BEHAVIOR ANALYSIS PRESENTED SYSYEM WITH FAILURE AND MAINTENANCE RATE WITH USING DEEP LEARNING ALGORITHMS

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Abstract

The paper discusses the behavioral analysis and dependability of a three-unit system utilizing RPGT for system parameters. Since all three units P, Q and R include parallel subcomponents, in the event that one of them fails, the system continues to operate although at a reduced capacity, but it is not profitable to run the system when two units are in reduced state hence considered failed state. The rates of failures are exponentially distributed, but the rates of repair are generalized, independent, and differ based on the operational unit. Fuzzy concept is used to declare/ determine whether the system is in failed/ reduced/ failed state. Graphs and tables are drawn to compare failure/repair effect on the parameters values. The system parameters are modelled using Regenerative Point graphical Technique (RPGT) and optimized using Deep learning methods such as Adam, SGD, RMS prop. The results of the optimization may be used to validate and challenge existing models and assumptions about the systems.

Keywords: MTSF, RPGT, Deep learning, Adaptive Moment Estimation, Stochastic Gradient Descent, RMS prop

I. Introduction

The paper analyzes system parameter reliability and behavioral analysis of three units using deep learning. Because the three units are all parallel subcomponents, the system may continue to function at a reduced capacity in the event that one or more fail. However, when two units work at a reduced capacity, the system is not profitable and is therefore deemed to be in a failed condition. The rates of failures exhibit exponential distribution, but the rates of repair are general, autonomous, and variable between different operational units. Units have varying capacity. The repairs are flawless. When two units are in a reduced state or any one unit is failing, the system is down. As in the system three are three units, P, Q, R all of which have parallel sub components initially when all the three units are good the system. The state S_0 [PQR], so upon their partial failures to states $\bar{P}$, $\bar{Q}$, $\bar{R}$ the failure rates for which are λ_1, λ_3, λ_5 the system enters the reduced states S_1 [$\bar{P}$QR], S_3 [P$\bar{Q}$R], S_6 [PQ$\bar{R}$].

There is a single repairman available in the system that can repair all the three type of units from partial as well as from full failed states so from partially failed states upon repair of partial failed units the system reenters the state so from state S_1 at repair rate w_1 of unit A, at a repair rate λ_3 of unit Q at a rate w_5 of unit R, from the partially states S_1, S_3, S_6 these units may fail further to full/ partial states. The system is considered to be in a failed state if one unit is in a failed state or if two or more units are in a reduced the state Fuzzy concept is used to declare/ determine whether the system is in failed/ reduced/ failed state. In state S_1 if unit P fails fully then the system enters the failure state S_2 [pQR]. if the unit Bar R fail then the system enters the failed states S_9, or S_7. In reduced state S_3 if units P, Q, R fail partially/ fully the system enters the states S_9, S_4, S_5 respectively from the failed state S_9 and S_4 upon repair of the units the system enters the state S_3 from partially reduced state S_6 upon failure of units P, Q, R the system enters the failed states S_7, S_5, S_8 respectively from these failed states as the repairman is free to repair the failed units, so as repair of these units the system again enters the state S_6 when more than one unit fail, the system is in failed state in these states the priority order of repairs is $\bar{P} > \bar{Q} > \bar{R} >$. Taking the transition failure and repair rates the system may be stable in the states S_i ($0 \le I \le 9$) as shown in the figure 1.

Hsieh et al. [1] has discussed Reliability of two dimensions consecutive lower bounds system. John et al. [2] has study reliability multi hardware and software system multi-hardware–software system interaction failure less attention. Kumar [3] study investigated help of mathematical modelling find out of reliability. Kumar et al. [4] has study minimizing the risk of machine failure urea fertilizer plant. Kim. H.K et al. [5] discussed demonstrate transparent or flexible capacitive designed multi touch screen. Khan. M. F et al. [6] has study three stage mathematical formulation computational procedures, numerical has two distinct approaches. Singla et al. [7] have discussed comparison of availability of a pipe and sub system of independent failure. Raghav et al. [8] has study maximize the availability and minimize the cost of function with help of PSO. Singha. A. K. [9] has done the study of x -rays and computed tomography scans images of corona virus. Kumari et al. [10] have discussed with help of RPGT profit analysis of thresher plant three sub system blower, concave, hopper more result. Singla et al. [11] has study polytube manufacturing plant solve by using of RK method. Saliva et al. [12] has study failure probability comparison with usual 1- dimension model. Singla et al. [13] with mathematical model find availability under the reduces capacity using chapman Kolmogorov method. Singla et al. [14] all three units of different capacities in working in parallel in which two or three unit in full working. Singla et al. [15] with help of GA mathematical model depend availability with working time. Singla et al. [16] has study3 out of 4 good system optimizations modelled and analysis. An analysis on reliability parameters using an algorithm ABC, has been discussed by Ahmadini et al. [17]. Singla et al. [18] studied the two unit repairable system under the concept of fuzzy linguistic and discussed the overall availability.

The total of five sections are included in this study. The 2nd section includes model description with assumption used and different mathematical values used in the study. The methodology is covered in section 3rd. The results and conclusion is studied in section 4th and 5th respectively.

II. Assumption, Notation and Transformation Diagram

- The repair procedure arises soon after a unit flops.
- Repaired unit is as if a new one.
- Failure/repair rates of units are exponential.
- Server facility is 24x7 hours.
- S_0 = PQR, $S_1 = \bar{P}$QR, S_2 = pQR, $S_3 = \text{P}\bar{Q}$R, S_4 = PqR,
- $S_5 = \text{P}\overline{QR}$, $S_6 = \text{PQ}\bar{R}$, $S_7 = \bar{P}\text{Q}\bar{R}$, S_8 = PQr, $S_9 = \overline{PQ}$R

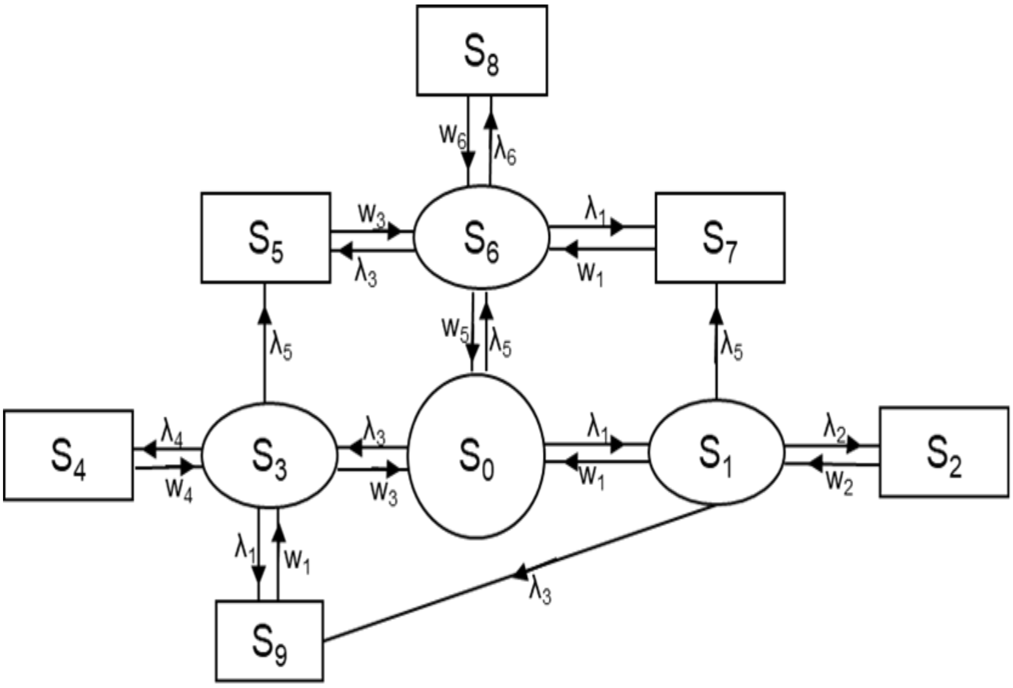

Figure 1: *Transformation Diagram*

2.1 Probability Density function ($q_{i,j}^{(t)}$)

The probability density function associated with the transformation diagram from different states to other is given below.

$q_{0,1}= \lambda_1 e^{-(\lambda_1+\lambda_5+\lambda_3)t}$
$q_{0,3}= \lambda_3 e^{-(\lambda_1+\lambda_5+\lambda_3)t}$
$q_{0,6}= \lambda_5 e^{-(\lambda_1+\lambda_5+\lambda_3)t}$
$q_{1,0}= w_1 e^{-(\lambda_5+\lambda_2+\lambda_3+w_1)t}$
$q_{1,2}= \lambda_2 e^{-(\lambda_5+\lambda_2+\lambda_3+w_1)t}$
$q_{1,7}= \lambda_5 e^{-(\lambda_5+\lambda_2+w_1+\lambda_3)t}$
$q_{1,9}= \lambda_3 e^{-(\lambda_5+\lambda_2+\lambda_3+w_1)t}$
$q_{2,1}= w_2 e^{-w_2 t}$
$q_{3,0}= w_3 e^{-(w_3+\lambda_1+\lambda_5+\lambda_4)t}$
$q_{3,4}= \lambda_4 e^{-(w_3+\lambda_1+\lambda_5+\lambda_4)t}$
$q_{3,5}= \lambda_5 e^{-(w_3+\lambda_1+\lambda_5+\lambda_4)t}$
$q_{3,9}= \lambda_1 e^{-(w_3+\lambda_1+\lambda_5+\lambda_4)t}$
$q_{4,3}= w_4 e^{-w_4 t}$
$q_{5,6}= w_3 e^{-w_3 t}$
$q_{6,0}= w_5 e^{-(\lambda_3+\lambda_6+\lambda_1+w_5)t}$
$q_{6,5}= \lambda_3 e^{-(\lambda_3+\lambda_6+\lambda_1+w_5)t}$
$q_{6,7}= \lambda_1 e^{-(\lambda_3+\lambda_6+\lambda_1+w_5)t}$
$q_{6,8}= \lambda_6 e^{-(\lambda_3+\lambda_6+\lambda_1+w_5)t}$
$q_{7,6}= w_1 e^{-w_1 t}$
$q_{8,6}= w_6 e^{-w_6 t}$
$q_{9,3}= w_1 e^{-w_1 t}$

2.2 Cumulative probability density

Cumulative probability density functions in moving from state 'i' to state 'j' by taking Laplace Transforms of above function for infinite time interval is given as under.

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

$p_{0,1} = \lambda_1/(\lambda_1+\lambda_5+\lambda_3)$
$p_{0,3} = \lambda_3/(\lambda_1+\lambda_5+\lambda_3)$
$p_{0,6} = \lambda_5/(\lambda_1+\lambda_5+\lambda_3)$
$p_{1,0} = w_1/(\lambda_5+\lambda_2+\lambda_3+w_1)$
$p_{1,2} = \lambda_2/(\lambda_5+\lambda_2+\lambda_3+w_1)$
$p_{1,7} = \lambda_5/(\lambda_5+\lambda_2+w_1+\lambda_3)$
$p_{1,9} = \lambda_3/(\lambda_5+\lambda_2+\lambda_3+w_1)$
$p_{2,1} = w_2/w_2 = 1$
$p_{3,0} = w_3/(w_3+\lambda_1+\lambda_5+\lambda_4)$
$p_{3,4} = \lambda_4/(w_3+\lambda_1+\lambda_5+\lambda_4)$
$p_{3,5} = \lambda_5/(w_3+\lambda_1+\lambda_5+\lambda_4)$
$p_{3,9} = \lambda_1/(w_3+\lambda_1+\lambda_5+\lambda_4)$
$p_{4,3} = w_4/w_4 = 1$
$p_{5,6} = w_3/w_3 = 1$
$p_{6,0} = w_5/(\lambda_3+\lambda_6+\lambda_1+w_5)$
$p_{6,5} = \lambda_3/(\lambda_3+\lambda_6+\lambda_1+w_5)$
$p_{6,7} = \lambda_1/(\lambda_3+\lambda_6+\lambda_1+w_5)$
$p_{6,8} = \lambda_6/(\lambda_3+\lambda_6+\lambda_1+w_5)$
$p_{7,6} = w_1/w_1 = 1$
$p_{8,6} = w_6/w_6 = 1$
$p_{9,3} = w_1/w_1 = 1$

2.3 Mean Sojourn Transition rate ($R_i(t)$) for different states are

$R_0^{(t)} = e^{-(\lambda_1+\lambda_5+\lambda_3)t}$
$R_1^{(t)} = e^{-(\lambda_5+\lambda_2+\lambda_3+w_1)t}$
$R_2^{(t)} = e^{-w_2 t}$
$R_3^{(t)} = e^{-(w_3+\lambda_1+\lambda_5+\lambda_4)t}$
$R_4^{(t)} = e^{-w_4 t}$
$R_5^{(t)} = e^{-w_3 t}$
$R_6^{(t)} = e^{-(\lambda_3+\lambda_6+\lambda_1+w_5)t}$
$R_7^{(t)} = e^{-w_1 t}$
$R_8^{(t)} = e^{-w_6 t}$
$R_9^{(t)} = e^{-w_1 t}$

2.4 Mean Sojourn Time ($\mu_i = R_i^*(0)$) for different states are

$\mu_0 = 1/(\lambda_1+\lambda_5+\lambda_3)$
$\mu_1 = 1/(\lambda_5+\lambda_2+\lambda_3+w_1)$
$\mu_2 = 1/w_2$
$\mu_3 = 1/(w_3+\lambda_1+\lambda_5+\lambda_4)$
$\mu_4 = 1/w_4$
$\mu_5 = 1/w_3$
$\mu_6 = 1/(\lambda_3+\lambda_6+\lambda_1+w_5)$
$\mu_7 = 1/w_1$
$\mu_8 = 1/w_6$
$\mu_9 = 1/w_1$

2.5 Transition Probability

$V_{0,0} = 1$ (Verified)
$V_{0,1} = (0,1)/1\text{-}(1,2,1)$
$= p_{0,1}/(1\text{-}p_{1,2}p_{2,1})$
$= (\lambda_1/\lambda_5+\lambda_2+\lambda_3+w_1)/(\lambda_1+\lambda_5+\lambda_3)\ (\lambda_5+\lambda_3+w_1)$
$V_{0,2} = (0,1,2)/1\text{-}(1,2,1)$
$= (p_{0,1}p_{1,2}/1\text{-}p_{1,2}p_{2,1})$
$= \lambda_1\lambda_2/(\lambda_1+\lambda_5+\lambda_3)\ (\lambda_5+\lambda_3+w_1)$
$V_{0,3} = (0,3)/1\text{-}(3,4,3)1\text{-}(3,9,3) + (0,1,9,3)/1\text{-}(1,2,1)\ \{1\text{-}(9,3,9)/1\text{-}(3,4,3)\}1\text{-}(3,4,3)$
$= p_{0,3}/(1\text{-}p_{3,4}p_{4,3})\ (1\text{-}p_{3,9}p_{9,3}) + p_{0,1}p_{1,9}p_{9,3}/(1\text{-}p_{1,2}p_{2,1})\ \{(1\text{-}p_{3,4}p_{4,3}\text{-}p_{9,3}p_{3,9})/(1\text{-}p_{3,4}p_{4,3})\}\ (1\text{-}p_{3,4}p_{4,3})$
$= \lambda_3(\lambda_1+\lambda_4+\lambda_5+w_3)^2/(\lambda_1+\lambda_5+w_3)\ (\lambda_1+\lambda_3+\lambda_5)\ \{(\lambda_3\lambda_5+\lambda_3w_3+\lambda_5^2+\lambda_5w_3+w_1w_3+\lambda_1w_3+\lambda_1\lambda_4 +\lambda_1\lambda_5)/(w_3+\lambda_4+\lambda_5)\ (\lambda_3+\lambda_5+w_7)\ (\lambda_5+w_3)\}$
$V_{0,4} = (0,3,4)/1\text{-}(3,4,3)1\text{-}(3,9,3) + (0,1,9,3,4)/1\text{-}(1,2,1)\ \{1\text{-}(9,3,9)/1\text{-}(3,4,3)\}1\text{-}(3,4,3)$
$= p_{0,3}p_{3,4}/(1\text{-}p_{3,4}p_{4,3})\ (1\text{-}p_{3,9}p_{9,3}) + p_{0,1}p_{1,9}p_{9,3}p_{3,4}/(1\text{-}p_{1,2}p_{2,1})(1\text{-}p_{3,4}p_{4,3}\text{-}p_{9,3}p_{3,9})$
$= \lambda_3\lambda_4/(\lambda_1+\lambda_5+\lambda_3)\{(w_3+\lambda_1+\lambda_5+\lambda_4)(\lambda_5+\lambda_3+w_1)(w_3+\lambda_5)+\lambda_1(w_3+\lambda_1+\lambda_5)(w_3+\lambda_4+\lambda_5)/ (w_3+\lambda_1+\lambda_5)(w_3+\lambda_4+\lambda_5)(\lambda_5+\lambda_3+w_1)(\lambda_5+w_3)\}$

III. Methodology

3.1 MTSF(T_0)

Initial state '0', before joining down state are: 'i' = 0,1,3,6 taking initial state 'ξ' = '0'

$$\text{MTSF}\ (T_0) = \left[\sum_{i,sr}\left\{\frac{\left\{pr\left(\xi\xrightarrow{sr(sff)} i\right)\right\}\mu i}{\prod_{m_1\neq\xi}\{1\text{-}V_{\overline{m_1 m_1}}\}}\right\}\right] \div \left[1\text{-}\sum_{sr}\left\{\frac{\left\{pr\left(\xi\xrightarrow{sr(sff)} \xi\right)\right\}}{\prod_{m_2\neq\xi}\{1\text{-}V_{\overline{m_2 m_2}}\}}\right\}\right]$$

3.2 Availability of the System

The regenerative states at which the system is available are 'j' = 0,1,3,6 and the regenerative states are 'i' = 0 to 9 taking 'ξ' = '0' the availability for which the system is available is given by

$$A_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\to}j)\}fj,\mu j}{\prod_{m_1\neq\xi}\{1\text{-}V_{\overline{m_1 m_1}}\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr\to}i)\}\mu_i^1}{\prod_{m_2\neq\xi}\{1\text{-}V_{\overline{m_2 m_2}}\}}\right\}\right]$$

$$A_0 = \left[\sum_j V_{\xi,j}\,, f_j, \mu_j\right] \div \left[\sum_i V_{\xi,i}\,, f_j, \mu_i^1\right]$$

3.3 Busy Period of the Server

The states where the server is busy for doing some job are 'i' = 1 to 9, taking 'ξ' = '0', using RPGT busy period is given as

$$B_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\to}j)\},nj}{\prod_{m_1\neq\xi}\{1\text{-}V_{\overline{m_1 m_1}}\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr\to}i)\}\mu_i^1}{\prod_{m_2\neq\xi}\{1\text{-}V_{\overline{m_2 m_2}}\}}\right\}\right]$$

$$B_0 = \left[\sum_j V_{\xi,j}\,, n_j\right] \div \left[\sum_i V_{\xi,i}\,, \mu_i^1\right]$$

3.4 Expected Fractional Number of repairman's Visits

States 1, 3, and 6 are the regeneration states that the repairman visits first to complete this task. The repairman's visitation count is determined by

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

3.5 Dataset: Behavior analysis Using Deep Learning Algorithms

To perform optimization using deep learning, you would need a dataset that contains information on the input parameters and the system's output [5, 6]. 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, MTSF, and busy period.

Table 1: *Parameter*

W(w1,w2,--------,wn)	ƛ(ƛ1, ƛ2, … … . ƛn)	S(s,s2,-------sn)	p
(0-.100)	(0-.100)	(0-100)	(0-.68)

Table 2: *Performance of model*

Model	MTSF	Expected Number of Inspections by the repair man	Busy Period	Availability
Adam	0.928	.9067	0.8021	.9348
Sgd	.9128	.9007	.8123	.9128
MS prop	.9013	0.8710	.8101	0.9234

- Collection of 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 using 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. The output could include metrics such as system availability, MTSF, 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 optimization 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.

Optimization of a repairable system undertaken for analysis 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, MTSF, 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: Evaluate the trained 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.

IV. Results and discussion

The results and discussion of a Optimization of undertaken repairable system parameters using deep learning will depend on the specific system and dataset analyzed. However, here are general insights that could be gained from such an analysis:

- Identification of critical system parameters: The optimization could reveal which input parameters require the greatest effect on the output metric of interest. For example, it could show that system availability is most optimization to the frequency of care or the quality of the components used in the organization.
- 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 detect using traditional statistical methods. The optimization can provide insights into the shape and magnitude of these relationships.
- Validation of existing models and assumptions: The optimization's outcomes were used to support or refute preexisting theories and hypotheses about the system. The research may reveal, for instance, that a particular parameter significantly affects system performance more than previously believed.

Prediction of system behavior under different scenarios: The deep learning model applied to predict system performance under different setups, such as vagaries in operating conditions or maintenance schedules. This can support decision-makers assess the impact of changed strategies and style informed verdicts. Overall, Behavior analysis presented sysyem with failure and maintenance rate Using Deep Learning Methods can provide valuable insights into the factors that affect system performance, (MTSF), Expected Fractional Number of repairman's Visits Busy Period and Availability of the System are shown in figure 2, 3, 4 and 5. valuable insights into the factors that affect system performance, (MTSF), Expected Fractional Number of repairman's Visits Busy Period and Availability of the System are shown in figure 2, 3, 4 and 5.

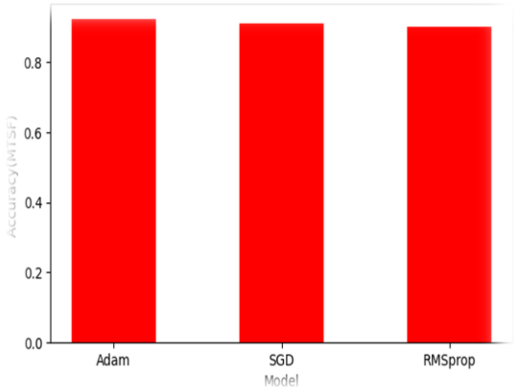

Figure 2: *comparing between models according to MTSF*

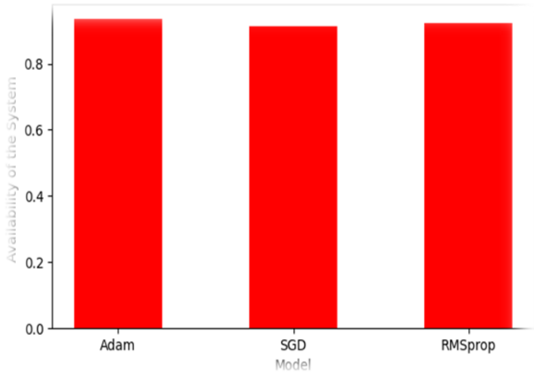

Figure 3: *comparing between models according to Availability*

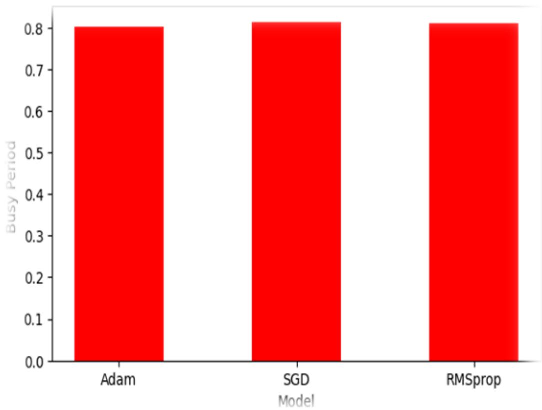

Figure 4: *comparing between models according to busy period*

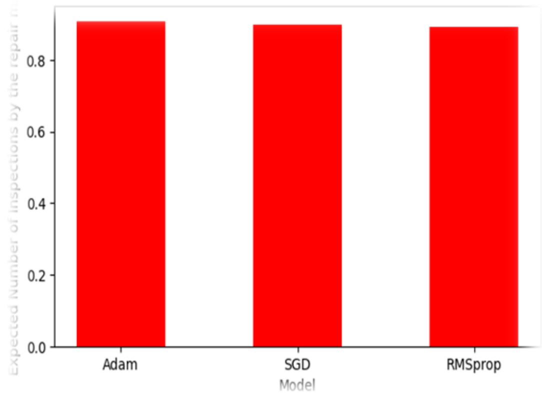

Figure 5: *comparing between models according to Expected Fractional Number of repairman's Visit*

V.Conclusion

In conclusion, the Behavior analysis presented sysyem with failure and maintenance rate with using deep learning as the optimization tool has provided valuable insights into the dynamics and performance of the system across various operational scenarios. Through comprehensive experimentation and simulation, we have gained a deeper understanding of the system's response to different configurations, maintenance policies, and environmental factors. The results demonstrate the effectiveness of the deep learning guided approach in optimizing maintenance schedules and resource allocation to maximize system reliability and availability. By iteratively refining maintenance strategies, significant improvements in key performance metrics such as mean time to failure (MTTF), mean time to repair (MTTR), and overall system uptime have been achieved. This highlights the potential of deep learning to adaptively optimize complex systems in dynamic environments.

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