores system parameter modeling, sensitivity analysis, and optimization. Through the use of the Regenerative Point Graphical Technique (RPGT), the research offers a thorough comprehension of the dynamics of the system. The edible oil refinery's division into discrete subsystems, each with its own special traits and interdependencies, emphasizes how important effective repair techniques and superior subsystems are to preserving system performance as a whole. The state transition diagram's use of a Markov process improves comprehension of the system's dependability and possible weaknesses. Comparative investigation using machine learning models—Logistic Regression and Linear Classifier, in particular—shows that the linear classifier is better at predicting and improving system parameters. This discovery emphasizes the significance of choosing suitable models for precise forecasts in the context of edible oil refinery operations in addition to adding to the analytical toolset for system optimization. To put it briefly, the study's findings offer practical advice to decision-makers and practitioners in the sector, helping them to put efficient system optimization techniques into practice. Through highlighting the significance of reducing repair rates and optimizing subsystem quality, the study supports the overarching objective of augmenting the effectiveness, prestige, and financial gain of the edible oil refinery sector.

Conflict of interest

There is no conflict of authors.

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