ISSN: 2752-3829 Vol. 4 No.1, (June, 2024)

Stochastic Modelling and Computational Sciences

MATHEMATICAL MODELLING AND OPTIMIZATION OF SYSTEM PARAMETERS OF A TWO UNIT WARM STANDBY SYSTEM USING MACHINE LEARNING

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ABSTRACT

This study examines the system parameters of a Warm Stand-by system consisting of two unit, wherein an imperfect switch-over device is present. The system prioritizes the repair of the main unit over the switch-over device during steady state conditions. The systems are simulated using the Rational Polynomial Coefficient Generation Technique (RPGT) and subsequently enhanced through the application of machine learning algorithms for optimization purposes. There exists a solitary server that operates continuously, providing comprehensive system repair services at all times. The expectation is that a unit, after undergoing repair, should exhibit the same level of performance and quality as a brand new unit. The failure and repair rates of units in a steady state are assumed to follow an exponential distribution and are considered to be statistically independent. In general, sensitivity analysis offers significant insights into the correlation between input variables and the output variable within the industry. These insights have the potential to be utilized in order to optimize processing parameters, enhance the quality of raw materials, and ultimately augment the efficiency and profitability of the industry.

Keywords: Machine Learning Algorithms, Standby, Regenerative Point graphical technique (RPGT)

1. INTRODUCTION

The utilization of individual units is of utmost importance in processing systems that employ a switch-over mechanism, which may exhibit unreliability in activating a standby unit in the event of a failure of the online unit. Furthermore, the standby unit may experience malfunctions due to its limited shelf life or other potential factors. In order for the mechanical system to operate at its maximum capacity, it is imperative that each individual component within the system is in proper working order. The overall system experiences a complete failure in the event of a malfunction in any individual component. This paper examines the behavior of a Warm Standby System utilizing Redundant Power Generation Technology (RPGT). The study investigates both perfect and imperfect switch-over devices and explores the optimization of system performance through the application of machine learning techniques. The utilization of fuzzy logic is employed for the purpose of detecting the malfunction of a given unit. There exists a single server, referred to as the repairman, who is accessible at all times (24x7) to handle units and the switch-over device. In the event that standby unit 'B' experiences a failure and is subsequently undergoing repairs, should the main unit 'A' also fail during this period, standby unit 'B' that is currently being repaired will be added to the queue of failed units. The analysis of the system focuses on its parameters during steady state conditions, assuming that the failure and repair rates of the units follow an exponential distribution and are statistically independent. In order to examine the impact of failure and repair rates on system parameters, the study employs the use of tables and graphs.

2. Model Description of Single Unit Warm Stand-by System:

A stand-by system is a backup system in which a secondary unit is available to take over when the primary unit fails. In this type of system, the primary unit operates continuously while the secondary unit is set aside in a standby mode. When the primary unit flops, the secondary unit takes over. In such a system, the switch-over device plays a critical role in ensuring the smooth transition from the primary unit to the secondary unit and so on in above Equations (1), (2), (3), and (4). However, in practice, switch-over devices are often imperfect and may fail to function properly, leading to a delay or failure in the switch-over process. The sensitivity analysis of such a system involves analyzing how changes in many parameters affect the recital of the scheme. In this case, the parameters of interest are the reliability of the primary and secondary units, the reliability of the switch-over device, and the repair times of each component. To model the system, we can use a Machine Learning, which is a stochastic model that describes the system's behavior as it moves from one state to another. In this case, the states correspond to the different operational modes of the system, such as normal operation, primary unit failure, switch-over delay, and switch-over failure [2, 3, 10]. For example, we can analyze how changes in the switch-over device's reliability affect the system's availability or how changes in the overhaul times of primary and secondary units affect the organization's downtime. The practical application of sensitivity analysis for a two unit warm stand-by system can help identify critical components and determine optimal maintenance strategies. By identifying which parameters have the greatest impact on system performance, we can prioritize maintenance efforts and allocate resources effectively. This information can also be used to optimize the design of the system and improve its reliability.

3. Machine Learning Algorithms

Performing sensitivity analysis on a two unit warm stand-by system with an imperfect switch-over device can be challenging, but machine learning algorithms can help simplify the process. The first step in performing sensitivity analysis is to identify the variables that are likely to have the greatest impact on the performance of the system. In this case, the variables may include the time it takes for the switch-over device to activate, the probability of the switch-over device failing, and the time it takes for the stand-by unit to become fully operational [4, 9]. Once these variables have been identified, machine learning algorithms can be used to analyze the relationships between them and the overall performance of the system. One approach would be to use regression analysis to determine how changes in each variable impact the overall reliability and efficiency of the system. Another approach would be to use machine learning algorithms to simulate the performance of the system under different conditions. This would involve creating a model of the system that considers the variables identified earlier and using the model to predict how the system would perform under different scenarios. The model could be trained using historical data to ensure that it accurately reflects the behavior of the system in real-world conditions. Overall, machine learning algorithms can be a powerful tool for performing sensitivity analysis on complex systems like a single unit warm stand-by system with an imperfect switch-over device [9]. By using these algorithms, it is possible to identify the variables that have the greatest impact on the system's performance and develop strategies to improve reliability and efficiency.

(a) Linear SVC Classifier

Linear SVC (Support Vector Classifier) is anxious by fit statistics that current revenues a "best fit" hyper-plane to catalog divides and the statistics. Anywhere after getting a hyper-plane, subsequently those dismiss feed features keen on the classifier to grow what "predicted" session. That completes that algorithm relatively than fit our needs; yet it can use that in many conditions [7].

(b) Logistic Regression (LR) Classifier

LR is a linear classifier by verdict boundary of θ^t x = 0. LR predicts possibilities rather than programs. The aim of LR is to train data after the possibility of variable Y life 1 or 0 specific x. The variables data set collection is **X** $\epsilon \boldsymbol{R}^{nxd}$. We require a binary cataloguing issue; the Bernoulli mix models the function ought to be applied [8].

(c) Combining Instance-Based Learning and LR:

The LR model names the likelihood of binary production yi = {1, 0} assumed the input xi. Then can be estimate likelihood as:

Where: $\Pi 0 = p\ (y0 = +1|yi)$

$$\frac{\Pi 0}{1-\Pi 0} = \frac{p(yi|y0=+1)}{p(yi|y0=+1)} \cdot \frac{p0}{1-p0} \qquad (5)$$

Where p is the probability rate it can be rewritten as:

$$\frac{\Pi 0}{1-\Pi 0} = p.\frac{p0}{1-p0}$$

$$\log\left(\frac{\Pi 0}{1-\Pi 0}\right) = \log(p) + w0$$

With respect to:

$$w0 = \log(p0) - \log(1 - p0) \qquad (6)$$

To serve the essential principle underlies instance-based on learning [122], the classifier must be distancing di function. P is large if di → 0 then δi = +1, and unimportant for yi = -1. P must be nearby to 1 if δi → α; then, neither within support of y0 = +1, nor into support of y0 = -1, then the parameter utility is as below:

Finally, $s = p(\delta) = \exp(yi\,\frac{\alpha}{\delta})$

$$\log\left(\frac{\Pi 0}{1-\Pi 0}\right) = w0 + \alpha \sum_{xi \in N(x0)} k(x0, xi).yi \qquad (7)$$

Where k (x0, xi) is the same measure.

(d) Model Evaluation

Sensitivity analysis is a method used to identify how changes in the input parameters of a system affect its output. In the case of a single unit warm standby system with an imperfect switch-over device, the system can be modeled and evaluated to identify the key strictures and their impact on the organization's performance.

To evaluate the implementation of our model performance, we have estimated different execution evaluation confusion matrix (Recall, Accuracy Precision, and F1- Measure). The evaluation of the model phase proposes to evaluate the generalization precision accuracy of the design model on an unseen, i.e., test dataset. Here we calculated this accuracy by applying the precision (**Availability of the System)**, accuracy (The Medium-Term Strategic Framework (MTSF)), Recall (**Busy Period)**, f-score function, that are imported from the metrics module available into the Scikit-learn Python library that depends on the following formula. To perform a sensitivity analysis, one would typically vary each input parameter of the system, one at a time, while keeping all other parameters constant. Then, the output of the system is observed to see how it changes in response to the variation in each input parameter. In the case of a two unit warm standby system with an imperfect switch-over maneuver, some of the key parameters that might be varied in a sensitivity analysis could include:

a) **The reliability of the main unit**: This represents the probability that the main unit will function properly when it is needed. If the reliability of the main unit is low, then the system may be more reliant on the switch-over device to function properly, which could have implications for the system's overall performance.

b) **The reliability of the switch-over device**: This represents the likelihood that the switch-over device determinations function correctly when it is needed. If the reliability of the switch-over device is low, then the system may not function properly when the main unit fails, which could lead to downtime or other negative consequences.

c) **The period it takes for the switch-over device to activate**: This represents the period its takings for the switch-over device to detect that the main unit has failed and to switch over to the standby unit. If this time is too long, then the system may experience downtime or other negative consequences.

d) **The availability of spare parts for the switch-over device:** If spare parts for the switch-over device are not readily available, then it may be difficult to repair or replace the device if it fails, which could have implications for the system's overall reliability.

e) **The cost of the switch-over device**: If the switch-over device is expensive, then it may be cost-prohibitive to implement, which could affect the overall feasibility of the system.

By varying these and other key parameters one at a time and observing how the output of the system changes in response, it is possible to identify which parameters remain most critical to the organization's performance and to determine the optimal values for each parameter.

4. ASSUMPTIONS AND NOTATIONS

(i) Failures/repairs remain statistically independent.

(ii) Further it is assumed that a single repair capacity is accessible on behalf of all units and switch-over device.

(iii) Repair facility is available immediate.

(iv) Repair is perfect and repaired system is as a novel one.

(v) Nothing can fail further when the system is in failed state.

$\mu_i' = Waiting\ time\ invstate\ i,$

$f_j = fuzzy\ number$

Ri (t) : Reliability of system at time t, assumed that system go in the un-failed Regenerative state.

Ai (t)/ Bi (t)/ Vi (t) : Availability of the system in upstate/ attendant is busy/ expected No. of server visits at time ‘t’, specified that the system entered Re-forming state ‘i’ at t = 0.

$T_0 =$ Mean Time to System failure

$\mu_j = \int_0^\infty R_j(t)dt$

$\lambda/\ \lambda_1/\ \lambda_2$: Constant failure rates of units

$w_1/\ w_2/\ w_3$: Constant repair rates of units

A/a : Main unit A is in the operative / failed state.

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

‘’ : Dash denotes derivative

p = probability that switch is good

μ_i : Mean sojourn time spent in state i

$w_i/\ \lambda_i$: Denote repair failure rates of units

Working State

○

Failed State

□

5. Transition Diagram of the System (TDS): - Following the above assumptions and notations the TDS is specified in Figure 1

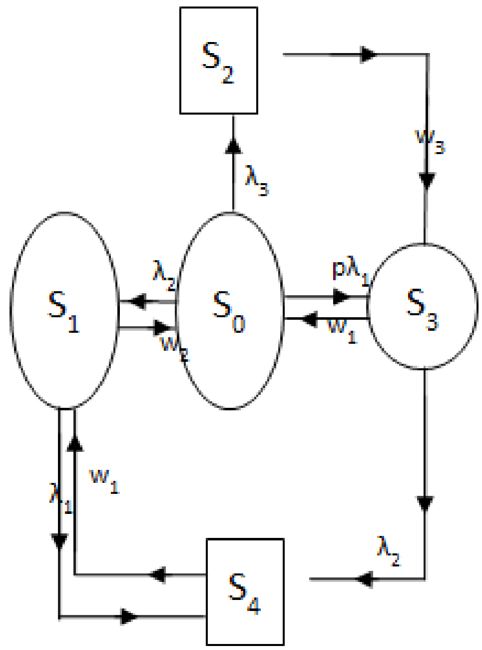

Figure 1: Transition Diagram

$S_0 = A(B)$ $S_1 = A(b)$ $S_2 = a(B)$

$S_3 = aB$ $S_4 = ab$ $q = 1\text{-}p$

6. Transition Probability and Mean sojourn times.

Table 1: Transition Probabilities

$q_{i,j}(t)$	$P_{ij} = q^*_{i,j}(0)$
$q_{0,1} = \lambda_2 e^{-(p\lambda_1+\lambda_2+\bar{p}\lambda_1)t} = \lambda_2 e^{-(\lambda_1+\lambda_2)t}$ $q_{0,2} = \bar{p}\lambda_1 e^{-(\bar{p}\lambda_1+p\lambda_1+\lambda_2)t} = \bar{p}\lambda_1 e^{-(\lambda_1+\lambda_2)t}$ $q_{0,3} = p\lambda_1 e^{-(p\lambda_1+\lambda_2+\bar{p}\lambda_1)t} = p\lambda_1 e^{(\lambda_1+\lambda_2)t}$	$P_{0,1}= \lambda_2/(\lambda_1+\lambda_2)$ $P_{0,2}= \bar{p}\ \lambda_1/(\lambda_1+\lambda_2)$ $P_{0,3}= p\lambda_1/(\lambda_1+\lambda_2)$
$q_{1,0} = w_2 e^{-(w_2+\lambda_1)t}$ $q_{1,4} = \lambda_1 e^{-(w_2+\lambda_1)t}$	$P_{1,0}= w_2/\lambda_1+w_2$ $P_{1,4}= \lambda_1/\lambda_1+w_2$
$q_{2,3} = w_3 e^{-w_3 t}$	$P_{2,3}= w_3/w_3 = 1$
$q_{3,0} = w_1 e^{-(w_1+\lambda_2)t}$ $q_{3,4} = \lambda_2 e^{-(w_1+\lambda_2)t}$	$P_{3,0}= w_1/\lambda_2+w_1$ $P_{3,4}= \lambda_2/\lambda_2+w_1$
$q_{4,1} = w_1 e^{-w_1 t}$	$P_{4,1}= w_1/w_1 = 1$

7. Mean Sojourn Times

Table 2: Mean Sojourn Times

$R_i(t)$	$\mu_i = R_i^*(0)$
$R_0^{(t)} = e^{-(\lambda_1+\lambda_2)t}$	$\mu_0 = 1/(\lambda_1+\lambda_2)$
$R_1^{(t)} = e^{-(\lambda_1+w_2)t}$	$\mu_1 = 1/(w_2+\lambda_1)$
$R_2^{(t)} = e^{-w_3 t}$	$\mu_2 = 1/w_3$

$R_3^{(t)} = e^{-(\lambda_2+w_1)t}$	$\mu_3 = 1/(w_1+\lambda_2)$
$R_4^{(t)} = e^{-w_1 t}$	$\mu_4 = 1/w_1$

8. **Evaluation of Parameters**

The various path probabilities of the system are

$V_{0,0} = 1$ (verified)

$V_{0,1} = \lambda_2(\lambda_1+\lambda_2+w_1)/(\lambda_1+\lambda_2)(\lambda_2+w_1)$

$V_{0,2} = \ldots\ldots$ and so on.

9. **MTSF (T_0): The mean time to system failure** (initial state '0'), working states before the system enters down state are: 'i' = 0, 1, 3 taking base state 'ξ' = 0, using RPGT is given by:

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

$T_0 = [(0, 0)\ \mu_0+(0, 1)\ \mu_1+(0, 3)\ \mu_3] \div [1-(0, 1, 0) -(0, 3, 0)]$

$= [\lambda_1 w_1+w_1 w_2+\lambda_2 w_1+p\lambda_1^2 w_1+p\lambda_1 w_1 w_2+\lambda_1\lambda_2+w_2\lambda_2+\lambda_2^2+p\lambda_1^2\lambda_2+p\lambda_1\lambda_2 w_2]$

$/[\lambda_1^2 w_1+\lambda_1^2\lambda_2+\lambda_1 w_1 w_2+\lambda_1\lambda_2 w_2+\lambda_1\lambda_2 w_1+\lambda_1\lambda_2^2-p\lambda_1^2 w_1-p\lambda_1 w_1 w_2]$

10. **Availability (A_0):** The states where the system is working in reduced or full capacity are 'j' = 0, 1, 3 and regenerative states are 'i' = 0 to 4, taking base state as 'ξ' = '0', availability of the system using RPGT is given as

$$A_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\rightarrow} j)\} f j, \mu j}{\prod_{m_1\neq\xi}\{1-V_{\overline{m_1 m_1}}\}}\right\}\right] \div \left[\sum_{i,sr}\left\{\frac{\{pr(\xi^{sr\rightarrow} i)\}\mu_i^1}{\prod_{m_2\neq\xi}\{1-V_{\overline{m_2 m_2}}\}}\right\}\right] \quad (2)$$

$A_0 = \{1/(\lambda_2+\lambda_1) +\lambda_2(\lambda_2+\lambda_1+w_1)/(\lambda_1+\lambda_2)(\lambda_2+w_1)(\lambda_1+w_2) +\lambda_1/(\lambda_1+\lambda_2)(w_1+\lambda_2)\}$

$/\{1/(\lambda_2+\lambda_1) +\lambda_2(\lambda_2+\lambda_1+w_1)/(\lambda_1+\lambda_2)(\lambda_2+w_1)(\lambda_1+w_2) +\bar{p}\lambda_1/(\lambda_1+\lambda_2) w_3+\lambda_1/(\lambda_1+\lambda_2)(w_1+\lambda_2) +\lambda_1\lambda_2/(\lambda_1+\lambda_2)[1/(\lambda_2+w_1) +1/(\lambda_1+w_2)](1/w_1)\}$

11. **Busy Period (B_0):** The situations where the attendant is busy to do repair are 'j' = 1 to 4 and reformative states remain 'i' = 0 to 4, taking base state ξ = '0', is

$$B_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\rightarrow} j)\}, nj}{\prod_{m_1\neq\xi}\{1-V_{\overline{m_1 m_1}}\}}\right\}\right] \div \left[\sum_{i,sr}\left\{\frac{\{pr(\xi^{sr\rightarrow} i)\}\mu_i^1}{\prod_{m_2\neq\xi}\{1-V_{\overline{m_2 m_2}}\}}\right\}\right] \quad (3)$$

$B_0 = \{[\lambda_2(\lambda_2+\lambda_1+w_1)/(\lambda_1+\lambda_2)(\lambda_2+w_1)(\lambda_1+w_2) +\bar{p}\lambda_1/(\lambda_1+\lambda_2) w_3+\lambda_1/(\lambda_1+\lambda_2)(w_1+\lambda_2) +[(\lambda_1\lambda_2/(\lambda_1+\lambda_2))[1/(\lambda_2+w_1)+1/(\lambda_1+w_2)](1/w_1)\}/\{1/(\lambda_1+\lambda_2)+$

$\lambda_2(\lambda_2+\lambda_1+w_1)/(\lambda_1+\lambda_2)(w_1+\lambda_2)(\lambda_1+w_2) +\bar{p}\lambda_1/(\lambda_1+\lambda_2) w_3+\lambda_1/(\lambda_1+\lambda_2)(w_1+\lambda_2)$

$+[\lambda_1\lambda_2/(\lambda_1+\lambda_2)][1/(\lambda_2+w_1) +1/(\lambda_1+w_2)](1/w_1)\}$

12. **Expected Number of Examinations by repair man V_0:** Reformative states where restoration man ensures this job stay j = 1 to 3 taking 'ξ' = '0'

$$V_0 = \left[\Sigma_{j,sr}\left\{\frac{\{pr(\xi^{sr\to}j)\}}{\Pi_{k_1\neq\xi}\{1-V_{\overline{k_1k_1}}\}}\right\}\right] \div \left[\Sigma_{i,sr}\left\{\frac{\{pr(\xi^{sr\to}i)\}\mu_i^1}{\Pi_{k_2\neq\xi}\{1-V_{\overline{k_2k_2}}\}}\right\}\right] \tag{4}$$

$V_0 = \{\lambda_2(\lambda_1+\lambda_2+w_1)/(\lambda_1+\lambda_2)\ (\lambda_2+w_1)\ +\bar{p}\lambda_1/(\lambda_1+\lambda_2)\ +\lambda_1/(\lambda_1+\lambda_2)\}/\{1/(\lambda_1+\lambda_2)\ +\lambda_2(\lambda_1+\lambda_2+w_1)/(\lambda_1+\lambda_2)\ (\lambda_2+w_1)\ (\lambda_1+w_2)\ +\bar{p}\lambda_1/(\lambda_1+\lambda_2)\ w_3+\lambda_1/(\lambda_1+\lambda_2)(w_1+\lambda_2)+(\lambda_1\lambda_2/(\lambda_1+\lambda_2))1/(\lambda_2+w_1)\ +1/(\lambda_1+w_2)]\ (1/w_1)\}$

Corollary: Results can be derived for perfect switch taking p=1.

13.RESULTS AND DISCUSSION

The results of the sensitivity analysis of a dataset related to the single unit can provide valuable insights into the impact of changes in input variables on the output variable, such as the quality of the single unit. In contrast, the failure rate of the standby unit may have less impact on system availability because the standby unit is not in use until the primary unit fails. The repair time for each unit may also have less impact because the system is designed to be in a warm standby configuration, meaning that the units are already partially operational and can quickly be brought up to full capacity.

Results of sensitivity analysis for this system may indicate that the failure rate of the primary unit has the greatest impact on system availability. This is because the primary unit is the active unit and is responsible for providing service. If it fails, the standby unit must take over, and the imperfect switch-over device introduces additional delay and uncertainty. In contrast, the disappointment rate of the standby unit may have less impact on system availability because the standby unit is not in use until the primary unit fails. The repair time for each unit may also have less impact because the system is designed to be in a warm standby configuration, meaning that the units are already partially operational and can quickly be brought up to full capacity. The switch-over time for the imperfect device may have a significant impact on system availability because it introduces additional delay and uncertainty into the system of parameter in Table 3. A longer switch-over time may result in a lower system availability, as there is a greater chance that the system will not be operational when it is needed in performance of model in Table 4 as follow and comparison of model in figure 2, 3, 4, and 5.

Table 3: Table of parameter

W (w1, w2,--------,wn)	$\lambda(\lambda 1, \lambda 2, \dots \dots .\lambda n)$	S (s1, s2, -------, sn)	P
(0-.100)	(0-.100)	(0-100)	(0-.68)

Table 4: Table of Performance of Model.

Model	MTSF	Server's Visit	Busy Period	Availability
Linear SVC Classifier (LC)	**0.934**	0.952	0.931	0.963
Logistic Regression (LR)	0.922	0.933	0.938	0.957
Decision Tree Classifier (DT)	0.911	0.925	0.929	0.930
AdaBoost Classifier (AC)	0.901	0.946	0.921	**0.985**
Multinomial NB(MN)	0.869	0.923	0.987	0.903
k-nearest neighbors (k-NN)	0.833	**0.851**	**0.853**	0.859

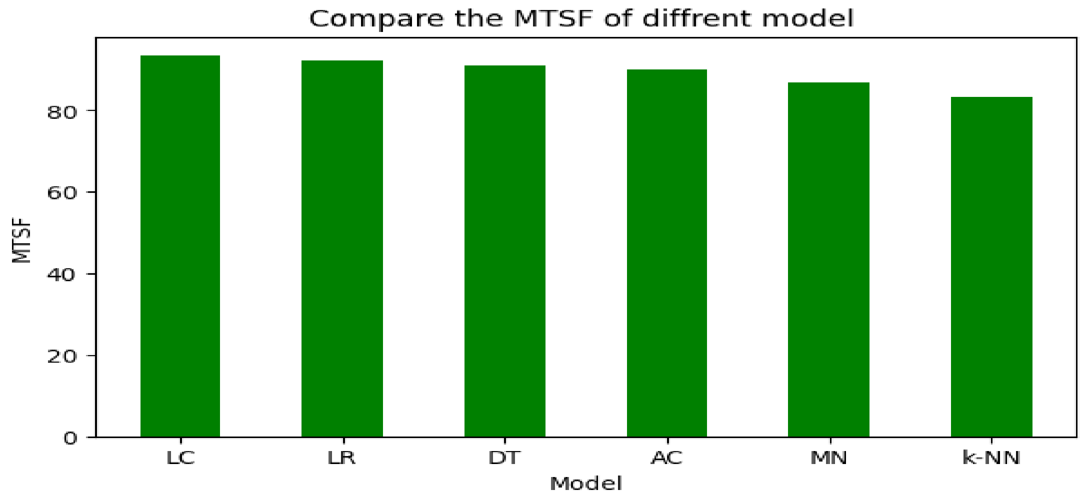

Figure 2: Comparison of the MTSF of different Models.

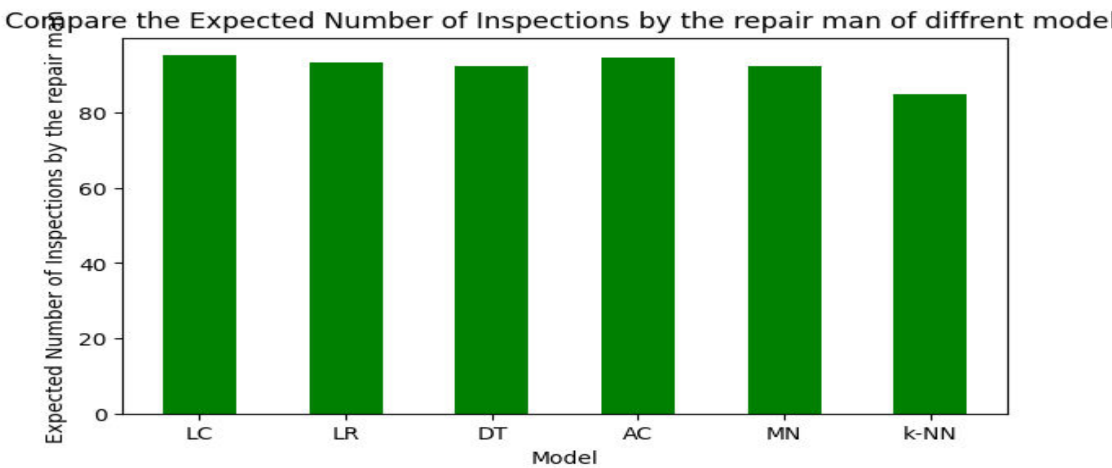

Figure 3: Comparison of the expected number of inspections by the repair man of different model.

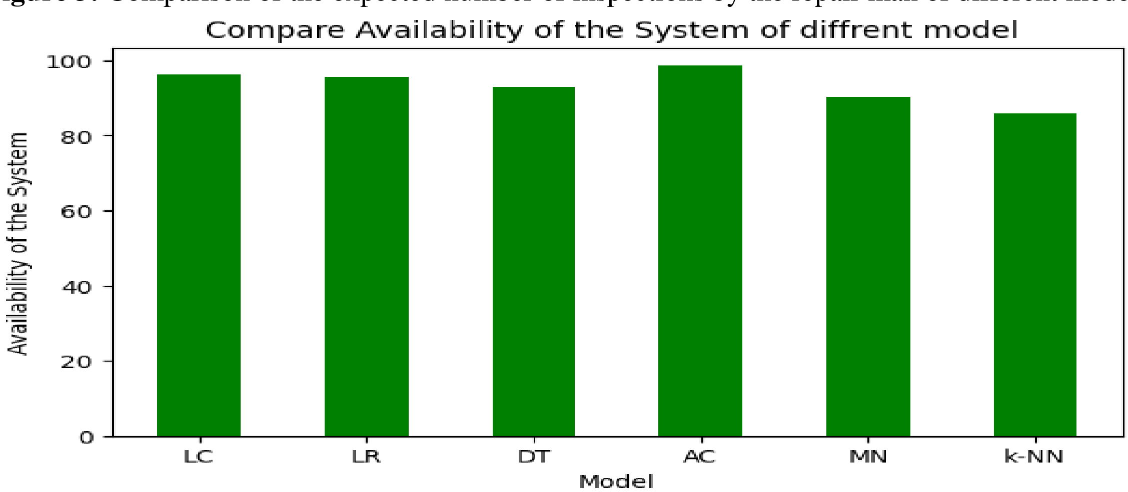

Figure 4: Compare of Availability of system of different models.

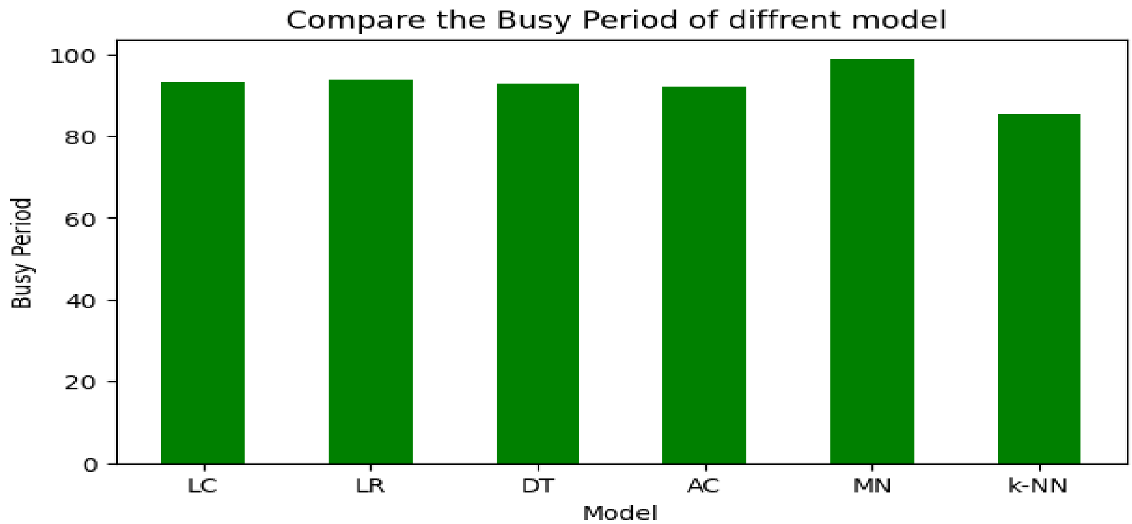

Figure 5: Comparison of the busy period of different models.

14. CONCLUSION

The results of the sensitivity analysis of a dataset related to the two unit can provide valuable insights into the impact of changes in input variables on the output variable, such as the quality of the single unit. In contrast, the letdown rate of the standby unit may have less impact on system availability because the standby unit is not in use until the primary unit nosedives. The repair time for each unit may also have less impact because the system is designed to be in a warm standby configuration, meaning that the units are already partially operational and can quickly be brought up to full capacity. This can help to improve the efficiency and profitability of the industry, as well as the quality of the final product. The switch-over time for the imperfect device may have a significant impact on system availability because it introduces additional delay and uncertainty into the system of parameter in Table 3. A longer switch-over time may result in a lower system availability, as there is a greater chance that the system will not be operational when it is needed in performance of model in Table 4 as follow and comparison of model in figure 2, 3, 4, and 5. Overall, sensitivity analysis can provide valuable insights into the relationship between input variables and the output variable in the industry. These insights can be used to optimize processing parameters, improve the quality of raw materials, and ultimately increase the efficiency and profitability of the industry.

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