Reliability and Availability Analysis of Non-Markovian Single Unit Redundant System with Server Failure

Sanju Kumari[1], Sangeeta Malik[1] and Jai Bhagwan[2]
[1]*Department of Mathematics, Baba Mastnath University Asthal Bohar, Rohtak, Haryana, India*
[2]*Department of Mathematics, Govt P. G. Nehru College, Jhajjar, Haryana, India*

Keywords: Non-Markovian, Availability, MTSF.

Abstract: In this paper reliability and availability modeling of a single unit having identical subunits in parallel with cold standby redundant unit non- Markovian system having server which may also fail using Regenerative Point Graphical Technique (RPGT) is developed aimed at deriving system parameters of the system followed by analysis. A system can involve of several units and specific units obligate great importance in the proper functioning of a system. Repairing of failed unit(s), is carried out, when it is completely failed by the server (S) and is available in the system thereafter, who is to replace the failed units and responsible for the optimum operation/functioning and maintenance of the system, which may also fail and is repaired by a specialist on call is discussed and repair of unit A is imperfect and that of cold standby unit B is perfect, upon failure of server or its non-availability a specialist is called for the operation and maintenance of system. Priority order in repair is S>B>A. Various path probabilities, mean sojourn time and system behavior is discussed by drawing tables for increasing failure/repair rates and graphs.

1 INTRODUCTION

Non-Markovian Process: Any process that depends on all the past states is a non-Markovian process, which implies that the memory of the previously visited sites changes the distribution.

Here, for the reliability and availability modelling of a single unit system A by a cold standby unit B is considered, in which unit A have identical subunits in parallel, hence if one/more of its subunit(s) flop, then the system workings in reduced capacity and if the number of subunits failure is superior than a predefined number, then the system is in the failed state, then the standby redundant unit B is replaced with failed unit A, further upon failure of the standby unit B, causes the whole arrangement to be in failed state. A single server who is called in only when the unit A is in failed state, and is available in the system thereafter, who is to replace the failed units and responsible for the proper operation/functioning and maintenance of the system, which may also fail and is repaired by a specialist on call is discussed. Repair of failed unit A is imperfect. So, here the duration during which the system stays in initial state S0, depicts reliability of the system and availability is evaluated from the subsequent states in which system works in reduced states. Priority order in repair is S>B>A. Taking failure/repair rates of units' exponential, independent differently distributed and enchanting into deliberation various transition likelihoods, a state transition diagram of the organization is industrialized to find different levels of primary, secondary and tertiary circuits. Problem is attempted using RPGT to model system parameters. Various path probabilities mean sojourn time and system behavior is discussed by drawing tables for increasing failure/repair rates and graphs. (Devi and Garg 2022) discussed the three algorithms specifically HA, COGA and HGAPSO are applied to solve RAP. Present paper carriages a comprehensive literature review to classify, evaluate and intercept the standing studies related to the RAP (Devi et al. 2023) behavior of a bread plant was examined by (Kumar et al. 2018). To do a sensitivity analysis on a cold standby framework made up of two identical units with server failure and prioritized for preventative maintenance, (Kumar et al. 2019) used RPGT, two halves make up the paper, one of which is in use and the other of which is in cold standby mode. (Kumar et al. 2019) investigated mathematical formulation and behavior study of a paper mill washing unit, PSO was used by (Kumari et al. 2021) to research limited

Kumari, S., Malik, S. and Bhagwan, J.
Reliability and Availability Analysis of Non-Markovian Single Unit Redundant System with Server Failure.
DOI: 10.5220/0012609900003739

In *Proceedings of the 1st International Conference on Artificial Intelligence for Internet of Things: Accelerating Innovation in Industry and Consumer Electronics (AI4IoT 2023)*, pages 571-577
ISBN: 978-989-758-661-3

situations. Using a heuristic approach, (Rajbala et al. 2022) investigated the redundancy allocation problem in the cylinder manufacturing plant.

Model Description. Initially, system is in full capacity working state S0[A(B)S], from which if the unit A fails directly with transition rate α, then failed unit A is replaced with standby unit B with the help of server S, then the system enters the reduced state S2[aBS] from which unit A is repaired imperfectly with transition rate β2, then the system enters the state S1[$\bar{A}$(B)S] as the repair of unit A is imperfect and if one/more subcomponents of unit A fail in state S0[ABS] with transition rate α1, i.e., there is partial failure in unit A, then the system enters the state S1[$\bar{A}$(B)S], while in state S1[$\bar{A}$BS] if server fails whose transition rate is α3 then the system enters the failed state S3[$\bar{A}$Bs] from which server is repaired on priority at transition rate β3 and the system again reaches the state S1, if in state S1 the reduced unit $\bar{A}$ further fails to complete failure mode 'a' with transition rate α2, then the unit B is switched in with the help of the server and system enters the state S2[aBS], if in state S2, if the unit B fails with transition rate α4, then the organization enters the failed state S4[abS], upon its restoration by the server it re-joins the state S2, from which state if the server S fails with transition rate α3, then the system enters the failed state S5[aBs] as failed switch is unable to keep the system in operation, from which the server is given priority in repair with rate β3, so after repair the system enters the state S2[aBS].

2 ASSUMPTIONS AND NOTATIONS

1. There is one repairman whose availability is 24/7 after joining the system and specialist server is called on need basis.
2. The distributions of disappointment and repair times are constant, different and statistically independent.
3. Nothing can flop when the organization is in failed state.

α: Direct continuous failure rate of main unit A to α

α1: Failure rate of unit A to reduced state $\bar{A}$.

α2/ β2: Failure/repair rate of unit A since reduced/failed state

α3/ β3: Failure/repair rate of server S

α4/ β4: Failure/repair rate of standby unit B.

A/$\bar{A}$/a: Unit in complete capacity operational / reduced / failed state. B/(B)/b: Unit B is good online /cold standby /failed mode.

S/s: server in good/failed state

3 TRANSITION DIAGRAM DESCRIPTION

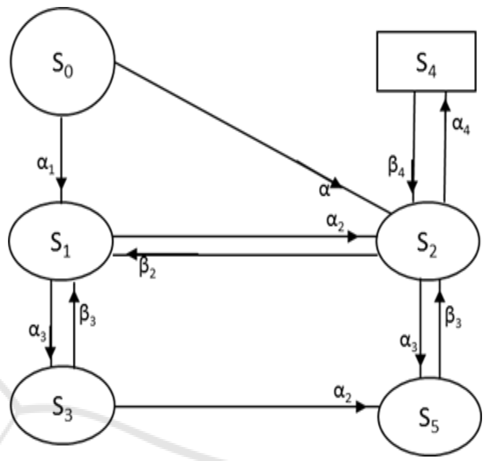

Figure 1: Transition Diagram.

Where various states are as under,

S_0 = A(B)S; S_1 = $\bar{A}$(B)S; S_2 = aBS; S_3 = $\bar{A}$(B)s; S_4 = abS; S_5 = a(B)s

3.1 Probability Density Function ($q_{i,j}^{(t)}$)

$q_{0,1}(t) = \alpha 1 e-(\alpha+\alpha 1)t$; $q_{0,2}(t) = \alpha e-(\alpha+\alpha 1)t$; $q_{1,2}(t) = \alpha 2 e-(\alpha 2+\alpha 3)t$; $q_{1,3}(t) = \alpha 3 e-(\alpha 2+\alpha 3)t$; $q_{2,4}(t) = \alpha 4 e-(\beta_2+\alpha 3+\alpha 4)t$; $q_{3,1}(t) = \beta 3 e-(\beta 3+\alpha 2)t$; $q_{3,5}(t) = \alpha 2 e-(\beta 3+\alpha 2)t$

$q_{4,2}(t) = \beta 4 e^{-\beta 4 t}$; $q_{5,2}(t) = \beta 3 e^{-\beta 3 t}$

$P_{ij} = q^*_{i,j}{}^{(t)}$

$p_{0,1}= \alpha_1/(\alpha+\alpha_1)$; $p_{0,2}= \alpha/(\alpha+\alpha_1)$; $p_{1,2}= \alpha_2/(\alpha_2+\alpha_3)$

$p_{1,3}= \alpha_3/(\alpha_2+\alpha_3)$; $p_{2,1}= \beta_2/(\beta_2+\alpha_3+\alpha_4)$; $p_{2,4}= \alpha_4/(\beta_2+\alpha_3+\alpha_4)$; $p_{2,5}= \alpha_3/(\beta_2+\alpha_3+\alpha_4)$; $p_{3,1}= \beta_2/(\beta_3+\alpha_2)$; $p_{3,5}= \alpha_2/(\beta_3+\alpha_2)$; $p_{4,2}= 1$; $p_{5,2}= 1$

3.2 Probability Density Functions $R_i(t)$ and Mean Sojourn times $\mu_i=R_i^*(0)$

$R_0(t)= e-(\alpha+\alpha 1)t$; $R_1(t)= e-(\alpha 2+\alpha 3)t$

$R_2(t)= e^{-(\beta_2+\alpha_3+\alpha_4)t}$; $R_3(t)= e^{-(\beta_3+\alpha_2)t}$
$R_4(t)= e^{-\beta_4 t}$; $R_5(t)= e^{-\beta_3 t}$

Value of the Parameter μ_i giving Mean Sojourn Times

$\mu_0 = 1/(\alpha+\alpha_1)$; $\mu_1 = 1/(\alpha_2+\alpha_3)$; $\mu_2 = 1/(\beta_2+\alpha_3+\alpha_4)$; $\mu_3 = 1/(\beta_3+\alpha_2)$ $\mu_4 = (1/\beta_4)$; $\mu_5 = (1/\beta_3)$

3.3 Evaluation of Parameters

Applying RPGT, path probabilities of reachable states from initial state to different vertices are as under

$V_{2,0} = 0$; $V_{2,1} = [\beta_2/(\beta_2+\alpha_3+\alpha_4)/\{1-\alpha_3/(\alpha_2+\alpha_3)\ \beta_2/(\beta_3+\alpha_2)\}]$; $V_{2,2} = 1$ (verified); $V_{2,3} = [\beta_2/(\beta_2+\alpha_3+\alpha_4\ \alpha_3/(\alpha_2+\alpha_3))/\{1-\alpha_3/(\alpha_2+\alpha_3)\ \beta_2/(\beta_3+\alpha_2)\}]$; $V_{2,4} = \alpha_4/(\beta_2+\alpha_3+\alpha_4)$; $V_{2,5} = \alpha_3/(\beta_2+\alpha_3+\alpha_4)$

3.3.1 MTSF (T_0)

States to which organization can transit (from initial state 0), before transiting/staying to any abortive state are j = 0, 1, 5 2, 3, attractive initial state as ‘ξ’ = ‘2’. Spread on RPGT, MTSF remains given as

$T_0=$

$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[\sum_{i,sr}^{\square}\square\left\{\frac{\{pr(\xi^{\,sr(sff)\rightarrow}\ i)\}\mu i}{\Pi_{m1\neq\xi}\left\{1-V_{\underline{m1m_1}}\right\}}\right\}\right]\div$$
$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[1-\sum_{sr}^{\square}\square\left\{\frac{\{pr(\xi^{\,sr(sff)\rightarrow}\ \xi)\}}{\Pi_{m_{2\neq\xi}}\left\{1-V_{\underline{m2m_2}}\right\}}\right\}\right] \quad (1)$$

3.3.2 Availability of the System

States at where organization is accessible are j = 0, 1, 2, 3, 5 and attractive base state as ‘ξ’ = ‘2’ system accessibility is specified by

$A_0=$

$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[\sum_{j,sr}^{\square}\square\left\{\frac{\{pr(\xi^{sr\rightarrow}j)\}fj,\mu j}{\Pi_{m_{1\neq\xi}}\left\{1-V_{\underline{m1m_1}}\right\}}\right\}\right]\div$$
$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[\sum_{i,s_r}^{\square}\square\left\{\frac{\{pr(\xi^{\,sr\rightarrow}\ i)\}\mu_i^1}{\Pi_{m2\neq\xi}\left\{1-V_{\underline{m2m_2}}\right\}}\right\}\right] \quad (2)$$
$$=\left[\sum_j^{\square}\square\, V_{\xi,j}, f_j, \mu_j\right]\div\left[\sum_i^{\square}\square\, V_{\xi,i}, f_j, \mu_i^1\right]$$

3.3.3 Busy Period of the Server

The recreating states where the server is busy while liability repairs are ‘j’ = 1 to 5 and the re-forming states remain ‘i’ = 0 to 2. Attractive ‘ξ’ = 2, the total fraction of period aimed at which the attendant remains busy is

$B_0=$

$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[\sum_{j,sr}^{\square}\square\left\{\frac{\{pr(\xi^{sr\rightarrow}j)\},nj}{\Pi_{m_{1\neq\xi}}\left\{1-V_{\underline{m1m_1}}\right\}}\right\}\right]\div$$
$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[\sum_{i,s_r}^{\square}\square\left\{\frac{\{pr(\xi^{\,sr\rightarrow}\ i)\}\mu_i^1}{\Pi_{m2\neq\xi}\left\{1-V_{\underline{m2m_2}}\right\}}\right\}\right] \quad (3)$$
$$=\left[\sum_j^{\square}\square\, V_{\xi,j}, n_j\right]\div\left[\sum_i^{\square}\square\, V_{\xi,i}, \mu_i^1\right]$$

3.3.4 Expected Number of Examinations by the Repair Man (V_0)

The re-forming states where the waitperson visits a fresh aimed at repair of organization stand ‘j’ = 1,2 and re-forming states stand ‘i’ = 1 to 11 aimed at ξ = 2,

$V_0=$

$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[\sum_{j,sr}^{\square}\square\left\{\frac{\{pr(\xi^{sr\rightarrow}j)\}}{\Pi_{k_{1\neq\xi}}\left\{1-V_{k1k_1}\right\}}\right\}\right]\div$$
$$\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}i\right)\right\}.\mu_i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1,m_1}}\right\}}\right\}\right]\div\left[1-\sum_{s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r(sff)}\xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2,m_2}}\right\}}\right\}\right]$$
$$\left[\sum_{i,s_r}^{\square}\square\left\{\frac{\{pr(\xi^{\,sr\rightarrow}\ i)\}\mu_i^1}{\Pi_{k2\neq\xi}\left\{1-V_{\underline{k2k_2}}\right\}}\right\}\right] \quad (4)$$
$$=\left[\sum_j^{\square}\square\, V_{\xi,j}\right]\div\left[\sum_i^{\square}\square\, V_{\xi,i}, \mu_i^1\right]$$
$$\left[\sum_{j,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r}j\right)\right\}.n_j}{\prod_{m_1\neq\xi}\left\{1-V_{m_1,m_1}\right\}}\right\}\right]\div\left[\sum_{i,s_r}\left\{\frac{\left\{pr\left(\xi\xrightarrow{s_r}i\right)\right\}.\mu_i^1}{\prod_{m_2\neq\xi}\left\{1-V_{m_2,m_2}\right\}}\right\}\right]$$

4 EXPERIMENT

Performing a reliability and availability of non markovian single unit redundant system with server failure using deep learning requires several steps in equation 1, 2, 3 and 4 to include for model to find different parameter. Here is an example experiment that you could perform:

- Collect data: Gather a dataset that contains information on the input parameters and the system's output. The input parameters could include factors such as the system's design, operating conditions, and maintenance schedule. The output could include metrics such as system availability, downtime, and failure rate in table 1 and table 2.
- Preprocess data: Clean and preprocess the dataset, splitting it into training, validation, and test sets.
- Train the model: Use a deep learning algorithm, such as a neural network, to model the connection among the input parameters and the output. Train the model by the training set and validate it using the set of values in table 1. You could use techniques such as early stopping and regularization to prevent over fitting.
- Appraise the model: After the model is proficient, appraise its performance by means of test set. Estimate metrics such as busy period.
- Perform sensitivity analysis: Using the trained model, vary the values of one parameter at a time while keeping the others constant. Record the effect on the system's output. Repeat this process for each input parameter, recording the impact of each parameter on the system's output.
- Interpret results: Analyze the consequences of the sensitivity examination to determine which input parameters need the most significant influence on the system's output. You could use systems such as nose importance and fractional dependence plots to increase understandings into the mockup's behavior.

4.1 Dataset

Sensitivity analysis is a way used to study how variations in the input parameters of an organization move the output. In the background of a reliability and availability of non markovian single unit redundant system can help determine which parameters have the most significant impact on the system's reliability. To perform sensitivity analysis using deep learning, you would need a dataset that contains information on the input parameters and the system's output. The output could include metrics such as system availability, Accuracy, and busy period Once you have a dataset, you could use a deep learning algorithm to model the relationship among the input parameters and the production. One approach could be to use a neural network, which can learn complex relationships between inputs and outputs. To perform sensitivity analysis using a neural network, you could first train the network on the dataset, using a portion of the data for training and another portion for validation. Once the network is trained, you could use it to make predictions on new input data, varying the values of one parameter at a time while keeping the others constant. By observing how changes in each parameter affect the system's output, you can determine which parameters have the most significant impact on the system's reliability to included dataset Table 1. Overall, sensitivity analysis using deep learning can be an influential tool for understanding the issues that pay to the reliability and availability of non markovian single unit redundant system. However, it requires a large and well-curated dataset, as well as expertise in deep learning techniques.

Table 1: Table of parameter.

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

5 RESULTS AND DISCUSSION

Reliability and availability of non markovian single unit redundant system using deep learning typically involves the following steps:

Data collection: Collect data on the input parameters and output metrics of the system. The input parameters could include factors such as the system's design, operating conditions, and maintenance schedule. The output metrics could include measures such as system availability, Accuracy, and busy period in show table 2 included.

Data preprocessing: Clean and preprocess the data, splitting it into training, validation, and test sets. Normalize the input variables to ensure that they are on the same scale.

Model selection: Choose appropriate deep learning optimization techniques (Adam, SGD, RMS prop) for the sensitivity analysis. Some options contain feed forward neural systems, convolutional neural systems, and regular neural networks. Consider influences such as the size of the dataset, the difficulty of the input-output connection, and the computational capitals existing.

Model training: Train the selected model on the training data. Use techniques such as stochastic gradient descent and back propagation to minimize the bust time. Monitor the performance of the model on the validation data, and adjust the hyper parameters as needed.

Model evaluation: Assess the qualified model on the test data. Calculate metrics such as mean absolute bust time and mean squared error to assess the model's performance of deep learning optimization in show table 1 and table 2.

Table 2: Performance of model.

Model	Accuracy (MTSF)	F1 Score (Expected Number of serverby the repair man)	Recall (Busy Period)	Precision
Adam	0.923	.9067	0.8012	0.9345
SGD	0.9123	0.9000	0.8123	0.9123
RMS prop	0.9012	0.8912	0.8103	0.9245

Sensitivity analysis: Use the trained model to perform sensitivity analysis on the input parameters. Vary the value of one input parameter at a time while holding the others constant. Record the effect on the output metric of interest. Repeat this process for each participation parameter to determine the sensitivity of the output metric to changes in each parameter.

Interpretation of results: Analyze the fallouts of the sensitivity examination to identify which input limits must the utmost impact on the output metric of interest. Use practices such as article importance and incomplete dependence plots to advance insights into the association amid the input limits and output metric.

Overall, performing reliability and availability of non markovian single unit redundant system using deep learning involves a combination of data collection, preprocessing, model selection, training, evaluation, and analysis.

It can be a commanding tool for understanding the influences that underwrite to the reliability of the system.

The results and discussion of a reliability and availability of non markovian single unit redundant system using deep learning will depend on the specific system and dataset analysed. However, here are some general insights that could be gained from such an analysis:

Identification of critical system parameters: The sensitivity analysis could reveal which input parameters require the greatest effect on the output metric of interest.

Understanding of the non-linear relationship amongst input strictures and output metrics: The deep learning model used in the analysis can capture non-linear relationships amongst input restrictions and output metrics, which could not be detected using traditional statistical methods.

Validation of existing models and assumptions: The results of the sensitivity analysis can be used to validate or challenge existing models and assumptions about the system.

Prediction of system behavior under different scenarios: The deep learning model can be used to predict system performance under different setups, such as vagaries in operating conditions or maintenance schedules.

Overall, sensitivity analysis of system parameters of a reliability and availability of non markovian single unit redundant system using deep learning can provide valuable insights into the factors that affect system performance, **Accuracy (MTSF),** Expected Number of Check-ups by the repair man, **Busy Period** and **Availability of the System and results in show in figure 2, 3, 4 and 5**.

Accuracy between the different model is Adam is best performance among them. And busy time of Adam is better among them of model.

6 CONCLUSION

The results of the sensitivity analysis can be used to validate or challenge existing models and assumptions about the system. For example, the analysis could show that a certain parameter has a much greater impact on system performance than previously thought. It can help optimize maintenance strategies, improve system design, and reduce downtime and maintenance costs.

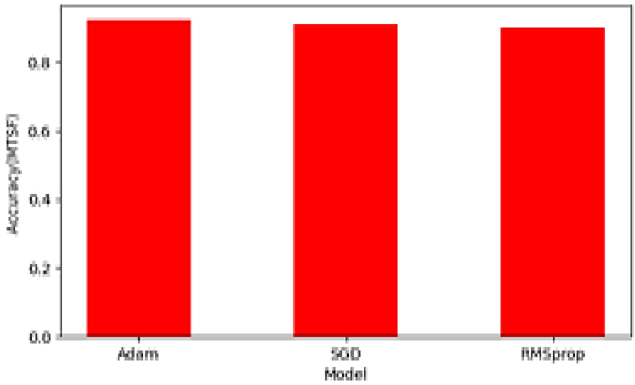

Figure 2: Comparison between Accuracy of models.

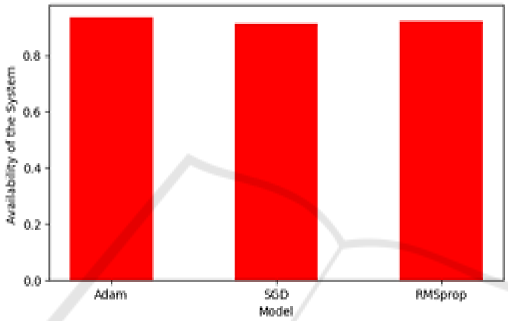

Figure 3: Comparison between Availability of model.

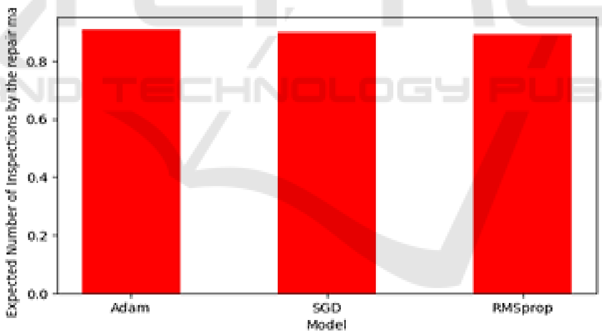

Figure 4: Comparison between Busy periods of models.

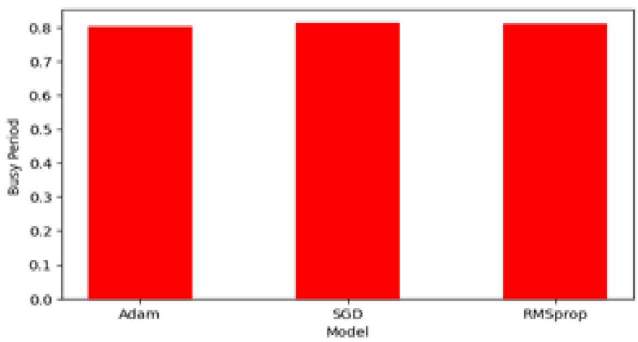

Figure 5: Comparison between models according to Expected Number of Examinations by the repair man.

REFERENCES

Devi, S., Garg, H. & Garg, D. (2023). A review of redundancy allocation problem for two decades: bibliometrics and future directions. *Artif Intell Rev*, **56**, 7457–7548.

Kumar, A., Garg, D., and Goel, P. (2019). Mathematical modelling and behavioral analysis of a washing unit in paper mill, *International Journal of System Assurance Engineering and Management*, 1(6), 1639-1645.

Kumar, A., Garg, D., and Goel, P. (2019). Sensitivity analysis of a cold standby system with priority for preventive maintenance, *Journal of Advance and Scholarly*

Devi, S., Garg, D. (2020). Hybrid genetic and particle swarm algorithm: redundancy allocation problem. *Int J Syst Assur Eng Manag* **11**, 313–319.

Kumar, A., Goel, P. and Garg, D. (2018). Behavior analysis of a bread making system, *International Journal of Statistics and Applied Mathematics,* 3(6),

Kumari, S., Khurana, P., Singla, S., Kumar, A. (2021). Solution of constrained problems using particle swarm optimization, *International Journal of System Assurance Engineering and Management*, 1-8.

Rajbala, Kumar, A. and Khurana, P. (2022). Redundancy allocation problem: Jayfe cylinder Manufacturing Plant. *International Journal of Engineering, Science & Mathematic*, 11(1), 1