Analysis of Reliability & Maintainability of IEEE RTS 24 Bus System

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DECLARATION

I, *Muhamad Zohaib Sohail* declares that thesis titled **"Analysis of Reliability & Maintainability of IEEE RTS 24 Bus System"** is my own. None of the material in this thesis has been submitted in support of any application for another degree or qualification from this or any other university or institute, organization and university.

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DEDICATION

This thesis is dedicated to my beloved parents, loving brothers and respected Teachers.

ACKNOWLEDGMENTS

I thank **Almighty Allah** who bestowed me with the knowledge and courage which is essential in order to complete this research work. As efforts in developing and writing this thesis are, definitely not mine, they are the gifts, blessings and mercies of Almighty Allah.

I owe a debt of gratitude to my supervisor Capt. Dr. Tariq Mairaj Rasool Khan who was so generous with his time and expertise. My deep appreciation and heartfelt thanks goes to him for his careful attention, unfailing courtesy, and professional support in completion of my thesis. Moreover I am very thankful to my supporters, guidance and evaluation committee members Capt. Dr. Aleem Mushtaq, Dr. Aqueel Shah from PNEC and Cdre. Dr. Muhammad Imran from NHQ for their technical and administrative support for completion of this thesis.

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LIST OF ABBREVIATIONS

RTS	Reliability Test System
IEEE	Institute of Electrical and Electronics Engineers
RAM	Reliability Availability and Maintainability
MTTR	Mean Time to Repair
MTTF	Mean Time to Failure
MTBF	Mean Time between Failure
MTBR	Mean Time between Repair
MLE	Maximum Likelihood Estimator
TTR	Time to Repair
PDF	Probability Distribution Function
CDF	Cumulative Distribution Function
LSTM	Long Short Term Memory
RMSE	Root Mean Square Error
ADAM	Adaptive Moment Estimation
SGDM	Stochastic Gradient Descent Momentum

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ABSTRACT

Power is a basic necessity of each individual and also for corporate sectors. So, uninterrupted power is the requirement of present days. Since, power systems often came across failures and breakdowns which cause an extensive effect on consumers. As, now a days each of the item is power dependent and without power it becomes miserable. The aim of this research is to improve the reliability of power system in order to overcome or minimize the failures occurs in power systems. In order to accomplish, a deep learning technique called Long Short Term Memory (LSTM) is proposed in this research to predict Time to Failures (TTF) of power systems. Prediction of time to failure is a key feature to improve the reliability of power system because of this failure can be reduced. In this approach i.e. long short term memory, since it is a deep learning technique there are different layers called input, output and hidden layers as well as different gates which are controlling the predicted values. Also LSTM can handle long term dependencies problem which is unlikely present in other recurrent techniques. There is segregation in dataset for LSTM i.e. training data and testing data. The results obtained are quite satisfactory because root mean square error (RMSE) between the actual values of time to failure and predicted (computed) TTF is reasonable (minimum), which shows better prediction of time to failure results in improving the overall reliability of the power system.

CHAPTER # 1 INTRODUCTION

1.1 Back Ground and Motivation

Power System consists of different components like, Transformers, Generators, Bus Bars, Switch gears etc. We often came across failures in power systems resulting in breakdown which causes huge loss of production for industries as well as other related sectors. Breakdowns normally occurs due to malfunctioning or failures in components installed in a power system.

Power is a basic requirement of every industries or an individual, without power lives become miserable. There are multiple factors for failures in power systems like failures arises in different equipment or components of a system, environmental or temperature effects, wear out failures etc. Causes of power failures can be minimized by different preventive measures for prediction of failures in power systems and also timely repair action can be done to overcome the system's failure and restore it in working mode.

Figure # 1: Power Grid System

In order to minimize the failures and its frequent restoration there is a concept of RAM parameters called Reliability, Availability and Maintainability.

1.2 Literature Review

In [1] B. Canizes and J. Soares developed two approaches for load curtailment and reduction in failure cost. First one is the global steady technique comprises for development of model in order to cater the faulty transmission power system, this model helps to reduce the time and cost resulting in unexpected failures. While the other one is the dynamic iterative technique which test all the components of power system and point out the component having frequent failures. The whole procedure continues iteration until the load curtailment may be minimized or even equal to zero. In these approaches combination of two method i.e. Fuzzy and Monte Carlo Simulation has been implemented to track the randomness and behavior of different components of power system.

Reliability and maintainability analysis for strudel production line for different machine workstation, and entire line level has been proposed. Statistics about the failure as well as repair data has been conducted and the significant index parameters were examined. Also different modes of failure and hazard rate for the whole system has also calculated by Panagiotis H. Tsarouhas in [2].

In [3] Descriptive Statistical analysis of failure as well as repair data for the food production lines has been carried out by P. H. Tsarouhas. A comparative study about the performance & evaluation between the production lines is conducted by using different statistical technique. Failure and repair data of various production lines has been collected then suitable distribution fitting is applied using goodness of fit test through Minitab software. Comparison of probability plots and hazard rate plots of different production lines are examined and analyzed.

In [4] the literature review has been carried out pertaining to Reliability, Availability, Maintainability Engineering and its related parameters. All of them were divided into different groups namely the Assessment of RAM parameters, the methodologies required to obtain various RAM parameters, design, support as well as life cycle cost etc., simulation and modelling for the Reliability, Availability and Maintainability. In [4] an additional parameter called Supportability has also been introduced which is also beneficial while study of RAM parameters. In supportability there is a concept of Information technology (IT) which is effective and key factor for implementation in different systems and other related sectors.

In [5] LSTM (Long Short Term Memory) an updated and modified type of traditional recurrent neural network has been implemented on the available data of reliability i.e. time to failures in order to compute and predict the reliability of system for future means those time instants where data is not available. The proposed LSTM technique is applied on an online service oriented system having composed of several individual components. Authors have conducted number of experiments and tests in order to analyze the overall performance and efficiency of the proposed approach and also compared it with related techniques for validation.

In [10], authors have implemented LSTM technique on different medical time series data. Various optimizers are used by authors in order to compare the efficiency of algorithm during training. The problem of exploding and vanishing of gradients during prediction has also been discussed and suggest different techniques to overcome it. Authors have proposed techniques to increase the accuracy by using the classification accuracy measurement.

1.3 Problem Statement

As Power failures are increasing day by day. The main reason behind failures of a power system is the fault arises in the installed components of a power system. In order to overcome the failures of power systems, behavior of each component i.e. its TTF (Time to Failure) is a significant feature for reliability improvement.

To predict Time to Failure i.e. future states of a power system is a challenging task. To compute Availability of a power system by using TTF in order to improve Reliability of the system.

1.4 Objective

To develop a model based on training data to predict the future states (TTF) of power system. And implementation of prediction based deep learning algorithm (LSTM) for computation of failures (TTF) of both overall failures and also for equipment failures in Power System.

1.5 Research Significance

By implementing long short term memory, we can predict the Time to failure of power system. Prediction of future TTF helps in proper repair action which results reduction in failure cost as well as production delay. Also computation of RMSE will help to find the efficiency of algorithm.

1.6 Research Methodology

Out of many techniques discussed in literature review, a novel Long Short Term Memory (LSTM) algorithm has been implemented in this study for prediction of time to failure of power system

In LSTM which is a specific type of recurrent neural network, it can handle long terms dependencies problems as well. There are multiple layers and gates in a single cell memory of LSTM and each of them are interconnected. Initially the input x_τ and hidden state $h_{\tau-1}$ are fed to the sigmoid function for the forget gate layer. Afterwards Input and modulation gate layer which computes i_τ and g_τ respectively through sigmoid and tangent activation functions. Then output layer o_τ computes the final output h_τ after multiplication of cell state c_τ with output layer.

1.7 Outline of Report

The whole work in this comprehensive study is regarding the improvement of power system reliability. This thesis report comprises of five chapters. First chapter consists of introduction having background as well as motivation, literature review i.e. previous work done on reliability improvement, problem statement, objective of the research also the research significance and research methodology. Second chapter contains the Theoretical background of research, it includes the fundamental concepts of reliability, different distribution fitting techniques involved as well as the description of prediction algorithms which have been implemented in this research. Chapter 3 comprises of Experimental work i.e. the step by step implementation of prediction algorithm for computation of desired results. Chapter 4 is based on the obtained results, calculation and discussion on the desired outcomes of this research study. Finally chapter 5 includes the conclusion, recommendation and future work on this study.

CHAPTER # 2 THEORETICAL BACKGROUND

2.1 Fundamental Concepts

The core objective of chapter 2 is to familiarize with the basic concepts of power system reliability. The technique and algorithm which have been used in this research are briefly described in this section. Moreover, this chapter also serves as a platform for understanding the concept of the study and its allied objectives.

2.1.1 Reliability

Reliability can be explained as the probability that an entity will continue to do its specific (desired) function without any kind of breakage or failure for a specified interval of time under some predefined conditions [6]. Improvement in reliability is preferred for better performance of systems.

Reliability function can be expressed as the probability of survival as a function of time. Since the cumulative distribution function (CDF) denoted as $F(t)$, is the probability that the random variable or in terms of survival time is less than or equal to a given point in time, the reliability function for a continuous probability distribution, $R(t)$, is the complement of the $F(t)$ i.e. cumulative distribution function, mathematically expressed as:

$$R(t) = 1 - F(t) \tag{1}$$

2.1.1.1 Mean Time to Failure

Mean Time to failure of a system is defined as the expected time a failure may arises in a system. Also called MTTF. Mathematically it is defined as,

$$\text{MTTF} = \int_0^\infty t\, f(t)\, dt \tag{2}$$

$$\text{MTTF} = \int_0^\infty R(t)\, dt \tag{3}$$

where,

f(t) is probability density function (PDF)

R(t) is Reliability Function

2.1.1.2 Mean Time Between Failure

It is normally applied for those systems which are repairable i.e. after following a failure respective item will be repaired. It is termed as MTBF. Mathematically it is defined as,

$$\text{MTBF} = \frac{T(t)}{f} \tag{4}$$

where,

T(t) is Total ON time / Operation time

'f' is Total num. of failures

2.1.1.3 Failure Rate

It is also called instantaneous failure rate. The rate at which failures occurs between the interval from t_0 to t_1 , the failure rate is defined as the ratio of probability that a failure may occurs in the interval, while it is given that the failure can't be occurred prior to the time t_0, the start of time interval, divided by its interval length. Mathematically it can be written as [6],

$$\lambda(t) = \frac{R(t0) - R(t1)}{(t1 - t0)\, R(t0)} \tag{5}$$

2.1.1.4 Time Dependency of Failure Rate

Time dependence of failure rate can be described by a familiar Bathtub curve in reliability, having different modes i.e. early period, constant failure period and the wear out time period.

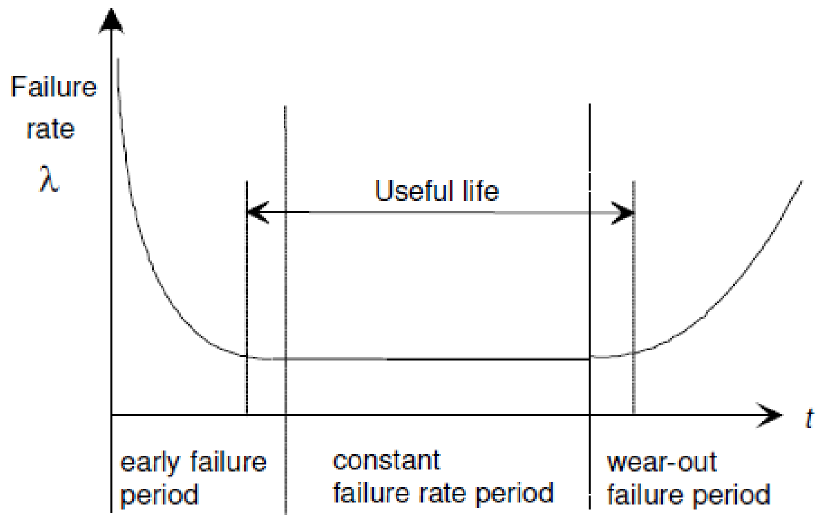

Figure # 2: Time dependence of Failure Rate

2.1.2 Maintainability

The probability that a failed item can be repaired in a specified interval of time using a specified set of resources [6]. It is a measure of action with which an equipment or item can be restored to its working state following occurrence of failure. Maintainability is a function of multiple aspects like equipment design as well as installation, personnel availability, adequacy of maintenance procedures, testing and troubleshooting equipment as well as the physical environment under which the procedure of maintenance is carried out. Maintainability can be denoted by M(t). Mathematically it is defined as,

$$\mathrm{M(t)} = \int_0^t g(t)\, dt \qquad (6)$$

where,

g(t) is Time to repair

Types of Maintainability

- Preventive (Scheduled) Maintenance
- Corrective (Un-Scheduled) Maintenance

2.1.2.1 Preventive (Scheduled) Maintenance

Preventive or scheduled maintenance takes place after a specific interval of time in-order to test the behavior and accuracy of each component installed in a system and if any malfunctioning occurs then desired repair action has been carried out to overcome it.

2.1.2.2 Corrective (Un-Scheduled) Maintenance

While corrective (un-scheduled) maintenance action takes place whenever system fails or failure arises in any part or section of the system. The main task of the maintenance personnel is to identify the specific component or any one of the section in system where there may arises a failure.

2.1.2.3 Time to Repair

Time to failure or the probability density function (pdf) in terms of reliability corresponds to the time to repair or the time to maintain g(t) pdf in maintainability. It is represented as,

$$g\,(t) = \mu(t)\,[\,1 - M(t)\,] \tag{7}$$

where,

$\mu(t)$ is the repair rate

$M(t)$ is the Maintainability Function

2.1.2.4 *Mean Time to Repair*

It is a fundamental measure as far as maintainability is concerned. It can be defined as the mean time which is required and necessary feature in order to complete a maintenance action. Mathematically defined as,

$$\mathrm{MTTR} = \int_{-\infty}^{\infty} t\, g(t) dt \tag{8}$$

Mean Time To Repair also termed as MTTR is a measure of average downtime i.e. the total maintenance downtime (overall time period of system in which system is non-operational) divided by the total maintenance actions for a given time period, It can be expressed as follows,

$$\mathrm{MTTR} = \frac{\text{Total Downtime}}{\text{Number of Failures}} = \frac{\mathrm{Td(t)}}{f} \tag{9}$$

Where,

Td(t) is Total down time

'f' is Total num. of failures

2.1.2.5 *Repair Rate (μ)*

The failure rate function term used reliability, corresponds to repair rate terms in maintainability. Repair rate can be defined as the rate through which a repair action can be carried out and it can be expressed in terms of the number of repair actions performed and also the successful completion of repair action per unit time.

$$\mu(\mathrm{t}) = \frac{g(t)}{1 - M(t)} \tag{10}$$

where,

g(t) is Time to Repair

M(t) Maintainability (Probability of successful maintenance)

2.2 Distribution Fitting

Different techniques for distribution fitting has been implemented in order to analyze the behavior or trend of the dataset. In [7] comparative analysis for the parameter estimation methods of Weibull Distribution and the analysis of accuracy among different methods for best parameter estimation methods, while in [8] Maintainability for various time intervals and Mean Time To Repair (MTTR) values of different shovels have been predicted on the basis of different fitted distribution models. Depending on the suitable and efficient distribution fitting, estimation of MTTR values for the mechanical system of Electric cable shovels.

There are different types of distribution fitting techniques like Maximum Likelihood Estimation (MLE), Least square Estimation, Method of moment, Quantile matching estimation, Goodness of fitting estimation etc.

2.2.1 Maximum Likelihood Estimation

Most common technique for parameter estimation is likelihood estimation. Likelihood estimation is a tool for finding evidence about the unknown parameters of different distributions.

Normally the unknown parameters of distribution denoted by the symbol θ. Let the joint PDF of sample $X = (X_1, X_2 \ldots\ldots X_n)$ is $f(x \mid \theta)$, where θ is an unknown parameter. $X = x$ is described as an observed sample point.

Now the function wrt 'θ' is defined as

$$L(\theta \mid x) = f(x \mid \theta) \qquad (11)$$

Equation 11 is the likelihood function. The log-likelihood function F (θ) is defined as the natural logarithm of the likelihood function L (θ).

More precisely, it can be expressed as:

$$F(\theta) = \ln L(\theta) \tag{12}$$

In many applications, the natural log (Logarithm) of likelihood function is called the log-likelihood. In order to find the value of unknown parameters, first find the maximum of function in equation 12, as maximizing can be obtained by taking the function's derivative. So, after taking the derivative and solve for the parameter to maximize put the equation equals to zero and it is often convenient when the function is being taken maximized is a log-likelihood rather than the actual (original) likelihood functions.

2.3 Prediction Algorithm

In literature review various prediction algorithms have been adopted for estimation of required data by researchers. Out of these techniques a novel algorithm has been implemented in this study for prediction of time to failure of power system.

2.3.1 Recurrent Neural Network (RNN) / Long Short Term Memory (LSTM)

RNN are the type of Neural Networks having feed forward network usually used for the prediction of time series data. As recurrent neural networks have a deficiency which could not be able to model those data or series having long term dependencies. So to overcome this problem another deep learning technique called Long Short Term Memory (LSTM) could be applied to model data having dependencies of long term in series [5].

In LSTM there are multiple small units (memory cells) in hidden layers. Normally, in any type of neural network we observe minimum three type of layers, namely input layer afterwards hidden layer and then an output layer will form a network. While in LSTM it has different layers and gates like forget gate layer, input gate layer, output layer, cell state, input modulation gate and output modulation gate [11] [12].

These gates are activated by different trigonometric functions like the sigmoid function which results values from range 0 to 1 while hyperbolic tanh function returns the value from range -1 to +1. LSTM network comprises of multiple cells interconnected with each other while takes the previous output of cell which becomes the recurrent input for the next cell and also the current input value will be fed. The weights for different layers are learned during the training process of the algorithm which also depends upon multiple parameters like choice of optimizer, number of hidden layers, learning rate, epoches etc. There must be a reasonable selection for these hyper parameters, because if parameters are not properly selected then it results in computation complexity, training time of algorithm may also increase and error in the resultant values. Figure 3 describes the basic memory cell block or unit of LSTM network.

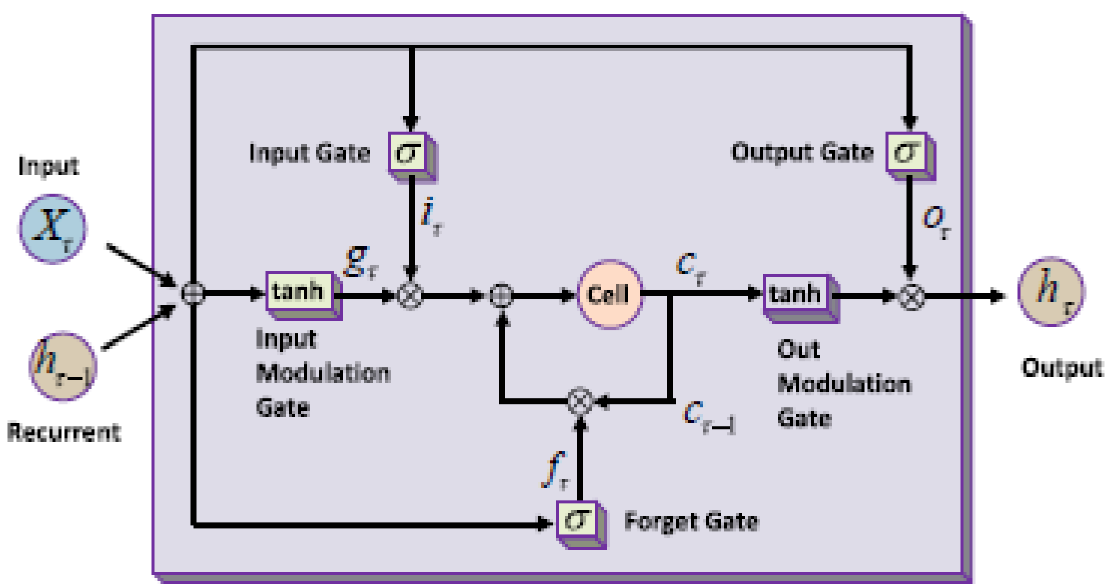

Figure # 3: Unit cell memory of LSTM

CHAPTER # 3 EXPERIMENTAL WORK

The purpose of this chapter is to describe the whole experimental work in this study for the prediction of Time to Failure (TTF) of power system by implementation prediction algorithm to obtain desired results.

3.1 Case Study

Occurrence of failures in power grids have become a common factor in power outages which are required to overcome. There are multiple causes of power failures like equipment faults, environmental effects, lightning, operating faults, damage in transmission and distribution lines etc. Power failures results in huge loss of production (for industrial consumers) as well as other related sectors if they lies for longer duration. On analyzing the dataset [9] frequent causes of power grid failure are the equipment and environmental faults. So in order to overcome this issue or minimize the power failures, prediction based approaches has been proposed in this study to predict the time to failure of power grids.

3.2 Dataset Description

The dataset comprises of Failures in Power Grids installed in different regions of Australia [9**].** Outages (failure) data consists of multiple parameters (features) like, failure region, failure's start date & time, average outage (shutdown/repair) time in minutes (TTR), Number of customers affected and reason or root cause of power failure in the power grid. As per dataset mostly failures in the power grids caused by equipment failures or through the environmental conditions, while the failures occurs due to other elements like operating faults and lightning are rare. Quarterly failure data of six years from 2013 to 2018 is available in dataset**.** As per the given source there were some constraints during compilation of dataset, the data contains information having failure duration of more than 5 minutes and customers affected by failures will be at least 50 or more. Out of many local government regions (areas) of Australia, Canterbury region among them is focused for the analysis throughout this study. Table 1 represents the sample dataset starting from the year 2013 having different aforementioned features.

Table # 1: Australian Power Grid Dataset sample

S #	LGA	Start Date	TTF (hrs.)	Start Time	TBF (hrs.)	Customers Interrupted	TTR (min)	Reason
1	Canterbury	5/1/2013	5	3:19 PM	0	1000	32	Equipment fault
2	Canterbury	8/1/2013	8	10:44 PM	79	99	105	Environmental
3	Canterbury	13/01/2013	13	5:05 PM	114	100	160	Equipment fault
4	Canterbury	16/01/2013	16	3:11 PM	70	188	219	Third party
5	Canterbury	18/01/2013	18	8:49 PM	53	66	356	Environmental
6	Canterbury	20/01/2013	20	11:34 AM	38	172	79	Equipment fault
7	Canterbury	25/01/2013	25	2:30 PM	122	64	75	Environmental
8	Canterbury	26/01/2013	26	6:03 PM	27	63	56	Equipment fault
9	Canterbury	19/02/2013	50	12:13 PM	570	80	87	Environmental
10	Canterbury	1/3/2013	60	10:25 AM	238	70	65	Environmental
11	Canterbury	17/03/2013	77	8:14 AM	381	85	55	Environmental
12	Canterbury	28/03/2013	88	5:16 PM	273	65	43	Third party
13	Canterbury	5/4/2013	95	5:14 AM	179	71	106	Equipment fault
14	Canterbury	5/4/2013	95.5	9:12 PM	15	79	93	Equipment fault
15	Canterbury	15/04/2013	105	8:56 AM	227	1128	85	Equipment fault
16	Canterbury	27/04/2013	117	9:55 AM	228	2102	44	Equipment fault
17	Canterbury	1/5/2013	121	1:24 PM	99	6326	25	Environmental
18	Canterbury	2/5/2013	122	9:38 PM	20	2088	126	Equipment fault
19	Canterbury	31/05/2013	151	12:10 AM	686	61	72	Environmental
20	Canterbury	31/05/2013	151.5	10:38 AM	10	62	297	Equipment fault

For distributing fitting on data, Weibull distribution is applied as shown in figure 4-9, and then for computation of Weibull parameters will be obtained by using MLE approach.

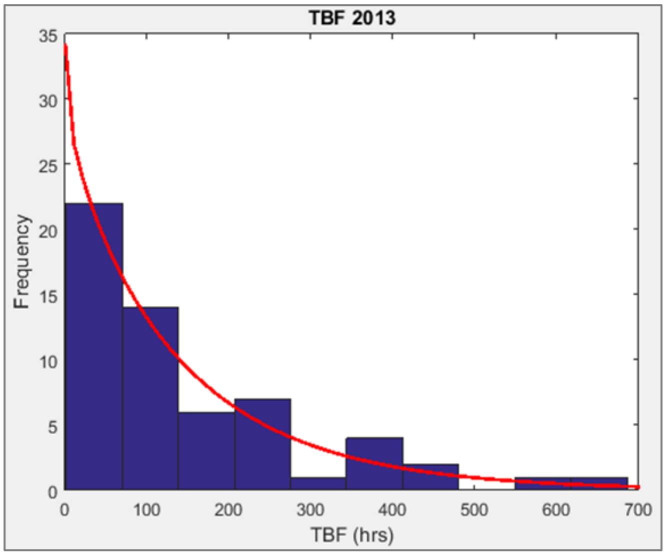

Figure # 4: Weibull Fit on TTF data for year 2013

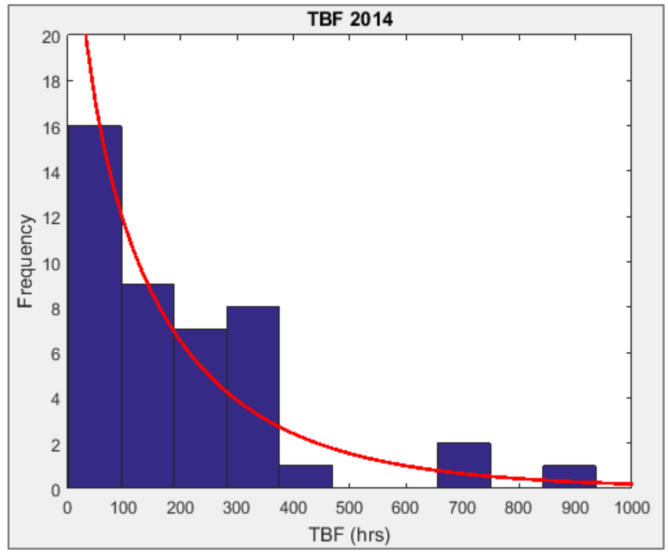

Figure # 5: Weibull Fit on TTF data for year 2014

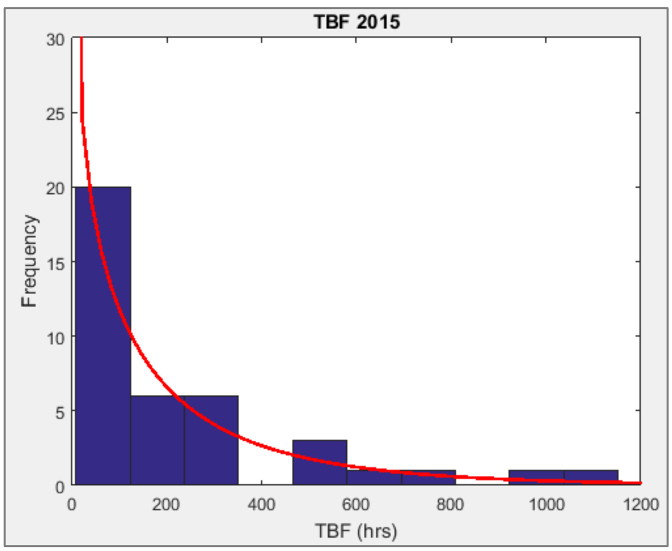

Figure # 6: Weibull Fit on TTF data for year 2015

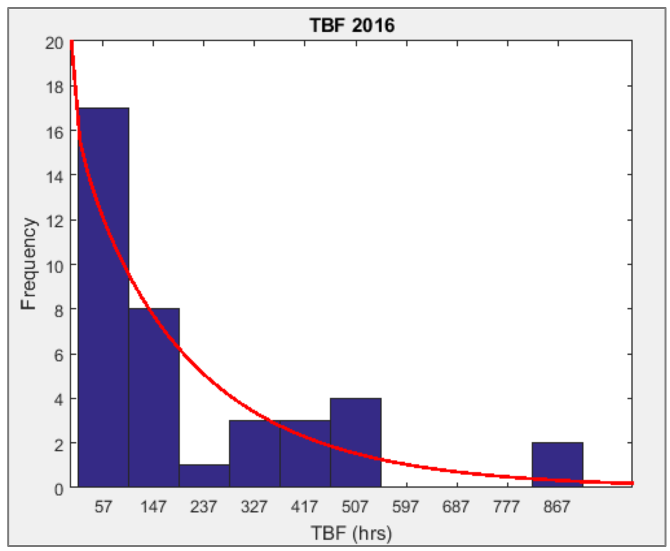

Figure # 7: Weibull Fit on TTF data for year 2016

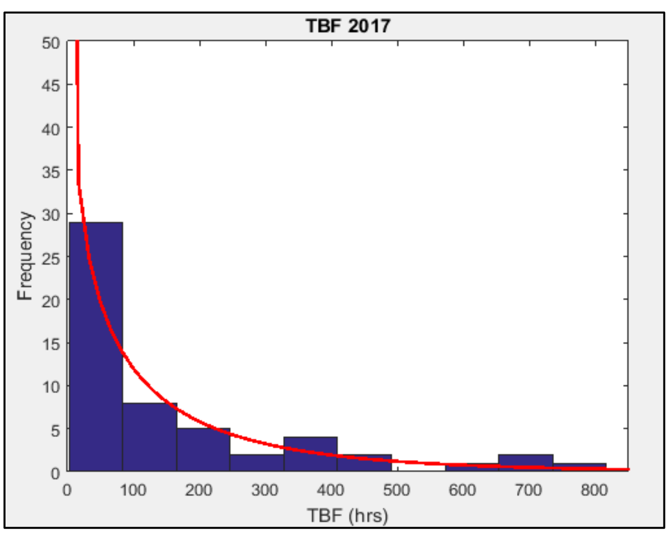

Figure # 8: Weibull Fit on TTF data for year 2017

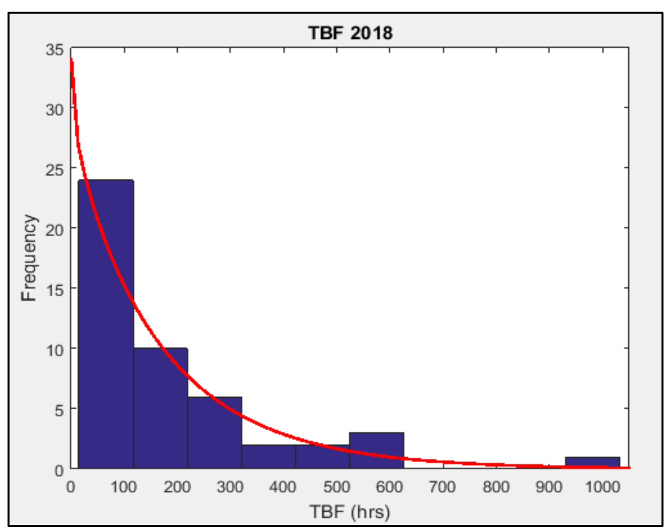

Figure # 9: Weibull Fit on TTF data for year 2018

Figure 10 consist of the probability plots of Time to failures for each year. Probability plots are the technique (graphically) to analyze that the said distribution which is applied on the given data is fitted (i.e. data set able to follow the distribution correctly or not). Since in following figure it can be observed that TTF data is approximately coincides and mapped on the straight line. So, distribution (Weibull) is fit on the dataset which results that TTF data of each years are following the Weibull distribution.

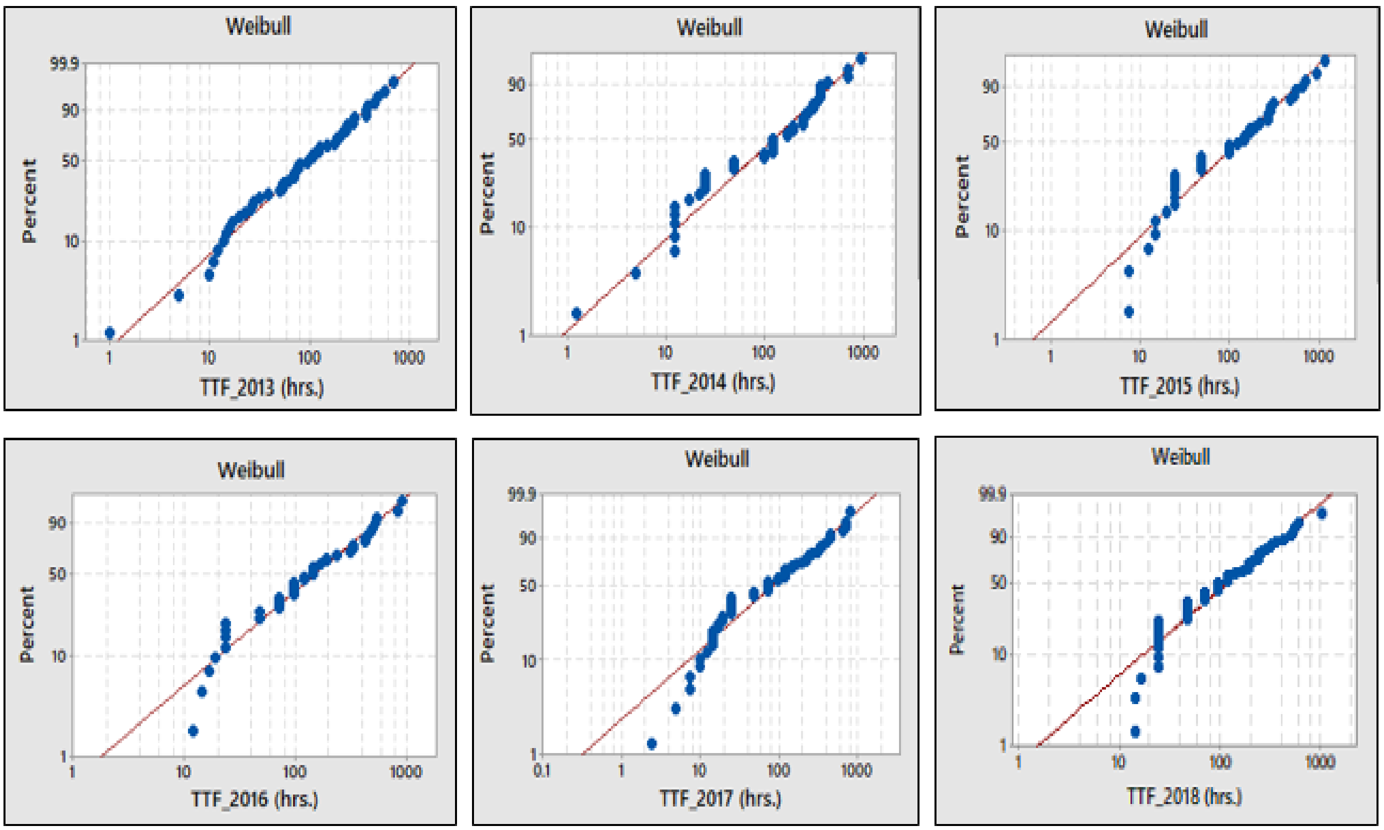

Figure # 10: Probability Plots of TTF (Years) 2013-2018)

Table 2 comprises for Weibull parameters (alpha and beta) i.e. scale and shape parameters respectively. Since all the values of Beta (i.e. shape parameter) are closer to unity (1) so it can be said that the Weibull distribution is identical to exponential distribution [7].

Table 2: TTF Weibull Parameters (2013 – 2018)

YEAR	ALPHA	BETA
2013	147.1614	0.9595
2014	180.781	0.861
2015	192.01	0.801
2016	217.7	0.958
2017	134.19	0.7575
2018	177.25	0.963

Following figure consist of the event plot obtained through Minitab Software. Normally event plot contains information about occurrence of multiple events on same plot. Similarly in following figure Time to Failure values of power system are plotted for each individual year starting from 2013 to 2018.

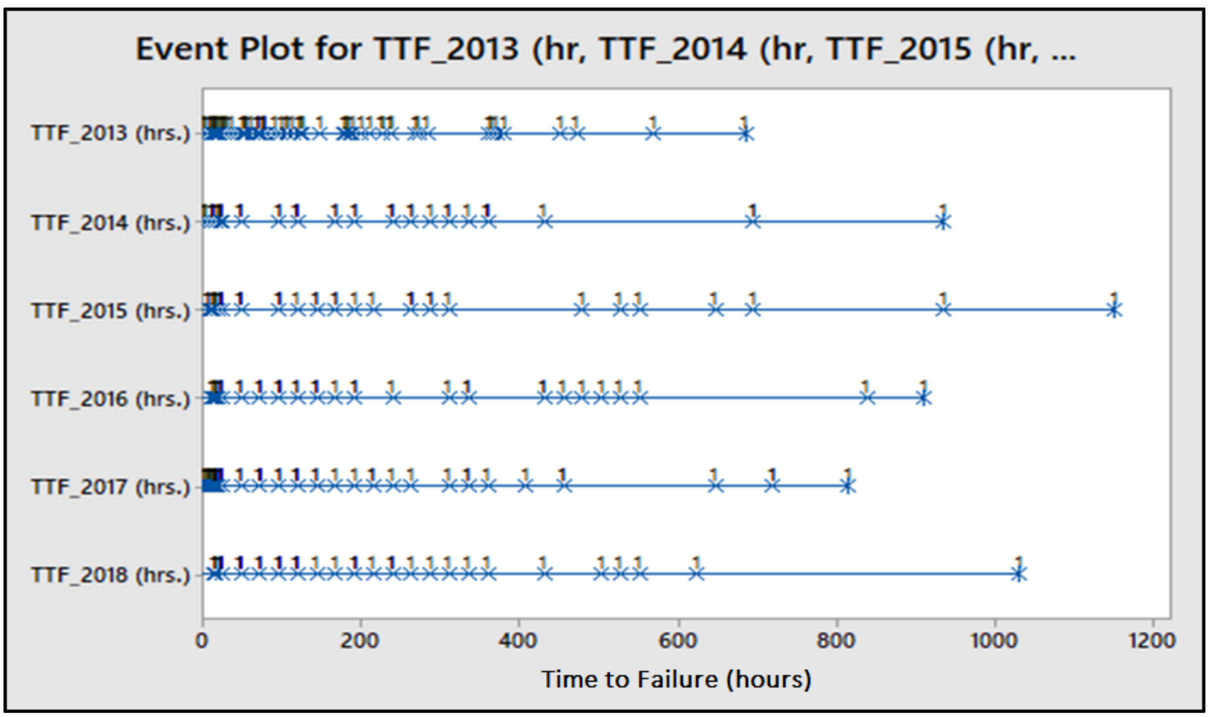

Figure # 11: Event Plots of TTF (Year 2013-2018)

3.3 Implementation of LSTM Algorithm

Initially the historical Time to Failure (TTF) data will be taken and then its will be standardized in order to perform pre-processing steps for better performance. Then, selection of different layers of network will be defined i.e. input layer, hidden layers (which would be responsible for computation of weights learned during the training process) and also the output layer for computation of results. Now, there are various parameters like epochs, optimizer, learning rate period and scheduler and many more. Afterwards training of LSTM model will begin with the help of different gates and layers of LSTM model. The weights are learned during the training process, therefore the computation complexity of training phase of LSTM is greater than the incoming testing phase. The reason is that in Testing (prediction) phase of LSTM model the already learned weights will be utilized to predict the future states of TTF. Also root mean square (RMSE) will also be computed for comparison of different datasets combination.

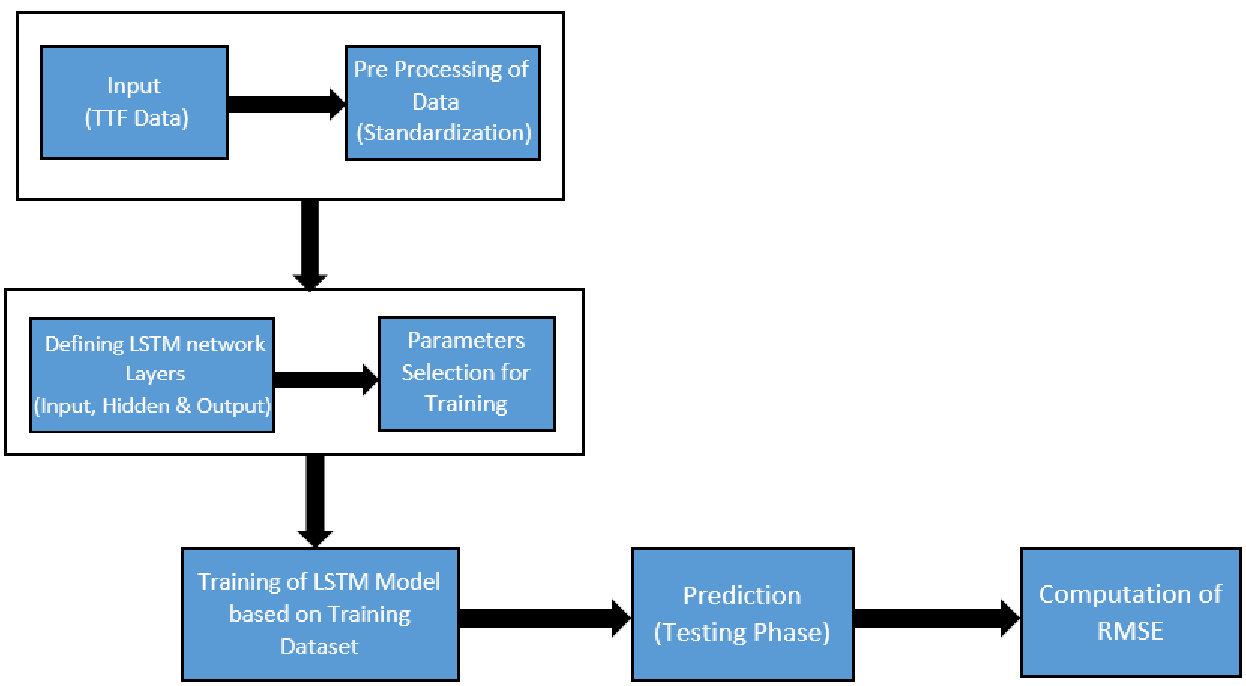

Figure # 12: Block Diagram for the implementation of Algorithm

In LSTM initially as shown in figure 13, there is forget gate. The purpose of forget gate layer is responsible for segregation of information i.e. whether to store or keep the information or neglect (forget) it. Since there is a sigmoid (σ) activation function which results in the values in range from 0 to 1. For values near to 0 indicates the value of cell state will be ignored while 1 indicates that information in cell state will be kept (hold). The mathematical equation for forget gate layer is,

$$f_{\tau=}\ \sigma\,(W_{xf}\,x_{\tau}\ +\ W_{hf}\,h_{\tau-1}\ + b_{f}\,) \tag{13}$$

Where,

σ is the Sigmoid Activation Function

W is the weight matrix

b is the bias term

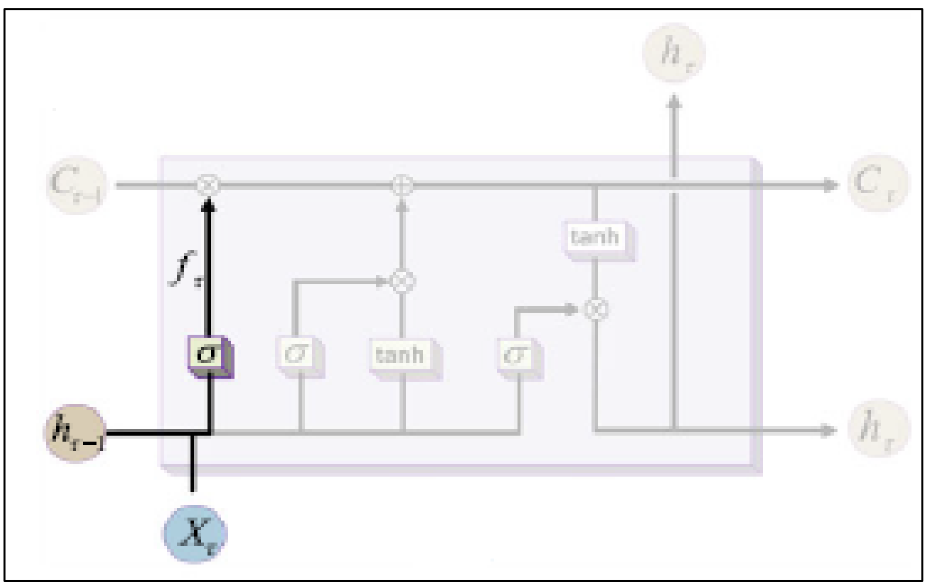

Figure # 13: Forget Layer for LSTM

In the next stage whose purpose is to compute a new contribution or addition to the cell state. Now the input x_{τ} and hidden state $h_{\tau-1}$ are fed to the sigmoid function as done in previous step. Afterwards using tangential (tanh) function creates a vector of new values (information) to the cell state. Then multiplication of two incoming gates i.e. i_τ and g_τ will be done and these will be added to the cell state through addition operation. Mathematical equation is shown below.

$$i_{\tau=} \ \sigma\,(W_{xi}\,x_\tau \ + \ W_{hi}\,h_{\tau-1} \ + b_i\,) \tag{14}$$

$$g_{\tau=} \ \tanh\,(W_{xg}\,x_\tau \ + \ W_{hg}\,h_{\tau-1} \ + b_g\,) \tag{15}$$

Where,

W is the weight matrix

b is the bias term

tanh is the hyperbolic tangent function

σ is the sigmoid function

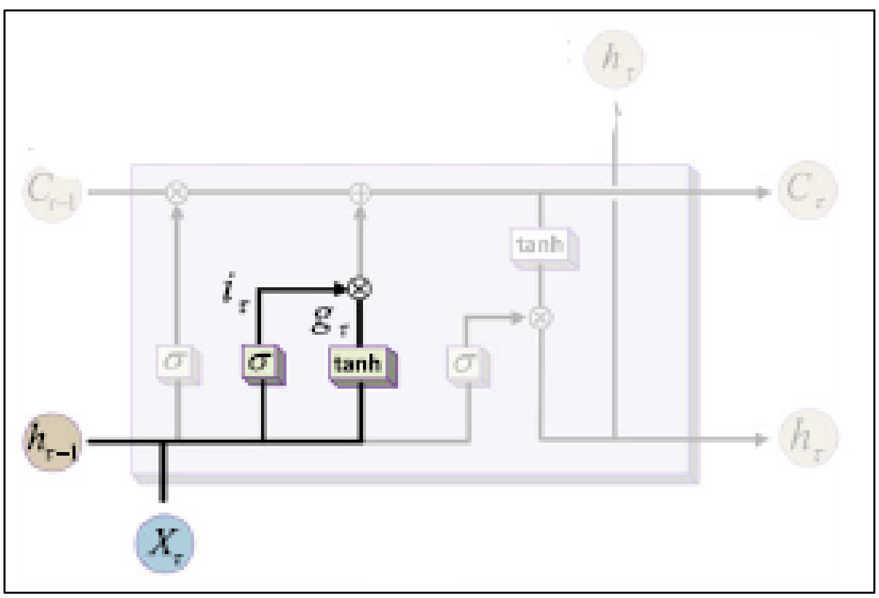

Figure # 14: Input and modulation gate layer for LSTM

In next step as given in figure 15 the top line indicating to the LSTM unit is the cell state. So update the previous value of cell state $c_{\tau-1}$ to the new state i.e. c_{τ} or in other terms we interpolate new cell values. The output of forget gate is multiplied with the previous cell state then add it with two incoming quantities i_{τ} and g_{τ} since these are the new candidate values. Cell state is important as far as the output of LSTM is concerned. It can be expressed as follows.

$$c_{\tau=} \; f_{\tau} \otimes c_{\tau-1} + i_{\tau} \otimes g_{\tau} \tag{16}$$

Where,

f_{τ} is the forget gate layer

i_{τ} is the input gate layer

g_{τ} is the input modulation gate

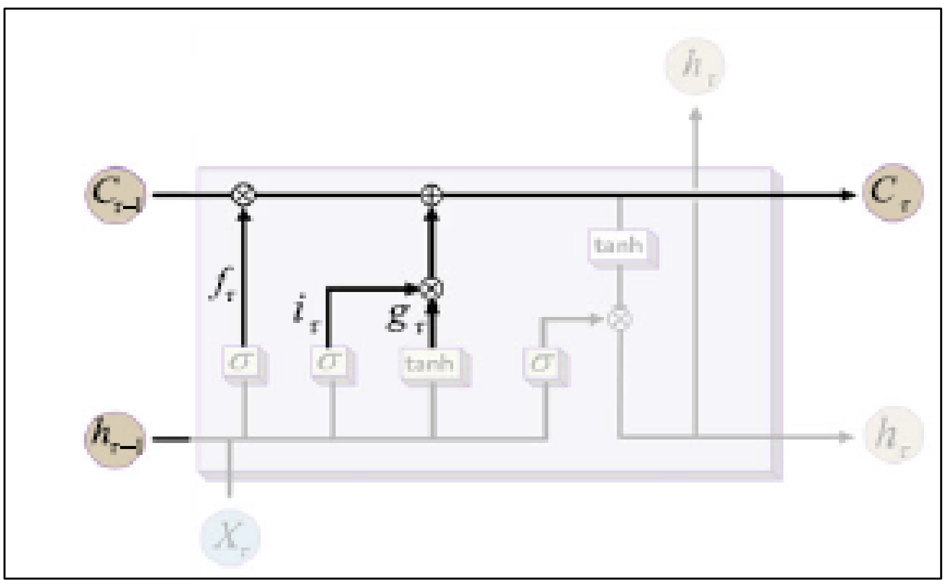

Figure # 15: Cell State for LSTM

In the last step for the final output the input and the previous hidden state will gain fed to the sigmoid function to obtain o_{τ} . Now the updated cell state will pass through the tanh activation function (which gives the values in the range from -1 to 1). This result will be multiplied with the previous obtained output from o_{τ} , and then the final result i.e. h_{τ} will be achieved. The mathematical expression of output gate h_{τ} and output layer o_{τ} is,

$$o_{\tau=} \sigma \left(W_{xo}\, x_{\tau} + W_{ho}\, h_{\tau-1} + b_{o}\right) \tag{17}$$

$$h_{\tau=} o_{\tau} \otimes \tanh(c_{\tau}) \tag{18}$$

$\boldsymbol{o_{\tau}}$ is the output layer

$\boldsymbol{h_{\tau-1}}$ is the previous output modulation gate

$\boldsymbol{c_{\tau}}$ is the cell state

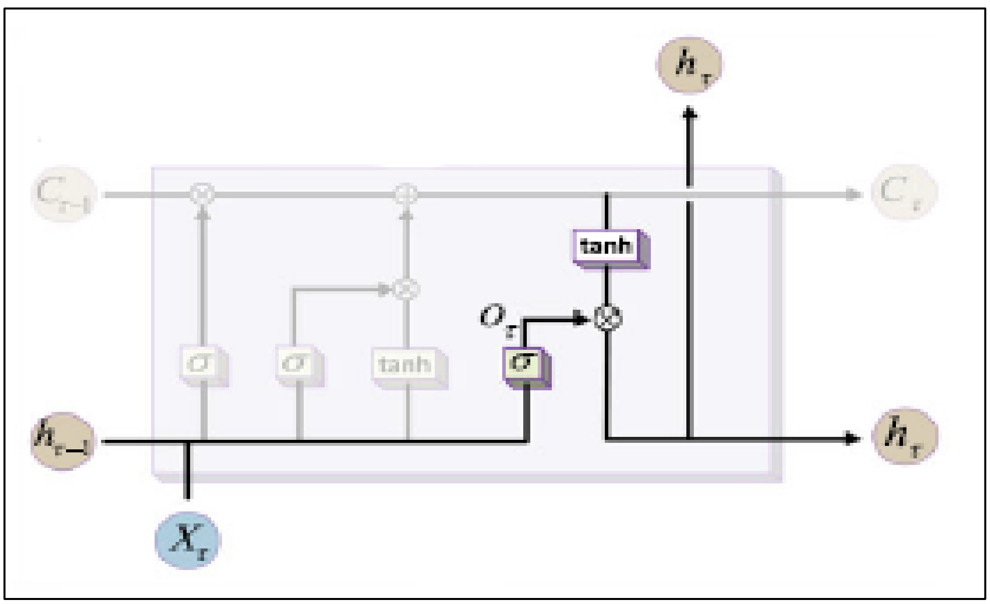

Figure # 16: Output Layer of LSTM

CHAPTER # 4 CALCULATION & RESULTS

This chapter consist of the observation, results and calculation obtained in this study. Also the discussion and analysis on the obtained results has also been carried out in this chapter.

4.1 Prediction of TTF using LSTM Technique

Time to failure data as the time sequence values for LSTM input to model for the training of algorithm. The dataset in case study gives information about the time to failure for power grids having 280 failure samples. There are two phases first one is training and the other one is testing (prediction). So initially 80% of the samples have been used to train the network while remaining 20% (each of the same number of samples will be utilized for prediction/testing purpose. In order to make LSTM model input size (size of sequence for input layer) is considered to be 1 since there is one temporal TTF feature. Also the output layer (number of fully connected layer) is also considered to be 1. And finally the main and paramount hidden layer (which correspond to number of neurons in Neural Networks) is taken to 200. For standardization of data mean and standard deviation is computed for the train data in order for normalization.

There are some additional training parameters selected for the better results during the training process and then prediction. First parameter is the selection of optimizer for training, there are different options for optimizer i.e. adam, sgdm and rmsprop but adam (adaptive moment estimation) and sgdm (stochastic gradient descent momentum) options are adopted form them because it identifies the decay rate for the gradient and for squared gradient moving averages. Second parameter is the number of Epoches (time instants for training).

Then few more parameters are gradient threshold. Initial learning rate, learn rate schedule, learn rate drop period, learn rate drop factor and verbose. The values which have been selected for training parameters are listed in following table.

Table 3: Parameters for Training process of All Power Failures in LSTM

S. No	Parameter	Value
1	Optimizer	adam
2	Max epochs	200
3	Gradient Threshold	1
4	Initial Learn Rate	0.003
5	Learn Rate Schedule	Piecewise
6	Learn Rate Drop Period	125
7	Learn Rate Drop Factor	0.2
8	Verbose	0

Table 4: Parameters for Training process of Equipment Failure in LSTM

S. No	Parameter	Value
1	Optimizer	Sgdm
2	Max epochs	200
3	Gradient Threshold	1
4	Initial Learn Rate	0.004
5	Learn Rate Schedule	Piecewise
6	Learn Rate Drop Period	125
7	Learn Rate Drop Factor	0.2
8	Verbose	0

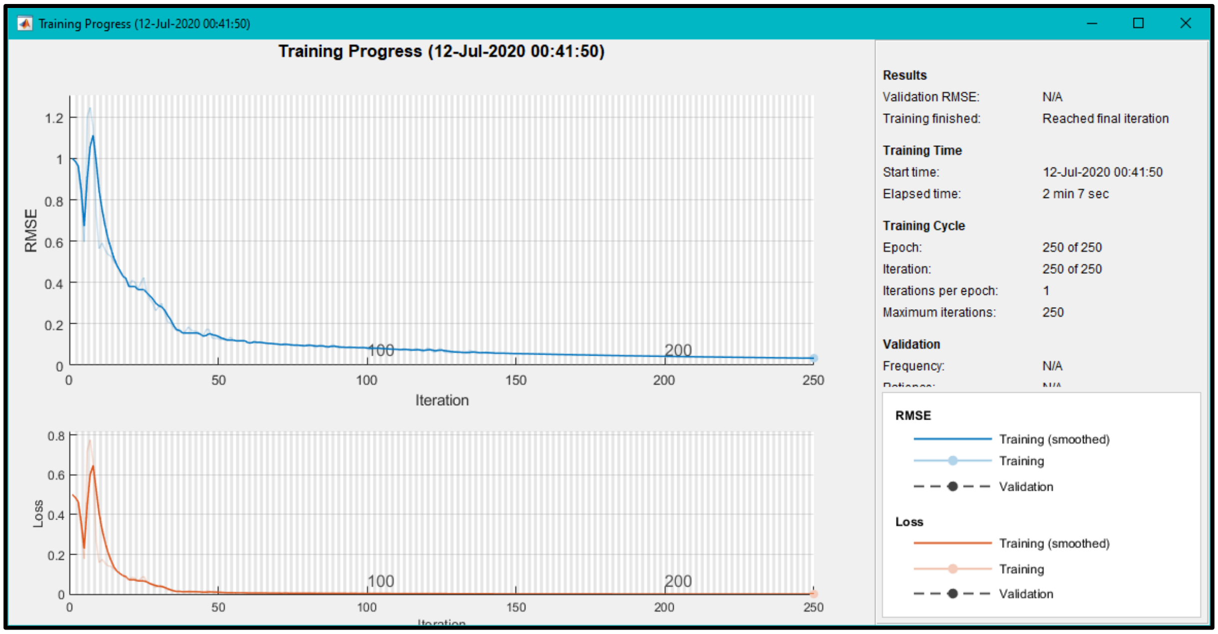

Figure # 17: ADAM Optimizer Training Progress

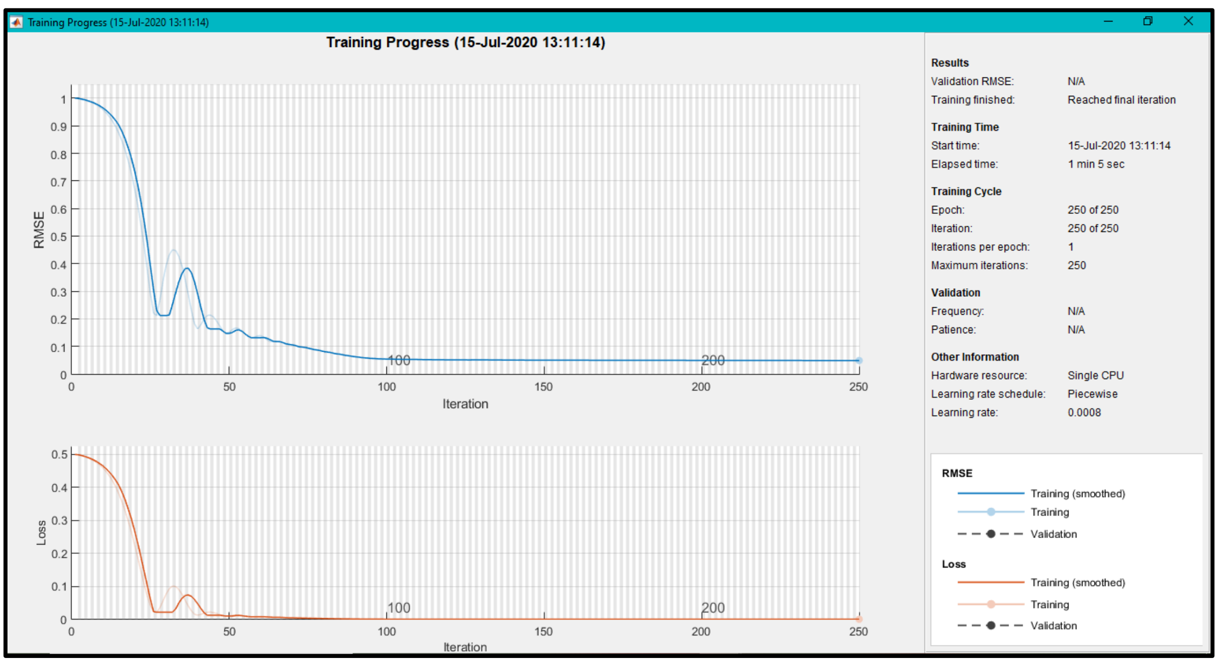

Figure # 18: SGDM Optimizer Training Progress

Afterwards for the training of model trainNetwork command is applied having parameters like train data, test data, number of layers and training options as discussed earlier. Now, to predict the future time steps, first model will be trained by using the training dataset. And after training the prediction of future time steps for test data will be computed by using the previously trained network. In order to predict the values of number of time steps in fore-coming future states, so a function called predictAndUpdateState will be applied to forecast the time step one at a time and then afterwards update the network state for each of the prediction. So, for every prediction of TTF values, usage of the previous prediction as an input value to the function is applied. Figure 19 shows the plot for training time series with the predicted (forecast) values.

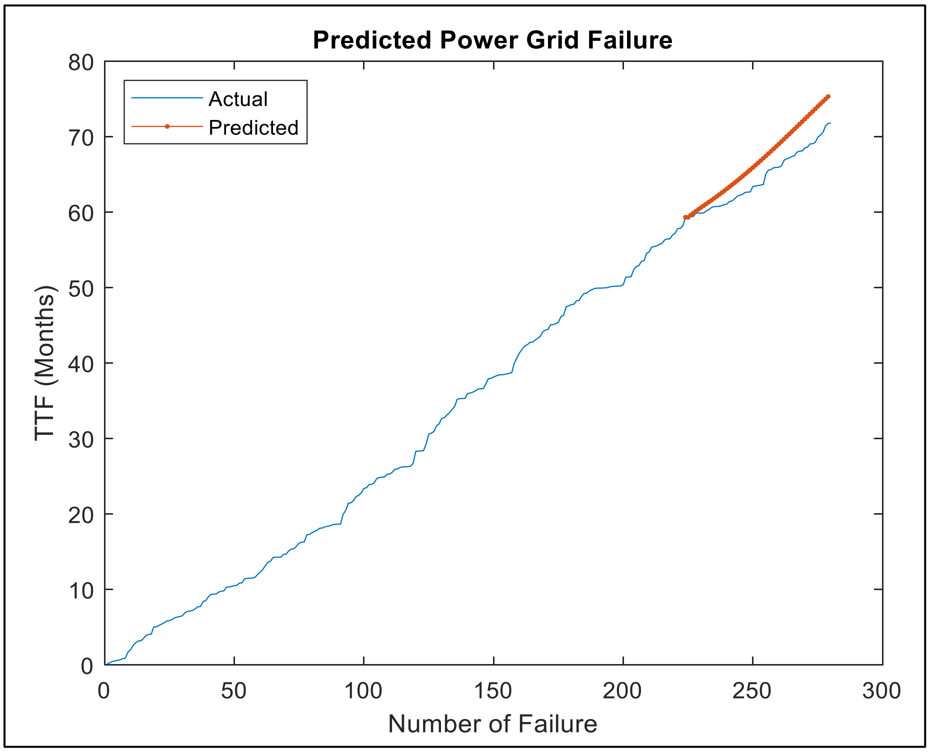

Figure # 19: Actual and Predicted TTF values without update (80 % Training)

In order to calculate the accuracy for prediction, root mean square error (RMSE) between the test and the predicted data is required to be computed. The purpose of RMSE is to find the difference (error) between the actual test value and the predicted value. First there is a need to unstandardized the data before finding RMSE. The mathematical expression for root mean square error is,

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}[(\mathrm{Predicted})_i - (\mathrm{Actual})_i]^2}{N}} \tag{19}$$

Figure 19 describes the plots of predicted and the actual test values of Time to failure of power grid, while in subplots of figure 20, calculated root mean square error (RMSE) and its plot between the predicted and the observed value of time to failure. Since this is only prediction i.e. having no update phenomena which results in high value of RMSE between the actual and predicted TTF.

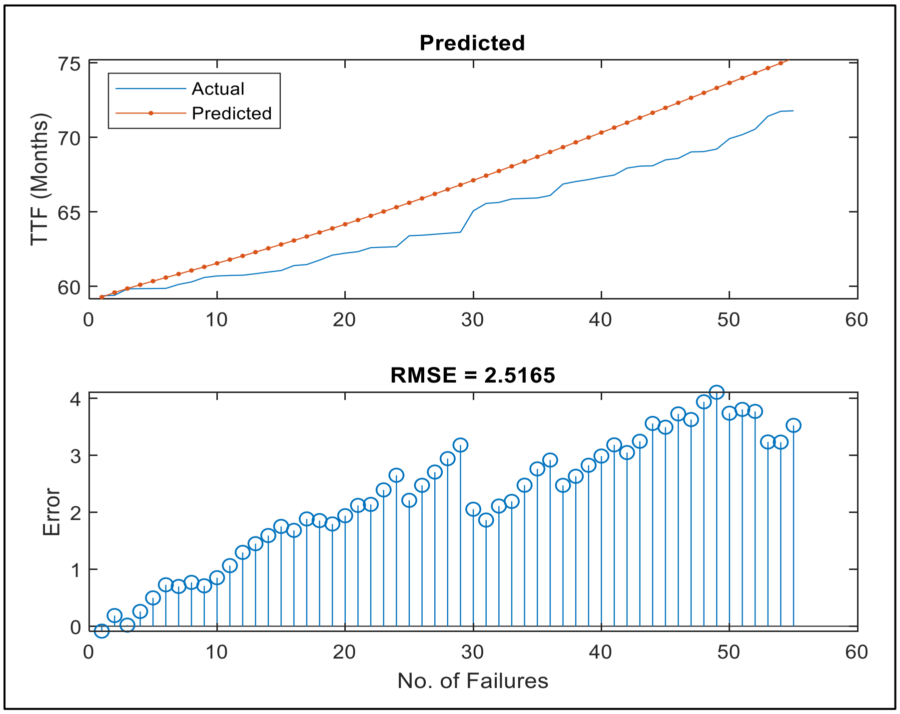

Figure # 20: Predicted TTF values without update with RMSE

Now for the update of prediction model, we need to consider observed values instead of predicted valued obtained before. First the network will be reset in order to prevent the previously obtained predictions to alter (effect) the predictions for the newly data. It can be observed in figure 21 that after reset and update the network with the observed values the prediction becomes better, which results the desired output.

Now when we obtain root mean square between the observed and newly predicted values using the equation 25. Since it can be observed that observed values are close the new predicted values, so RMSE becomes decreases which shows less error between them and comparatively better results as shown in figure 22.

4.2 Prediction Results of TTF of Power Grid Failures

Now, as discussed in dataset 280 time to failure values are present. So, 80% values among them were considered for training the model i.e. 225 values. Afterwards the remaining 55 steps were predicted through the trained model (by the weights which were learned during the training process). Figure 21 consist of actual TTF values and also the predicted and updated TTF values. By analyzing the predicted results with the actual values, it can be concluded that the obtained predicted values are reasonable.

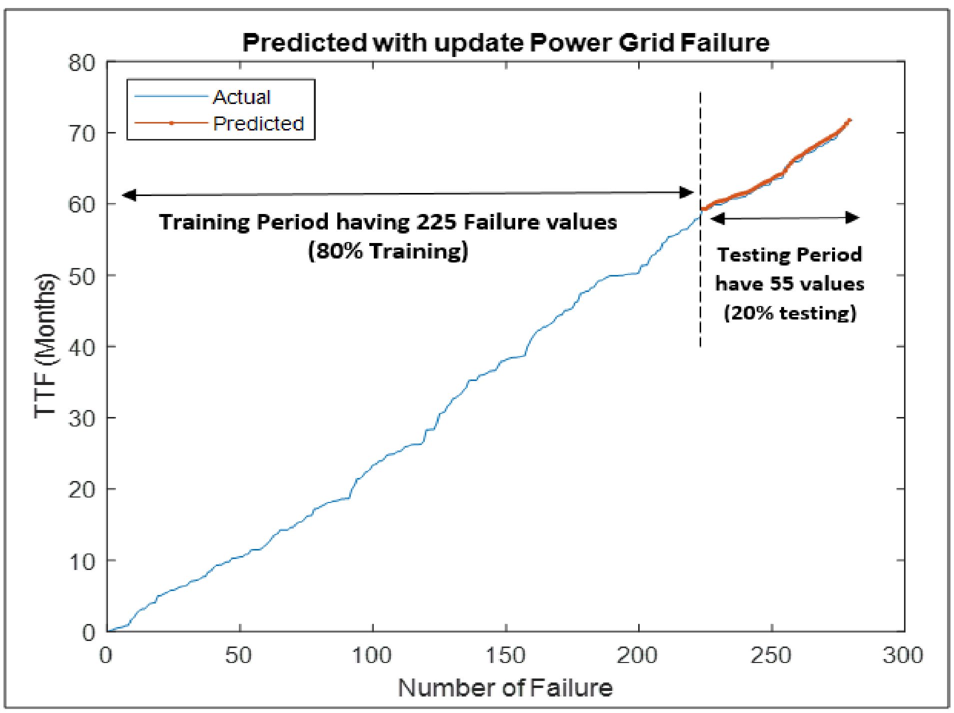

Figure # 21: Actual and Predicted TTF values with Update (80 % Training)

Figure 22 comprises of 55 predicted values (testing period) compared with the actual TTF values. Also RMSE has been calculated between the actual and predicted values. RMSE value is found to be 0.337 which means the predicted value is fine.

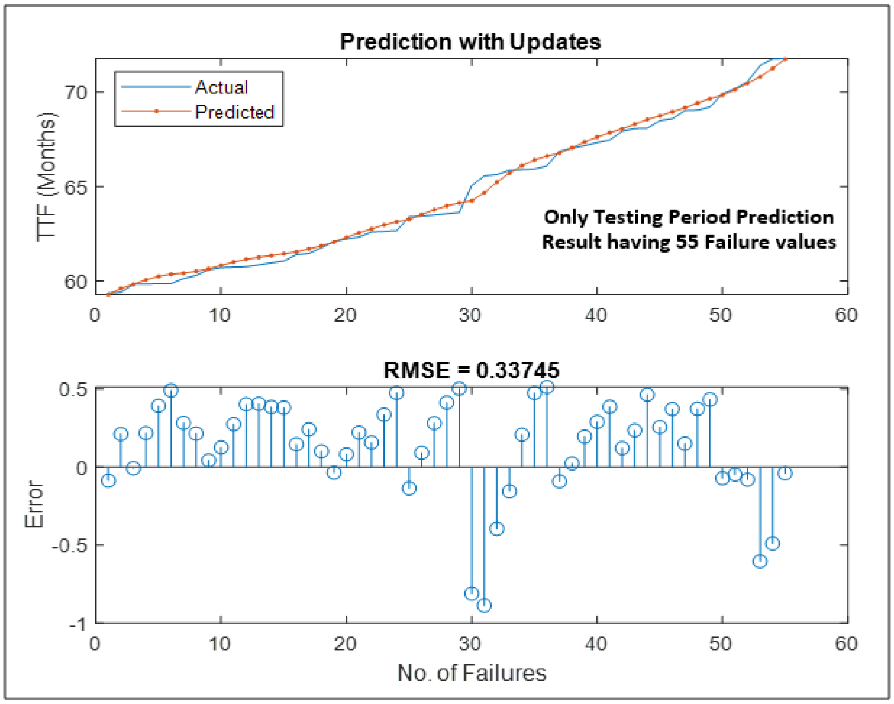

Figure # 22: Predicted TTF values with update having RMSE (80 % Training)

Now in next stage, 70% (195 values) were used for training the algorithm.

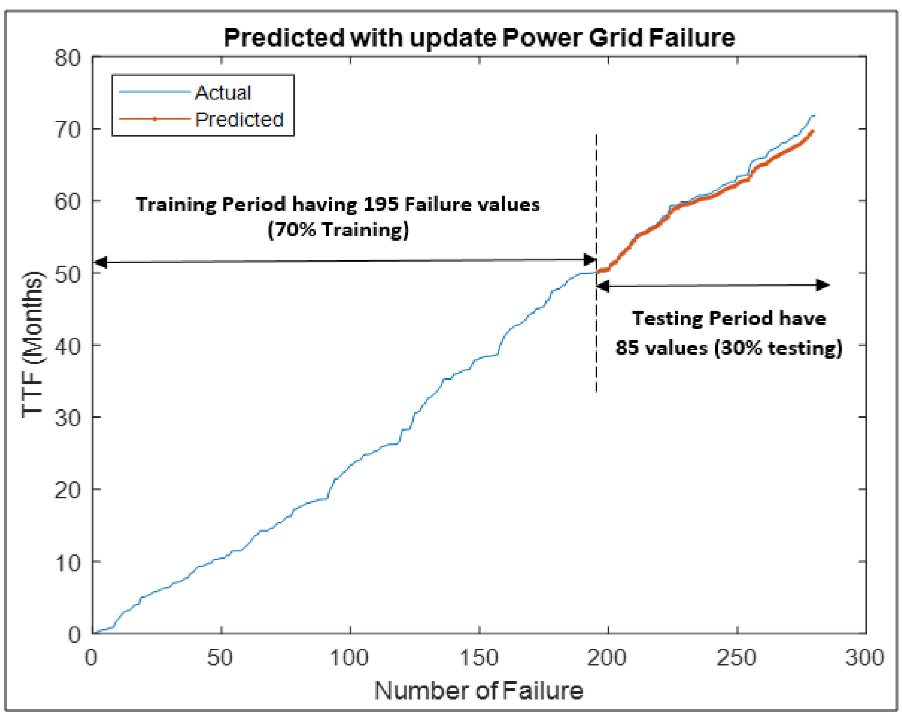

Figure # 23: Actual and Predicted TTF values with Update (70 % Training)

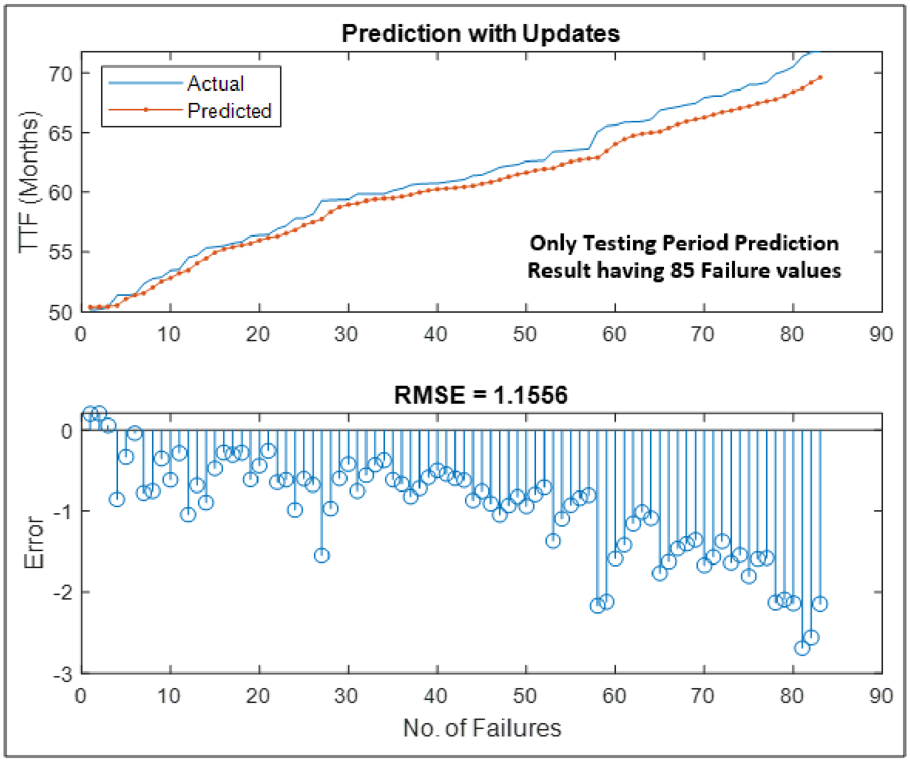

Figure # 24: Predicted TTF values with update having RMSE (70 % Training)

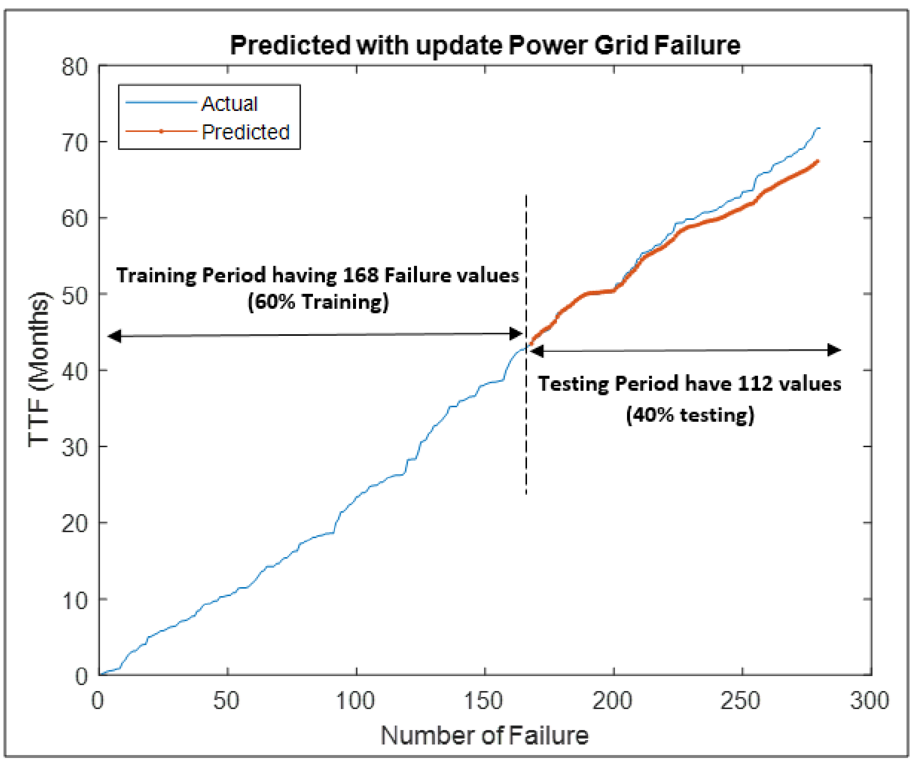

Figure # 25: Actual and Predicted TTF values with Update (60 % Training)

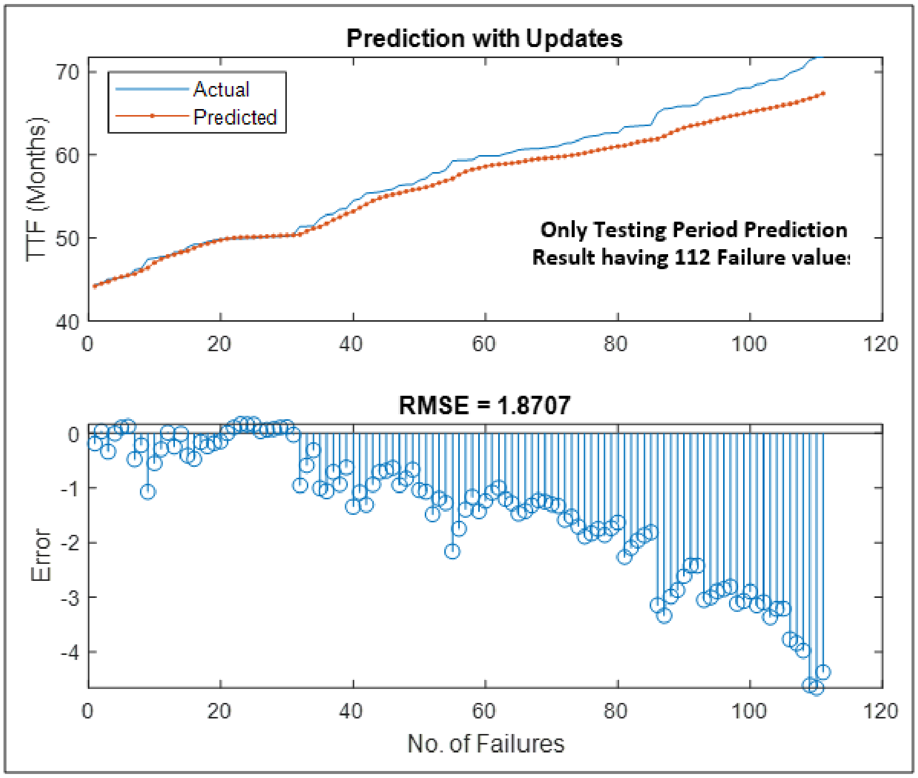

Figure # 26: Predicted TTF values with update having RMSE (60 % Training)

4.3 Prediction Results of TTF of Equipment Failures

Up-till prediction of time to failure were computed for the overall failure causes i.e. Environmental, Equipment faults, lightning etc. Now, there will be prediction for equipment failures in power systems. For this purpose, failures arises due to equipment faults were segregated from overall failures. So, 160 equipment failure values have been found. Equipment failures are the most frequent failure causes in power systems, so prediction of failures has been computed in upcoming results. Again, first 80% equipment failure data (i.e. around 128 values) considered for training the LSTM model and then prediction of remaining values. 32 Values has been computed (predicted) for Power grid equipment failures.

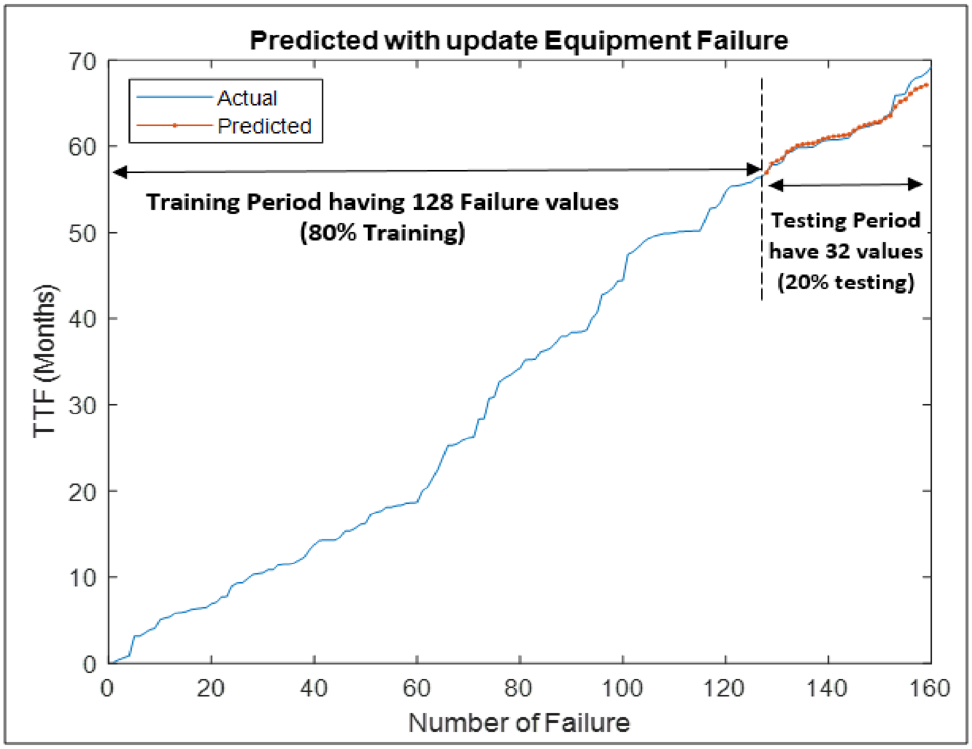

Figure # 27: Actual and Predicted Equipment Failure values (80 % Training)

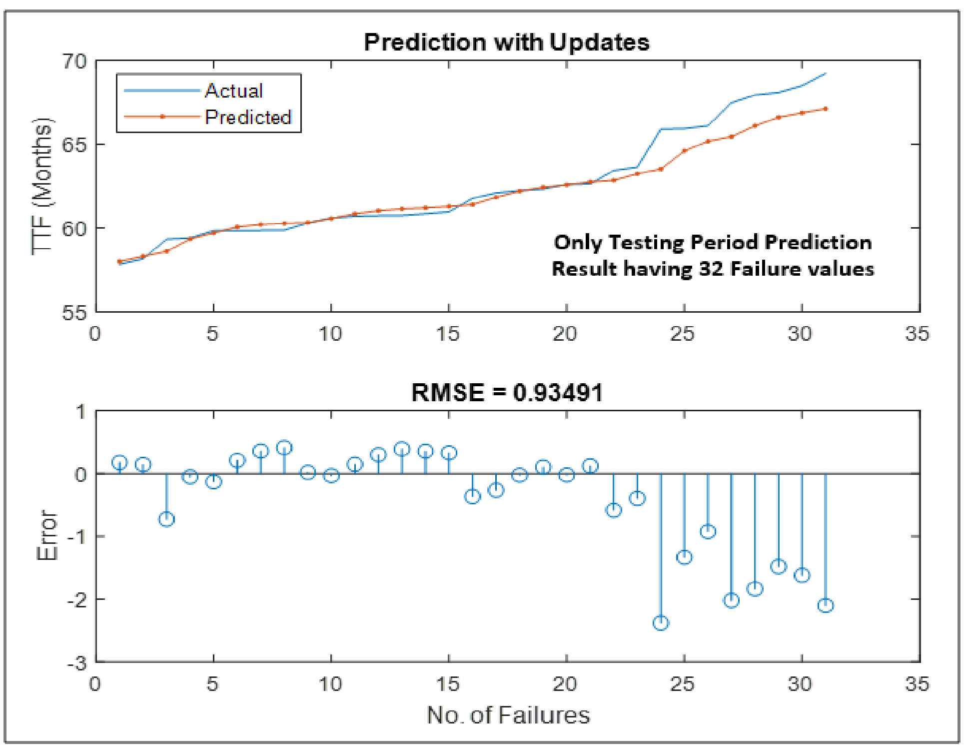

Figure # 28: Predicted Equipment Failure values having RMSE (80 % Training)

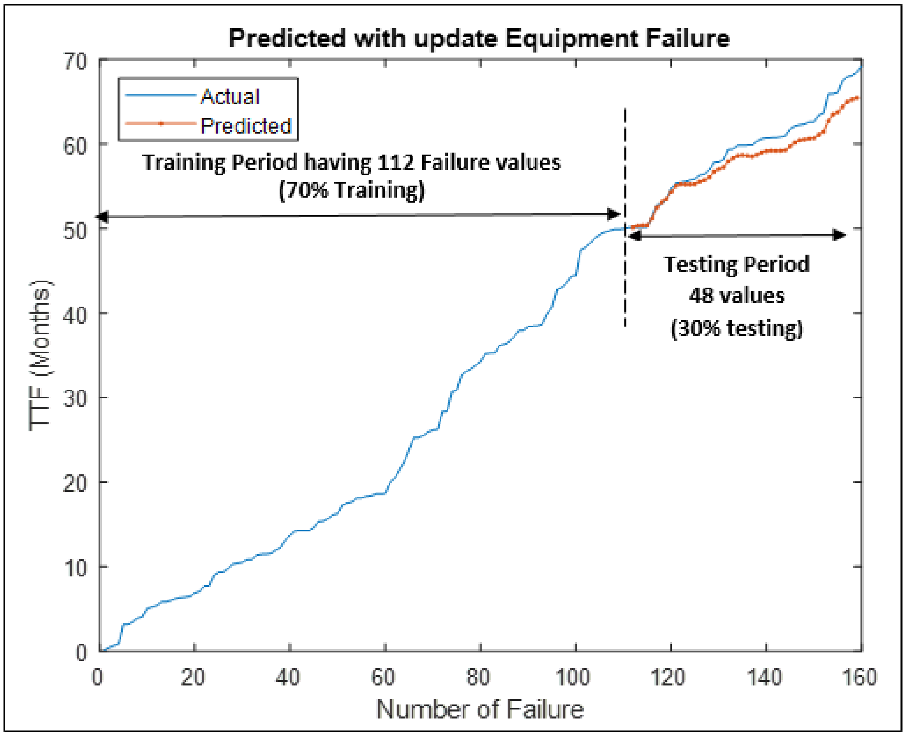

Figure # 29: Actual and Predicted Equipment Failure values (70 % Training)

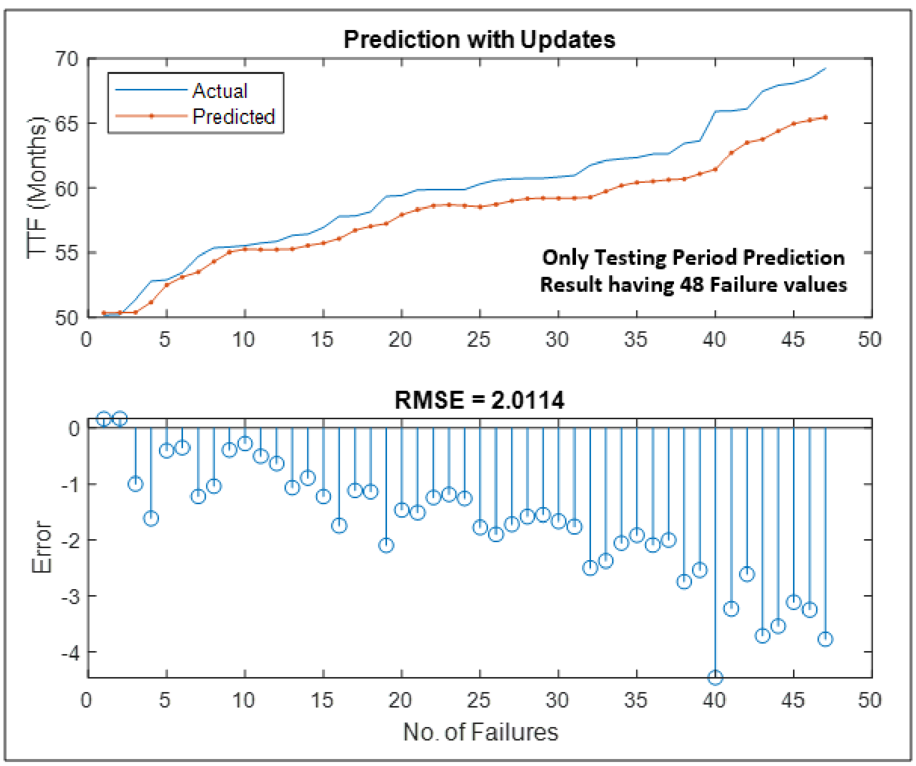

Figure # 30: Actual Equipment Failure values having RMSE (70 % Training)

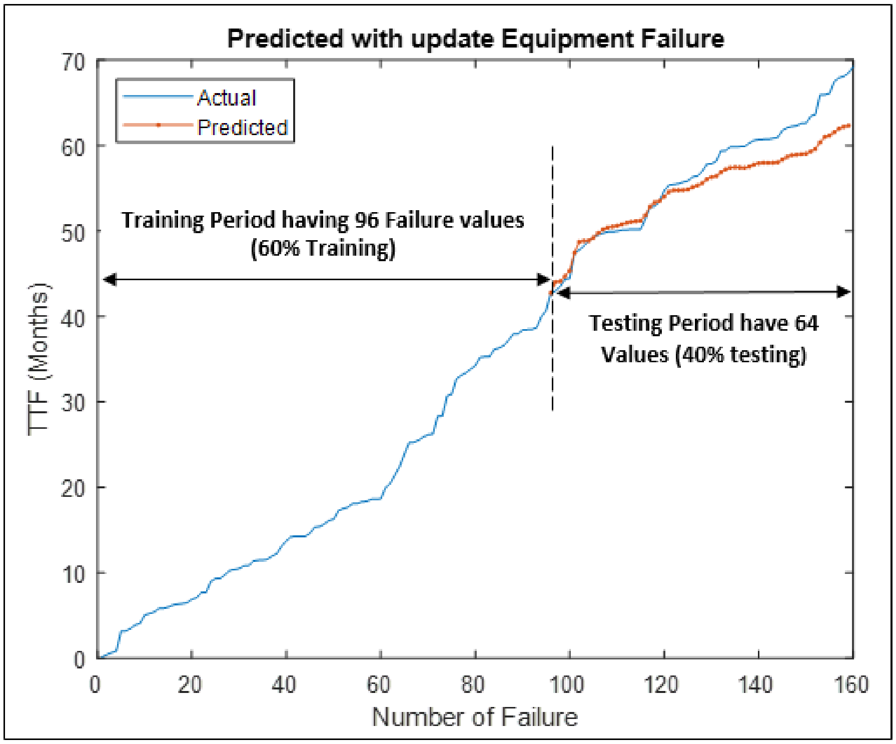

Figure # 31: Actual and Predicted Equipment Failure values (60 % Training)

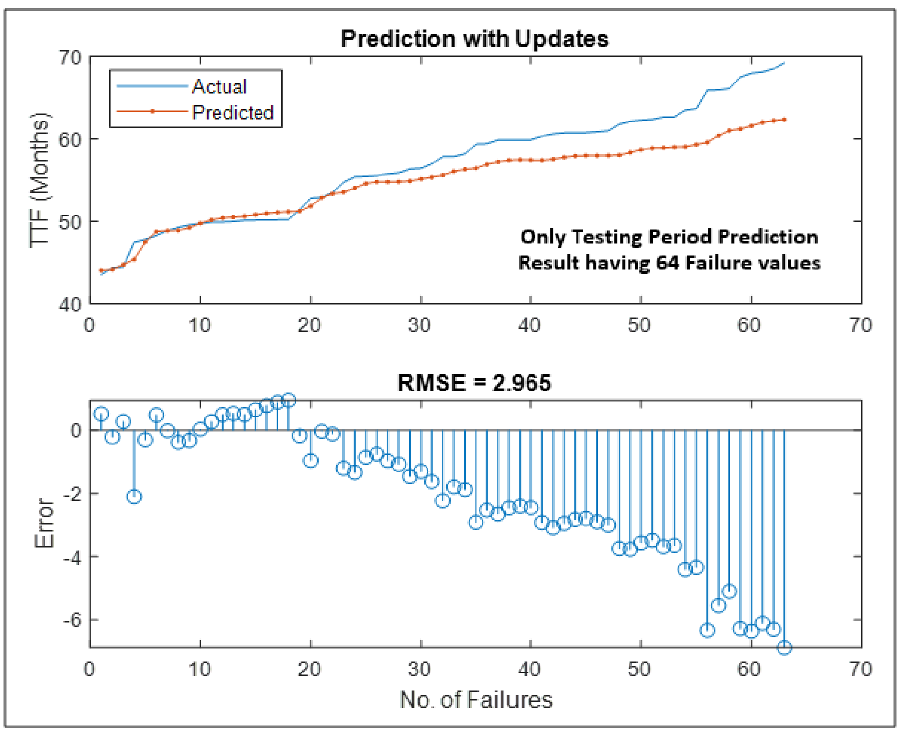

Figure # 32: Actual Equipment Failure values having RMSE (60 % Training)

4.4 RMSE values of Time to Failure Time Steps on different Training Datasets

4.4.1 Using ADAM Optimizer

By considering ADAM optimized in hyper parameters for the training of LSTM model. In adam optimizer initially updation of exponential moving average for the gradient is done and also the square of gradient which correspond to the estimation (computation) of the 1^{st} and 2^{nd} moment. Following table contains the RMSE values for different training periods for overall power grid failures as well as only Equipment failures.

Table 5: Computed RMSE Values on using ADAM optimizer in Training process

RMSE	80 % Training	70 % Training	60 % Training
Power Grid	**0.337**	**1.156**	**1.871**
Equipment	**0.935**	**2.011**	**2.965**

4.4.2 Using SGDM Optimizer

Also stochastic gradient descent moment (SGDM) optimizer is also considered for learning of algorithm (model) during training process. Table 6 consists of root mean square error values between actual and predicted values having different training periods for overall power grid failures as well as only Equipment failures

Table 6: Computed RMSE Values on using SGDM optimizer in Training process

RMSE	80 % Training	70 % Training	60 % Training
Power Grid	**1.207**	**2.693**	**3.155**
Equipment	**1.563**	**2.119**	**6.171**

CHAPTER # 5 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this comprehensive study deep learning algorithm called Long Short Term Memory (LSTM) has been implemented to compute the Time to failure of a Power Grid. Results achieved from LSTM techniques having ADAM (Adaptive moment estimation) optimized during training is found to be satisfactory and better prediction and computation of TTF. As root mean square error (RMSE) values obtained through ADAM is minimum as compared with SGDM optimized values. Prediction of Time to Failure of power grids will leads towards reduction in power outages because the power system's reliability would be improved. Afterwards timely measures will be taken in order to overcome or even reduce any future failure in power systems.

5.2 Future Work

The algorithm could be implemented on local available power failure data in order to minimize the power failures and challenges faced by power sectors within country.

Modelling of Maintainability i.e. time to repair action can be implemented with the prediction of failure to make the system more robust.

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