INTELLIGENT MAINTENANCE MANAGEMENT MODEL FOR CRITICAL MACHINES IN A SOLID TIRE MANUFACTURING FACTORY

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DECLARATION

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ABSTRACT

High machine reliability is an essential feature for a solid tire manufacturing plant. Most of the machines in those plants should be capable of 24 hour continuous running. Engineering department of a solid tire manufacturing company has a great responsibility to maintain the machine reliability level and to assist a trouble free operation. They conduct preventive maintenance and conditional monitoring regularly to minimize the breakdowns in the machines.

However, the current preventive maintenance practice of many engineering teams in solid tire manufacturing plants is a fixed schedule and it does not update with the condition monitoring data. Due to this, sometimes machines are serviced when maintenance is not needed and sometimes they are not serviced, when maintenance is needed. If there is a breakdown due to lack of maintenance and the maintenance team cannot rectify the problem, they have to get assistance from superior levels which may lead to high down times. This work aims to develop an intelligent system to dynamically change preventive maintenance schedule based on machine condition data and breakdown history for critical machines in the Camso Loadstar ETD2 solid tire manufacturing plant. In addition, this work applies artificial intelligence for troubleshooting.

The intelligent maintenance management system designed using artificial neural networks and expert system provides a dynamically updating maintenance schedules and troubleshooting assistance.

The performance of the designed system is evaluated separately for maintenance scheduling and the trouble shooting assistance. The performance of maintenance scheduling is analyzed using 10 critical machines by comparing predicted results with real achievements. The performance of trouble shooting assistance is evaluated by calculating the maturity level of the established expert system. The results show that the proposed intelligent system is a good solution for the existing issues related to maintenance of the critical machines in solid tire manufacturing plants.

ACKNOWLEDGEMENT

I would like to convey my sincere gratitude to Dr. Saranga K. Abeygunawardane for the valuable guidance given throughout the research period. At the same time, I highly appreciate the invaluable support given by the Camso Loadstar ETD2 team.

The support and encouragement given by my family members and friends is also highly appreciated.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

PM : Preventive Maintenance

ANN: Artificial Neural Network

NN: Neural Network

AI: Artificial Intelligence

PC: Personal Computer

KPI: Key Performance Indicator

Chapter 1

1. INTRODUCTION

1.1 Overview

Maintenance of continuously running machines is always a great challenge for maintenance teams in solid tire manufacturing plants. Existing machine maintenance techniques in local solid tire manufacturing plants include fixed scheduled preventive maintenance and condition based maintenance. Breakdown rectification systems are also used to send the information related to maintenance alarms to the maintenance team.

At the current situation, there is no direct link between the conditional monitoring data and the preventive maintenance schedule. There is a considerable amount of data to recognize the relationship between the preventive maintenance schedule and the conditional monitoring data. With that relationship, it is possible to maintain a dynamically updating machine maintenance schedule.

When the existing breakdown rectification system is taken into consideration, it is only used as a system to inform the maintenance team about the alarms related to machine breakdown events. The experience gained by the maintenance team members during the breakdown rectification is not systematically recorded in order to reuse it as trouble shooting assistance in future breakdowns. By introducing a systematic methodology to acquire the machine related breakdown data and learning procedure, this breakdown alarming system can be modified as a troubleshooting assistant for the maintenance members.

The above mentioned limitations in the existing maintenance and troubleshooting procedures motivate to develop an intelligent maintenance management system which provides dynamically updating maintenance schedules together with a troubleshooting assistance system.

1.2 Application of AI techniques for machine maintenance.

Application of Artificial intelligence in problem solving is becoming a popular trend in the world these days. The AI techniques give the power for a machine to act as a human being. Besides that, it can imitate some of the behaviours of humans, after a proper training. Majority of the skills of AI techniques are concerned with the development of the ability of computer to engage in learning process, reasoning and self-corrections as humans do [1] . Currently AI has gained influence from other fields such as psychology, neuron science, biology, sociology and philosophy. With that influence, there have been introduced several AI based techniques known as neural network systems, expert systems and genetic algorithms etc.

Artificial neural networks

Artificial neural networks (ANN) is a concept that is derived based on neural networks (NN). NN is another wonder of the nature. In humans, decision making is conducted by the brain through the central nervous system. Brain consists of a very large NN. But it is a quite complicated network. However, the basic characteristics of the NN structures [2],[3],[4] have been taken into consideration for building ANNs.

Expert systems

Expert systems are computer applications which have been built with the view of solving a complex problem which needs the human intelligence and expertise in the relevant field. Main features of the expert system are understandability, reliability, high responsiveness and high performance. With these capabilities expert systems can be implemented to use as systems for troubleshooting in a relevant field. As in [5],[6] this thesis applies an expert systems to develop a trouble shooting guidance tool for technicians.

Knowledgebase, interference engine and user interface are the main components of an expert system which are shown in detail in figure 1.

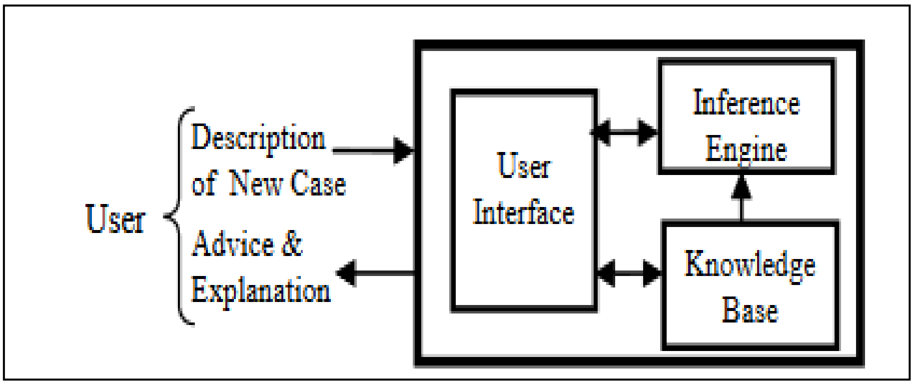

Figure 1: Summarized architecture for an expert system [8]

1.3 Problem statement

In local solid tire manufacturing facilities, a fixed machine maintenance schedule is maintained. That schedule is defined based on the life time of the different parts of the machines and the breakdown history of the machines at the time of preparation of the preventive maintenance schedule. These data has been fed into an ERP system called SAP. With that, the relevant preventive maintenance schedule is obtained. The conditional monitoring data is not linked with this currently available maintenance management system.

Besides this, in order to alarm the machine related breakdowns, another system is maintained. This is a software based interface and this only records the breakdowns. This system does not provide any troubleshooting assistance for the maintenance crew.

1.4 Literature Review

In literature, several research work has been already conducted related to machine maintenance with the use of AI technologies.

In [7], an intelligent predictive decision support system has been proposed for condition-based maintenance. This artificial intelligence integrated maintenance management system proposed in [7] is mainly to pre-plan and pre-schedule maintenance work, to reduce inventory costs for spare parts, to cut down unplanned forced outage and to minimize the risk of catastrophic failure. In this research work, a case study has shown that the AI based approach can enhance the efficiency of the maintenance functions of a large complex automated engineering plant. However, this work has been conucted for a power plant and it may not be possible to directly apply this work for a solid tire manufacturing plant which prefers to have a dynamically updating maintennace schedule and a troubleshooting assistant.

In [9], a methodology has been proposed to obtain the tool life of a PVD coated carbide when end milling of Ti6a14v alloy by the use of artificial neural networks.

In [10], it has been discussed a methodology to determine the optimal preventive maintenance policy and the optimal buffer allocation of a serial production line by means of genetic algorithms [10]. However, this work does not focus on dynamically changing maintenance plans and troubleshooting assistance techniques.

In [11] , an application of an expert system for trouble shooting of cars is discussed.

When considering the above discussed literature and the limitations of exixting maintenance mangament tools and troubleshooting assistant systems in solid tire factories mentione in subsection 1.5, development of an intelligent maintenance management system together with a troubleshooting asistant would greatly help the solid tire manufacturing industry and other similar industries.

1.5 Objectives and the Scope

There are two main objectives of this research work.

- To create an intelligent system to dynamically change the preventive maintenance schedule of critical machines based on their condition data and breakdown history
- To develop an expert system for troubleshooting by applying artificial intelligence

It should be noted that the intelligent maintenance management model and the troubleshooting assistance system proposed in this research work is designed specifically for critical machines in a solid tire manufacturing factory.

1.6 Methodology

The methodology of this research work is as follows.

- Analyze the past history of breakdown data/PM schedules/machine condition monitoring data of critical machines
- Selecting the proper AI technique for each objective
- Designing the architecture of the AI based maintenance management system
- Designing the software and databases of AI based dynamically changing maintenance management system
- Designing the interfaces and databases of AI based troubleshooting assistant
- Hardware implementation
- Testing and validation

Chapter2

2. THEORETICAL DEVELOPMENT

2.1 Historical data analysis for critical machines

For this study, the machine related data are gathered from January 2014 to March 2019.

A list of the collected machine related data is shown in Table 1.

Table 1: A list of machine related data

Data collected	**Source**
A list of the critical machines in the plant	Critical machine list in the plant
The breakdown history of the critical machines	Machine log books and break down analysis reports
No of days after last PM and production data	Machine log books
Condition monitoring data for critical machines	Condition monitoring data reports
Energy consumption and current reports	From SCADA system

The obtained critical machine list

Mill machines are identified as critical machines based on the process criticality.

10 machines are identified with machine names

Table 2: The critical machine list

Machine ID	**Machine description**
ML0031	T10 tred rolling mill
ML0029	T10 soft rolling mill
ML0030	T10 heel rolling mill
ML0033	T10 warming mill
ML0034	CON grey warming and rolling mill
ML0035	CON black warming and rolling mill
ML0036	T2 warming mill
ML0037	T2 rolling mill

2.1.1 Breakdown history of the critical machines

Critical machine related breakdown history is collected which includes the following details for each entry.

- Critical machine ID
- Date of the breakdown
- Number of Loss tire pieces
- Root cause
- Corrective action taken

2.1.2 Data obtained from machine log books

With the assistance of machine log books following data is obtained.

- No of days after last PM
- Production pieces against the date

2.1.3 Data obtained from condition monitoring data reports for critical machines

Vibration data and temperature data are obtained as per the point mapping of the critical machine. Figure 2 shows a typical point mapping for a mill machine.

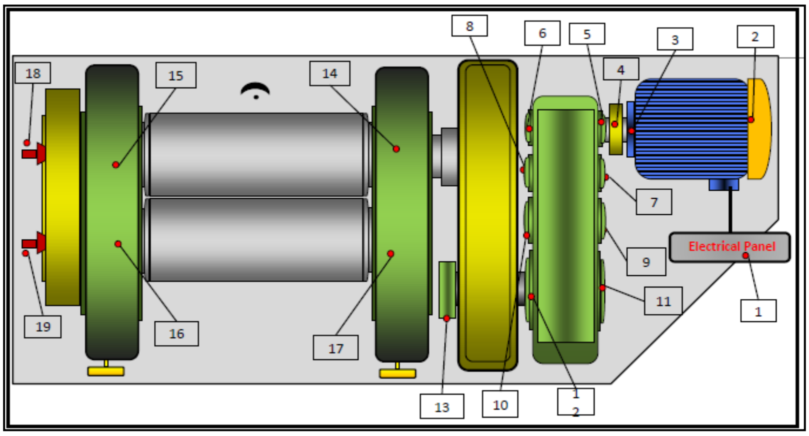

Figure 2: Point mapping for conditional monitoring of a critical mill machine

Point mapping description is as follows.

1-Electrical Panel

2-Motor Non drive end Bearing

3-Motor Drive end bearing

4-Coupling

5-Spericalroller bearing

6-Spericalroller bearing

7-Spericalroller bearing

8-Spericalroller bearing

9-Spericalroller bearing

10-Spericalroller bearing

11-Spericalroller bearing

12-Spericalroller bearing

13-Spericalroller bearing

14-Mill roller bearing

15-Mill roller bearing

16-Mill roller bearing

17-Mill roller bearing

2.2 Selection of the AI technology for the solution development

The AI technology to be used is selected based on the available historical data. The collected data should be used appropriately for the two main tasks, i.e. to create the dynamically changing PM system and to create the troubleshooting assistant. Since there are two kinds of data namely value based data and condition based data, different types of AI technologies should be used to achieve the two main tasks.

2.2.1 AI technology used for dynamically changing PM system

All the other data except root causes and corrective actions are used to develop the dynamically changing PM system. This system is developed based on the prediction of the optimum time span of the consecutive PMs based on the pattern of the existing quantified data. To predict the result based on the patterns of historical data, the artificial neural network is the most suitable AI tool. At the point of selecting the ANN as the AI tool for developing the dynamically changing PM system, several research work conducted for predicting the pattern data with the applications of ANNs have been taken into consideration [12].[13],[14].

2.2.2 The AI technology used for the troubleshooting assistance system

Root causes and corrective actions which are taken from the breakdown history of the critical machines are used as data for this. Since the root causes and corrective actions are the information which can be presented in a condition based manner, it is possible to create an expert system to be used as a troubleshooting assistant.

3. DEVELOPMENT OF THE INTELLIGENT MAINTENANCE MANAGEMENT SYSTEM

3.1 Solution architecture

Designed architecture of the AI based maintenance management system is shown in figure 3.

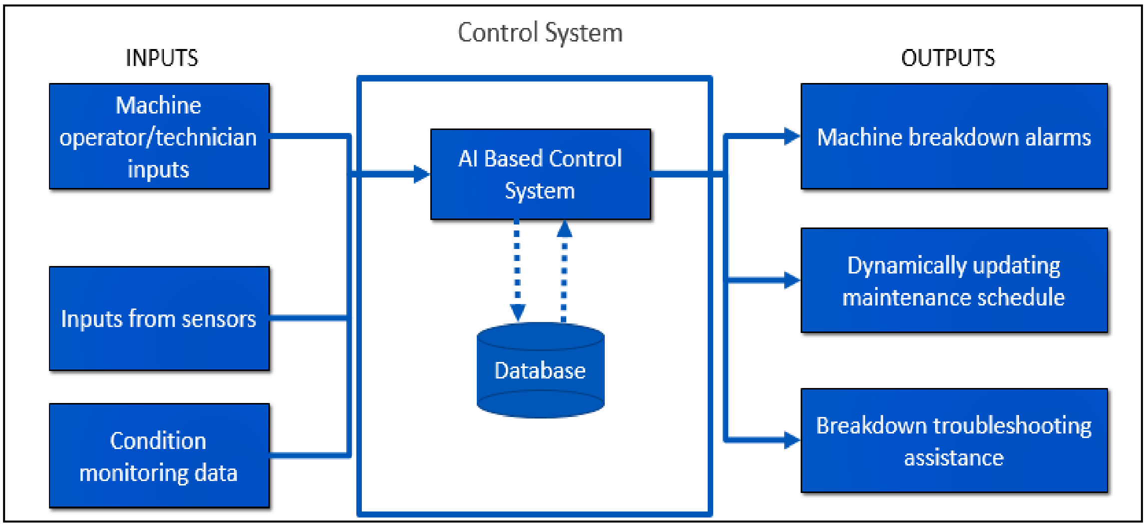

Figure 3: Designed architecture of the AI based maintenance management system

System architecture contains three main sections as inputs, control system and outputs. Inputs section is for getting the relevant inputs for the system. Inputs are to be taken under main categories defined as machine operator inputs, inputs from the sensors and condition monitoring data. Control system consists of two major components namely AI based control system and data base unit. From output section required outputs are taken as machine breakdown alarms, dynamically updating maintenance schedule and breakdown troubleshooting assistance.

Detailed explanation regarding subcategories in this main system is as follows.

- **Machine operator/technician inputs**

These are the details and information getting from machine operators and technicians regarding machine breakdowns. Details given by the machine operators are the breakdown details and the details given by the technicians are the feedback regarding the breakdowns and corrective actions.

- **Inputs from the sensors**

These are the parameter values that are taken to the system via sensors installed in critical machines. (eg: current values from power analyzers in the machine)

- **Condition monitoring data**

  These are the data described in 2.1.4 that are given into the system as input parameters.

- **AI based control system**

This includes the AI based techniques that are used with the proposed system. Subsystems of the AI based control system are shown in figure 4.

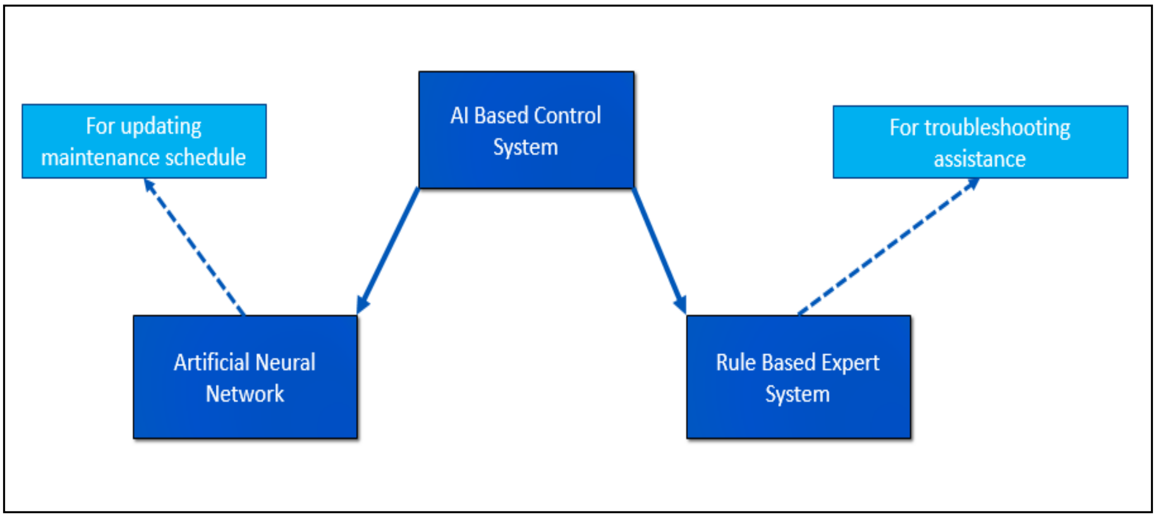

Figure 4: The proposed AI based control system

As shown in figure 10, the AI based control system consists of two sub systems namely; the artificial neural network and the rule based expert system which are dedicated for generating the dynamic PM schedule and for assisting the troubleshooting work, respectively.

- **Machine breakdown alarms**

  Breakdown alarms are generated after processing the inputs from the machine operator using the rule based system.

- **Dynamically updating maintenance schedule**

  This is the maintenance schedule which is dynamically updated via the artificial neural network.

- **Breakdown troubleshooting assistance**

This provides assistance for troubleshooting via the rule based expert system and the technicians' inputs.

3.2 Development of the artificial neural network system

The main task of the application of an ANN is to map the energy consumption (kWh), no load current (A), mill machine critical conditional monitoring data (vibration and temperature readings) and no of days after the last PM to cumulative loss pieces of the machine.

The data mentioned in 2.1 are used as the input data for the ANN. The processed input data obtained from point mapping in figure 8 is shown in table 3.

Table 3: The processed input data for the ANN.

Detail No	Point Location	Days after last PM
Detail_1		Per day Energy consumption(kWh)
Detail_2	1	No Load current phase 1
Detail_3	1	No Load current phase 2
Detail_4	1	No Load current phase 3
Detail_5	2	Motor Non drive end Bearing vibration(velocity(mm/s))
Detail_6	2	Motor Non drive end Bearing vibration(displacement peak(µm))
Detail_7	2	Motor Non drive end Bearing vibration (acceleration peak(µms-2))
Detail_8	2	Motor Non drive end Bearing temperature C
Detail_9	3	Motor Drive end bearing vibration(velocity(mm/s))
Detail_10	3	Motor Drive end Bearing vibration(displacement peak(µm))
Detail_11	3	Motor Drive end Bearing vibration (acceleration peak(µms-2))
Detail_12	3	Motor Drive end Bearing temperature C
Detail_13	4	Motor coupling temperature C
Detail_14	5	point 5 Spherical roller bearing vibration(velocity(mm/s))
Detail_15	5	point 5 Spherical roller bearing vibration(displacement peak(µm))
Detail_16	5	point 5 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_17	5	point 5 Spherical roller bearing temperature
Detail_18	6	point 6 Spherical roller bearing vibration(velocity(mm/s))
Detail_19	6	point 6 Spherical roller bearing vibration(displacement peak(µm))
Detail_20	6	point 6 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_21	6	point 6 Spherical roller bearing temperature
Detail_22	7	point 7 Spherical roller bearing vibration(velocity(mm/s))
Detail_23	7	point 7 Spherical roller bearing vibration(displacement peak(µm))
Detail_24	7	point 7 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_25	7	point 7 Spherical roller bearing temperature
Detail_26	8	point 8 Spherical roller bearing vibration(velocity(mm/s))
Detail_27	8	point 8 Spherical roller bearing vibration(displacement peak(µm))
Detail_28	8	point 8 Spherical roller bearing vibration(acceleration peak(µms-2))

Detail_29	8	point 8 Spherical roller bearing temperature
Detail_30	9	point 9 Spherical roller bearing vibration(velocity(mm/s))
Detail_31	9	point 9 Spherical roller bearing vibration(displacement peak(µm))
Detail_32	9	point 9 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_33	9	point 9 Spherical roller bearing temperature
Detail_34	10	point 10 Spherical roller bearing vibration(velocity(mm/s))
Detail_35	10	point 10 Spherical roller bearing vibration(displacement peak(µm))
Detail_36	10	point 10 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_37	10	point 10 Spherical roller bearing temperature
Detail_38	11	point 11 Spherical roller bearing vibration(velocity(mm/s))
Detail_39	11	point 11 Spherical roller bearing vibration(displacement peak(µm))
Detail_40	11	point 11 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_41	11	point 11 Spherical roller bearing temperature
Detail_42	12	point 12 Spherical roller bearing vibration(velocity(mm/s))
Detail_43	12	point 12 Spherical roller bearing vibration(displacement peak(µm))
Detail_44	12	point 12 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_45	12	point 12 Spherical roller bearing temperature
Detail_46	13	point 13 Spherical roller bearing vibration(velocity(mm/s))
Detail_47	13	point 13 Spherical roller bearing vibration(displacement peak(µm))
Detail_48	13	point 13 Spherical roller bearing vibration(acceleration peak(µms-2))
Detail_49	13	point 13 Spherical roller bearing temperature
Detail_50	14	point 14 Mill roller bearing vibration(velocity(mm/s))
Detail_51	14	point 14 Mill roller bearing vibration(displacement peak(µm))
Detail_52	14	point 14 Mill roller bearing vibration(acceleration peak(µms-2))
Detail_53	14	point 14 Mill roller bearing temperature
Detail_54	15	point 15 Mill roller bearing vibration(velocity(mm/s))
Detail_55	15	point 15 Mill roller bearing vibration(displacement peak(µm))
Detail_56	15	point 15 Mill roller bearing vibration(acceleration peak(µms-2))
Detail_57	15	point 15 Mill roller bearing temperature
Detail_58	16	point 16 Mill roller bearing vibration(velocity(mm/s))
Detail_59	16	point 16 Mill roller bearing vibration(displacement peak(µm))
Detail_60	16	point 16 Mill roller bearing vibration(acceleration peak(µms-2))
Detail_61	16	point 16 Mill roller bearing temperature
Detail_62	17	point 17 Mill roller bearing vibration(velocity(mm/s))
Detail_63	17	point 17 Mill roller bearing vibration(displacement peak(µm))
Detail_64	17	point 17 Mill roller bearing vibration(acceleration peak(µms-2))
Detail_65	17	point 17 Mill roller bearing temperature
Detail_66	N/A	No of days after last PM

In this list, there are sixty six independent input variables for the ANN. These data are collected by date wise and the data set contains at least one thousand and eight hundred rows for each critical machine. These data are directly mapped to the cumulative loss pieces of the machine after the last PM.

3.2.1 Building of the ANN network

When the architecture of an ANN is considered, layers and neurons are the key elements.

- **Input layer and input neurons**

When the layers are considered, three main layer categories can be identified as input, hidden and output layers. Input layer contains the relevant input neurons. From the table 3 it can be seen that there are 66 input parameters. Each of these parameters has a neuron in the input layer in the proposed architecture of the ANN. Therefore, there are 66 input neurons in this ANN architecture.

- **Hidden layers and input neurons**

No of hidden layers will affect the validation results. Trial and error methodology is practiced during the training process to obtain the optimum number of hidden layers . Default hidden layer size is taken as 10 for each of the ANN and it is changed accordingly based on the validation results.

- **Output layers**

  A single neuron is present in the output layer to get the relevant output from the ANN.

  Figure 5 shows the architecture of the proposed ANN with the layers an neurons mentioned above.

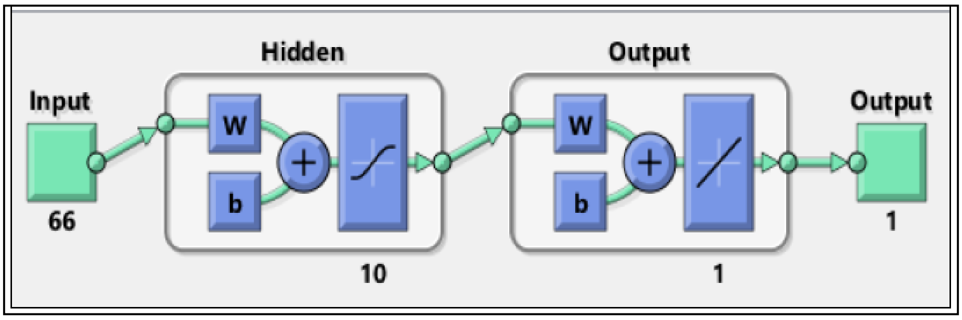

Figure 5: The architecture of the proposed ANN

3.2.2 Application of the data set for training and validation of the neural network.

The training methodology used for the ANNs built in this work is supervised training. During the building process of the ANN, the data is divided into three main categories as training data, validation data and testing data.

- **Training data**

  This is the dataset that is used to train the ANN. 70% of the data obtained is used for this.

- **Validation data**

  This is the data used to tune the parameters of the ANN structure such as neuron weights and no of hidden layers. 15% of data in the total data set is selected for this. A back propagation algorithm is used during the validation process. Stopping point of the back propagation algorithm is determined by the validation data.

- **Testing data**

  This is an independent data from training an validation data which is in the same total data set. This is used to inspect whether this data follow the same probability distribution as the training an validation data. 15% of data from the collected dataset is used as testing data.

3.2.3 Building the sample GUI in Matlab environment for ANN testing.

Matlab is a software tool developed by MathWorks in order to conduct complex simulations and calculations. Neural network toolkit in Matlab is another powerful tool to conduct ANN related activities. Followings can be conducted via Matlab and matlab neural network tool box. The work flow of ANN creation has seven primary steps [15].

- Data collection
- Create the network
- Configure the network
- Initialize the weights and biases

- Train the network
- Validate the network
- Use the network

Figure 6 shows the basic interface that is designed to find the expected tire loss for the given inputs.

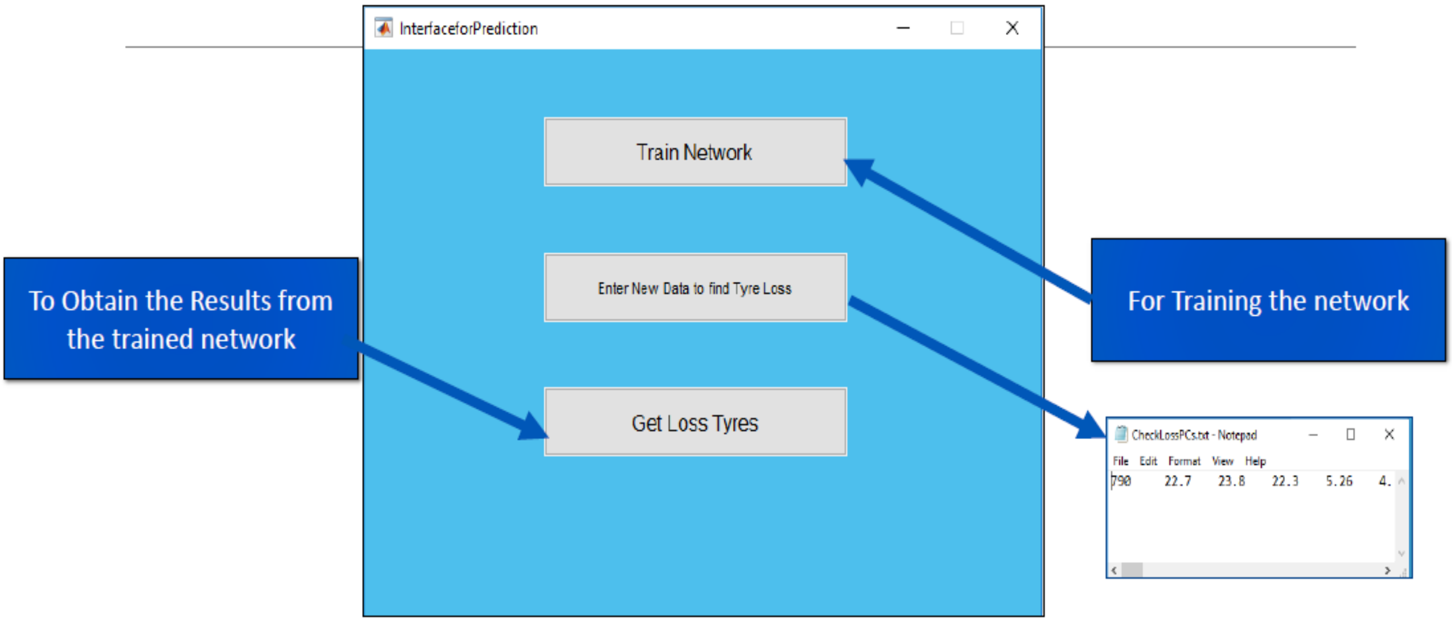

Figure 6: Basic test GUI for the ANN

With the GUI button, itis expected to get the followings done.

- Train Network button

  Create an ANN with the given set of data and conduct training, validation and testing of the ANN by properly allocating the data, i.e. 70% for training,15% for validation and 15% for testing.

- Enter new data set to find the expected tire loss

  Up-to-date machine data set is given to the system by means of a text file. With this button, the location of the relevant data file is given to the system.

- Get loss tires button

  The created ANN uses the data in the given text file and process them to give information regarding the expected tire loss according to the data in the file.

Note: Source codes for the GUI and ANN are given as appendices.

3.3 Development of the Maintenance planner system

The sample test module proposed in section 3.2 is successfully implemented, but it has some limitations when it is used for several number of critical machines. The data visibility during the time of inputting data is relatively very low. Since this neural network uses a large size data structure (i.e. the input size of 66), it is necessary to enter the data very carefully. Besides this, the matlab coding required by the system is very much time consuming. With the condition monitoring data and machine log data, the proposed system can predict only the expected tire loss after giving a relevant PM time span. However, for the analysis it is more intended to obtain the allowable time span to the target tire loss.

3.3.1 The interface of the maintenance planner

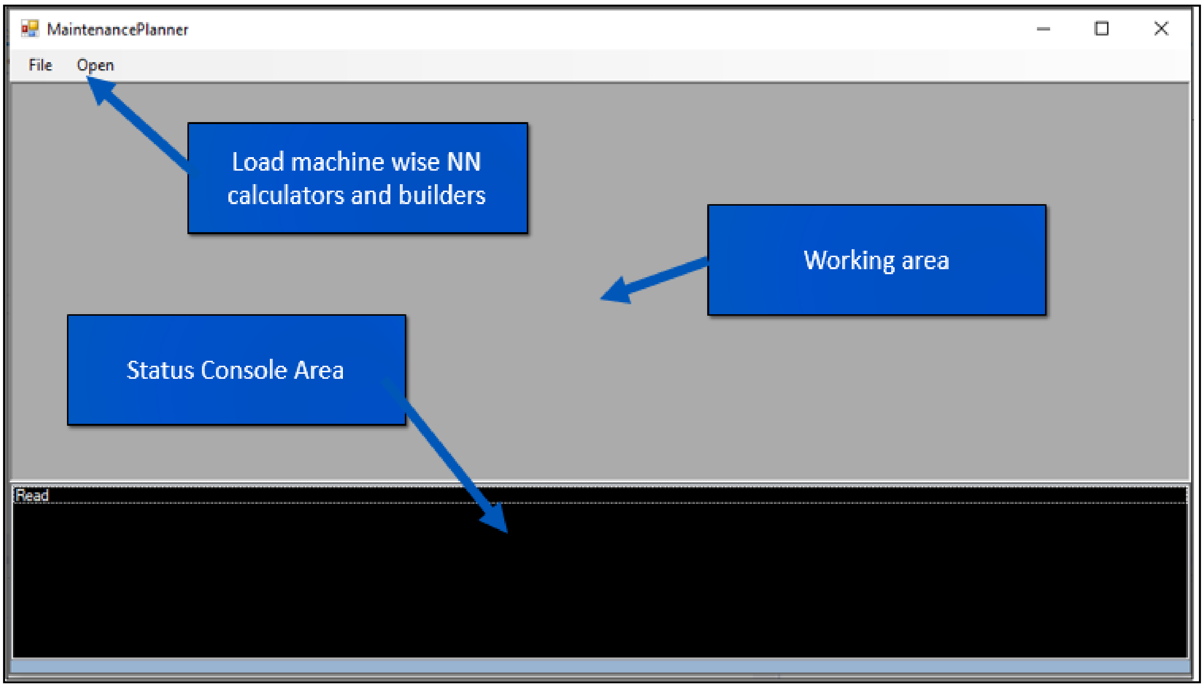

Figure 7: The main interface of the maintenance planner

This Maintenance Planner has been built using C# language and Matlab Runtime environment. The Matlab runtime is linked to C# run environment with the use of Interop.MLApp.dll, a dynamic link library which is used to set relevant connections of the Matlab environment with C# [16].

A summarized description of the labels an components of the main interface is given below.

- **Load machine wise ANN calculators and builders**

  This facility is provided to load interfaces designed for building\training ANNs for critical machines and calculating the results with trained ANNs

- **Working area**

  This working area works as a container for the ANN related interfaces

- **Status console Area**

  This console area is used to update the current progress of the procedures and calculations that is conducted with ANNs.

3.3.2 The training and build interface of the ANN

Following figure shows the interface that is used to train the ANN in user friendly manner. In this, the interface facility is used to provide the relevant training data set as input data and output data. For this, the interfaces in the network tool box [17] in Matlab are used.

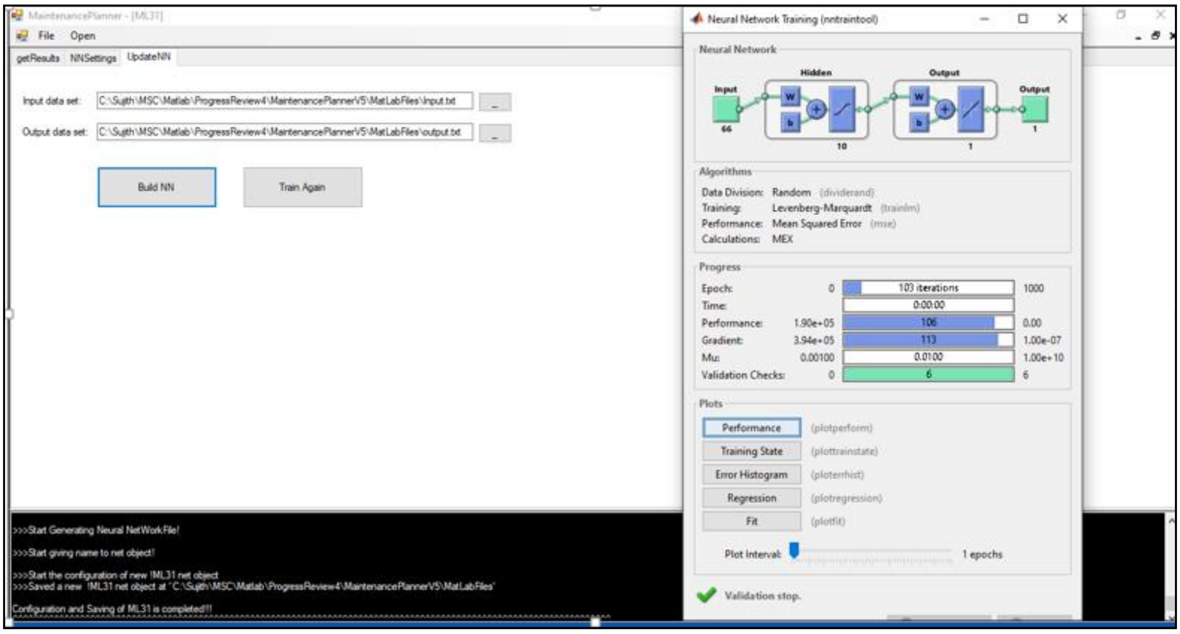

Figure 8: The training and build interface of the maintenance planner

The following shows the results obtained after building and training the ANN for ML0031.

- The validation of the performance of the ANN for ML0031 is shown in figures 9.

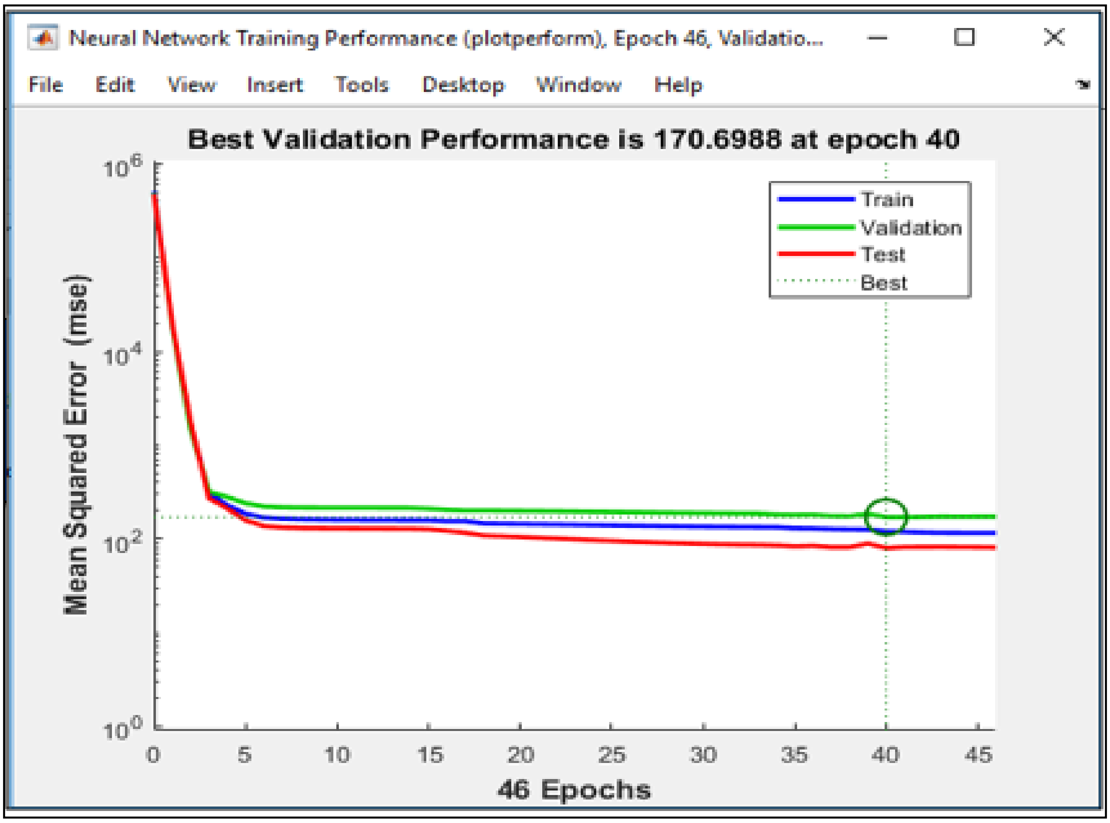

Figure 9: The validation of the performance of the ANN for ML0031

- The regression state of the ANN for ML0031 is shown in figure 10.

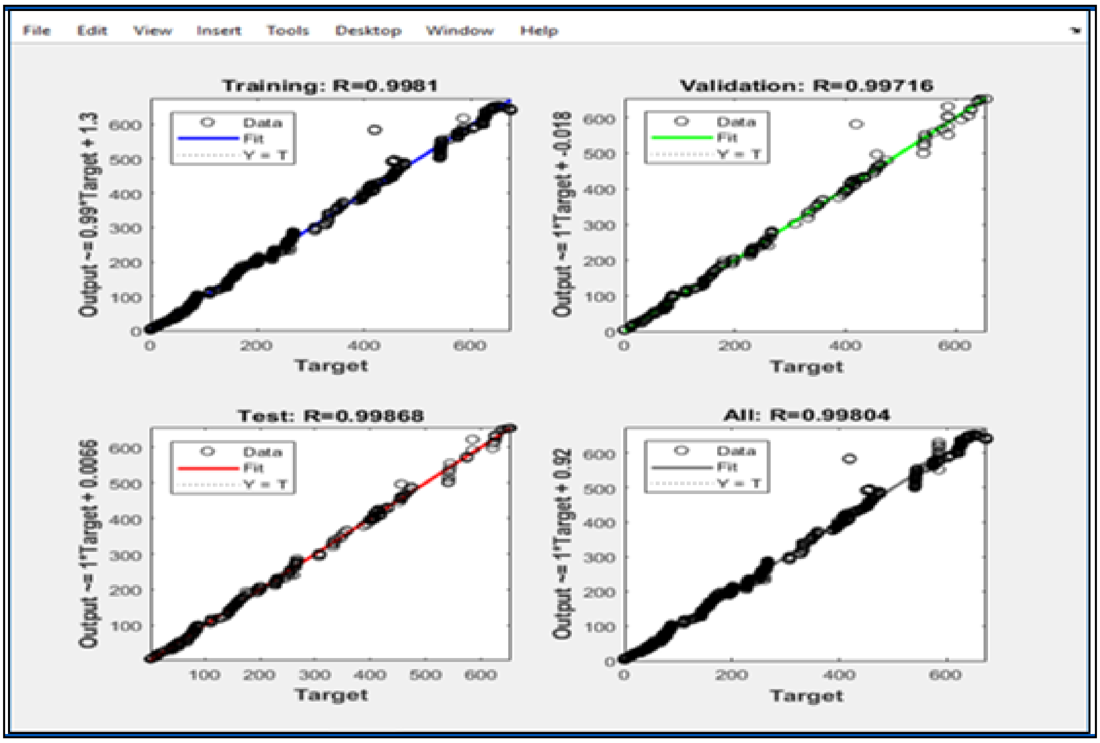

Figure 10: The regression state of the ANN for ML0031

- The error histogram of the ANN for ML0031 is shown in figure 11.

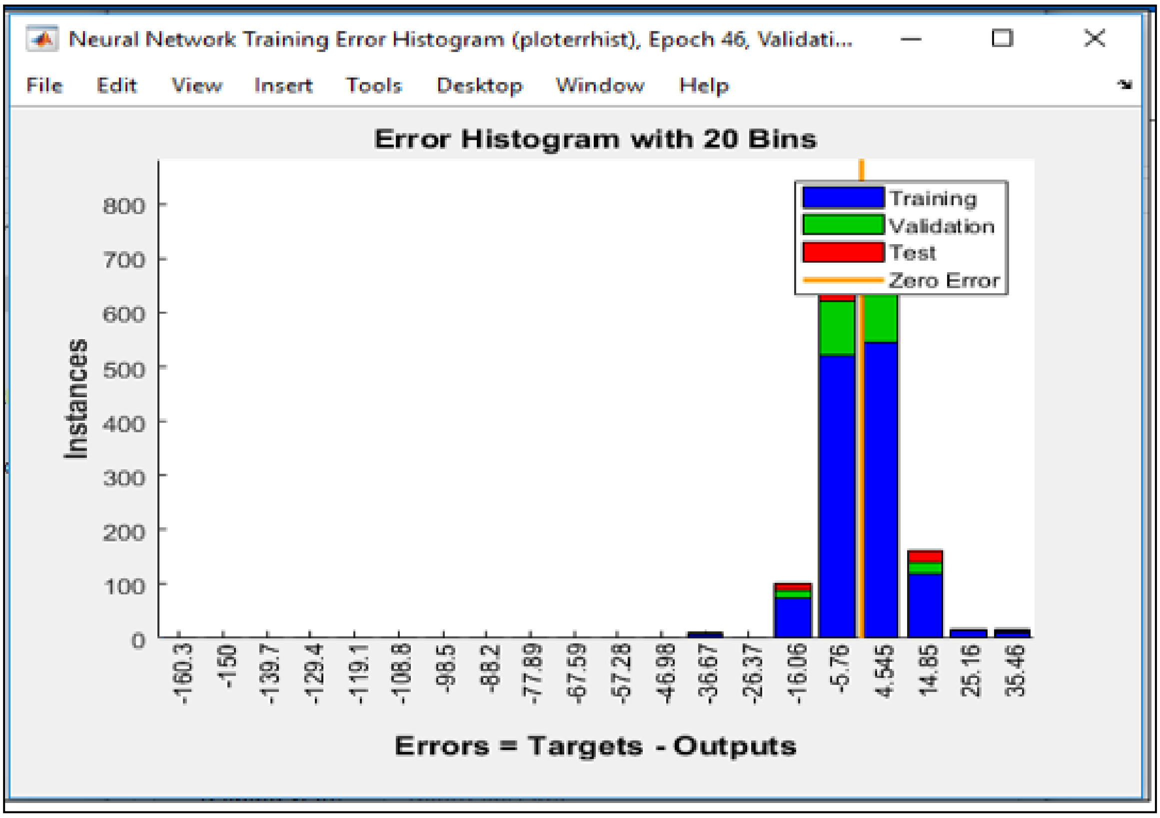

Figure 11: The error histogram for ML0031

From the above graphs which are obtained while training the ANN of ML0031, it can be seen that the ANN has a high regression value (i.e. the overall regression> 0.9). Regression describes how many of real scenario values coincides on the values obtained via the ANN which directly describes the accuracy level of the ANN. Error histogram of the ANN further describes how many of instances of high error portions available for the ANN. With these results, user can get an idea of the accuracy and applicability of the ANN.

Now, the ANN developed for ML0031 can be used to obtain the maintenance schedules.

3.3.3 The interface for obtaining the results of the maintenance planner

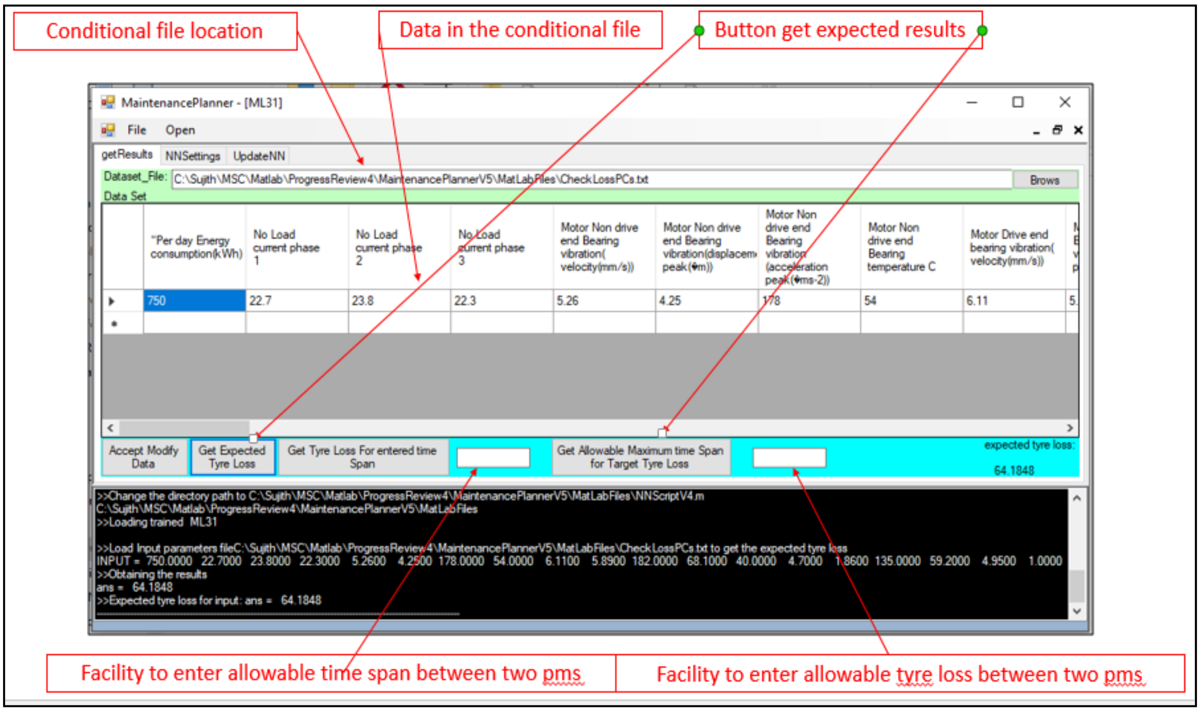

Figure 12: The interface for obtaining the results of the maintenance planner

After the proper training of the ANN, the interface shown in figure 12 can be used for obtaining the results i.e. the optimum time span between two PMs to an allowable loss pieces or loss pieces between two PMs in an allowable time period between two PMs. The interface in figure 12 uses the ANN trained for ML0031 and provides the expected tire loss pcs in a given time span with relevant condition data or the expected minimum days for the next PM with current condition data to the given loss pieces target.

As an example, if the allowable tire loss PCs between two PMs is given as 295 and press “Get Allowable Maximum time Span for the targeted Tire Loss” button, 88 is given by the system as the answer. Validation results of these figures are discussed in Table 5 in section 4.2.

3.3.4 Retraining criteria for neural network

With the time, sometimes it may need to retrain the ANNs maintained for the critical machines.

In the maintenance planner, retraining can be conducted at any time. However, it is recommended to retrain, if the expected tire loss variation is deviated related to the allowable real tire loss variation. This variation value can be either positive or negative. Besides this, if a full overhaul is conducted to the selected critical machine, it is better to build a new neural network for that machine after monitoring the data for at least 3 months.

3.4 Development of the breakdown expert system

This software tool named as "Breakdown expert" includes the following facilities.

- Generating alarms based on the machine operator's inputs
- Displaying pending breakdowns that is not attended by maintenance crew.
- Connecting to remote IO units based on the alarms
- Providing troubleshooting assistance for the maintenance crew
- Learning from the breakdowns to assist the maintenance crew in future breakdowns
- Validating breakdowns and corrective actions for the maintenance crew
- Validating breakdowns and corrective actions for the engineers
- Providing in-built validation status indicators
- Providing in-built self-effectiveness evaluation

This breakdown expert software tool consists of three components.

- User Interface: To interact with users (machine operators/maintenance crew/engineers) and software.
- Interference engine: This includes the forward chaining rule based logical tool (discussed under section 3.4.1) that is used to find root causes, corrective actions and relevant alarms.
- Knowledge base: Knowledge base is made with SQL database where the information is stored in a compatible manner to be used by the rule based interference engine.

3.4.1 Rule based system for interference engine.

For this, the forward chaining rule is used. Application of this type of rule based system is influenced by the problem sheets (which includes in breakdown history records) which are currently used by the solid tire manufacturing plant for the breakdowns. In these problem sheets, cause based analysis process is conducted. In cause based analysis each breakdown is analyzed from top level to bottom level till correct root cause is found. Figure:14 shows the cause based analysis in detail. This is very much same to the forward chaining. In the proposed system, this mechanism is installed to store the information as per the following tree view. By doing that it is possible for the interference engine to search relevant information by the issues and reasons with the forward chaining. Forward chaining process is shown in figure 13. Application of the logic of the rule based system is discussed in detail under the process flow charts in section 3.4.2.

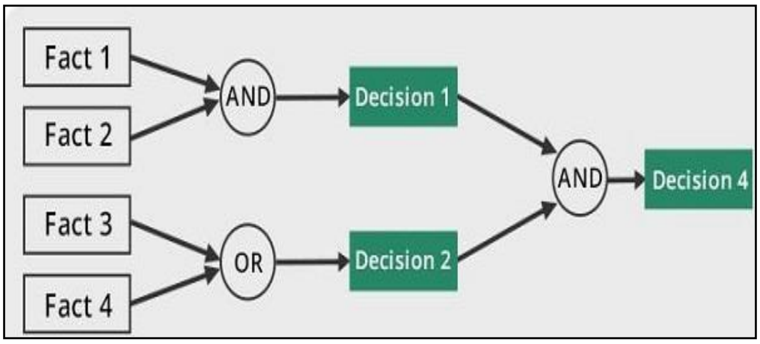

Figure 13: The overview of the forward chaining technique

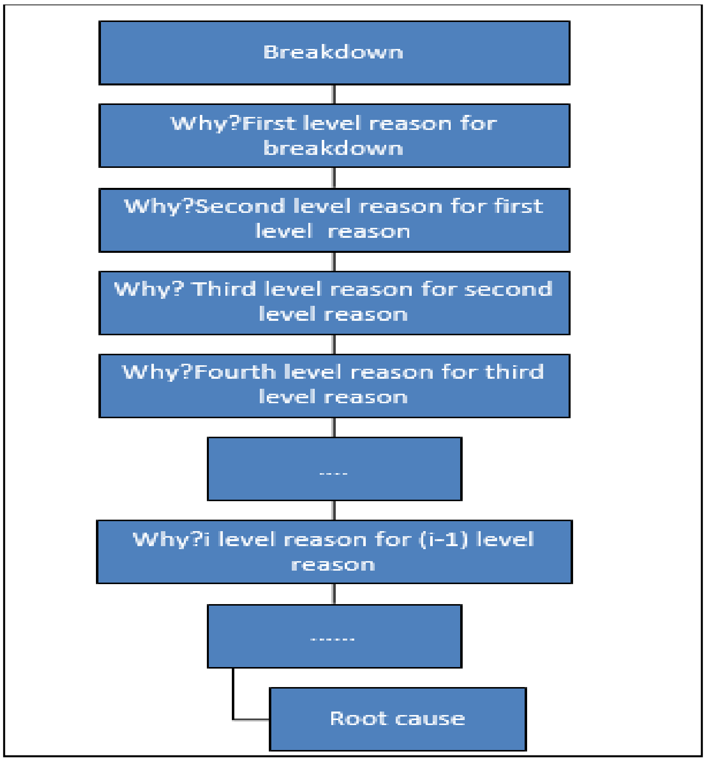

Figure 14:Cause based analysis used in problem sheets

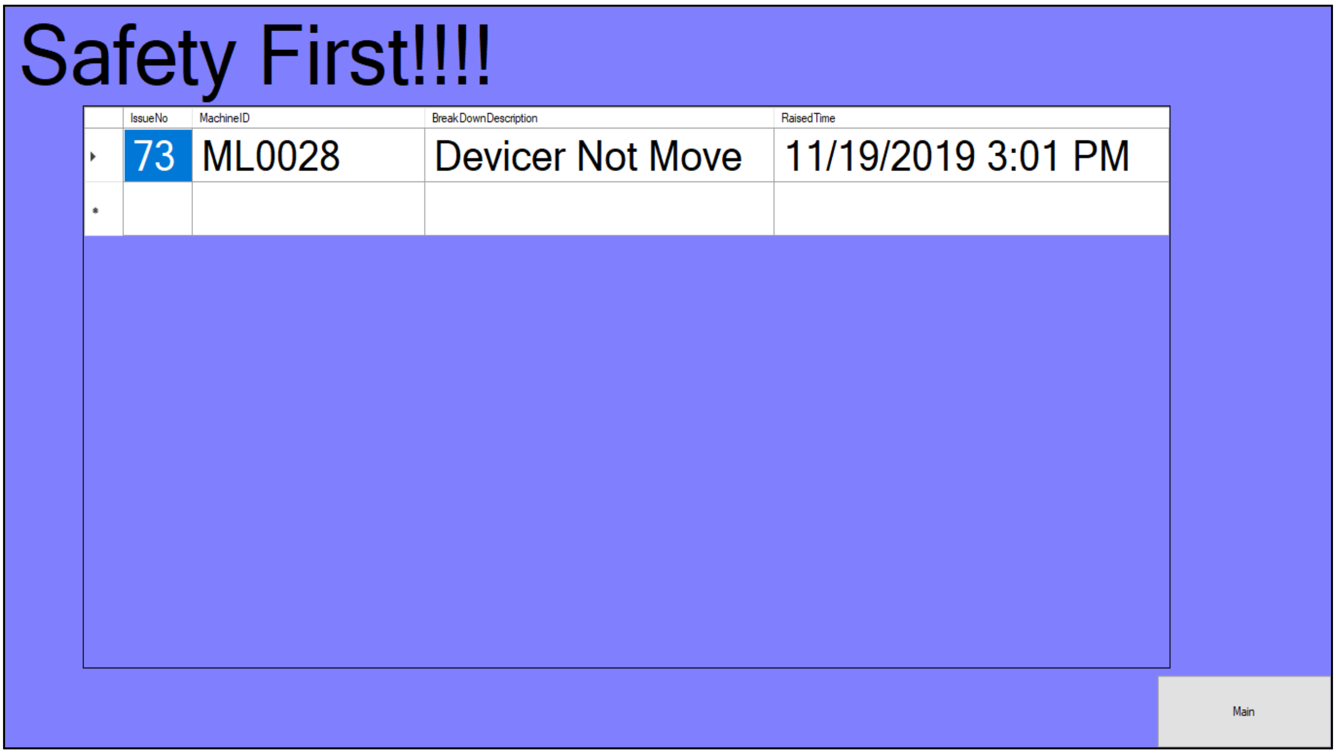

Figure 15: The main interface of the breakdown expert

As shown in figure 15, at the main screen of the breakdown expert provides the facility to display the pending breakdown alarms.

By clicking on the main button, the user can go to the selection form screen which is shown in figure 16.

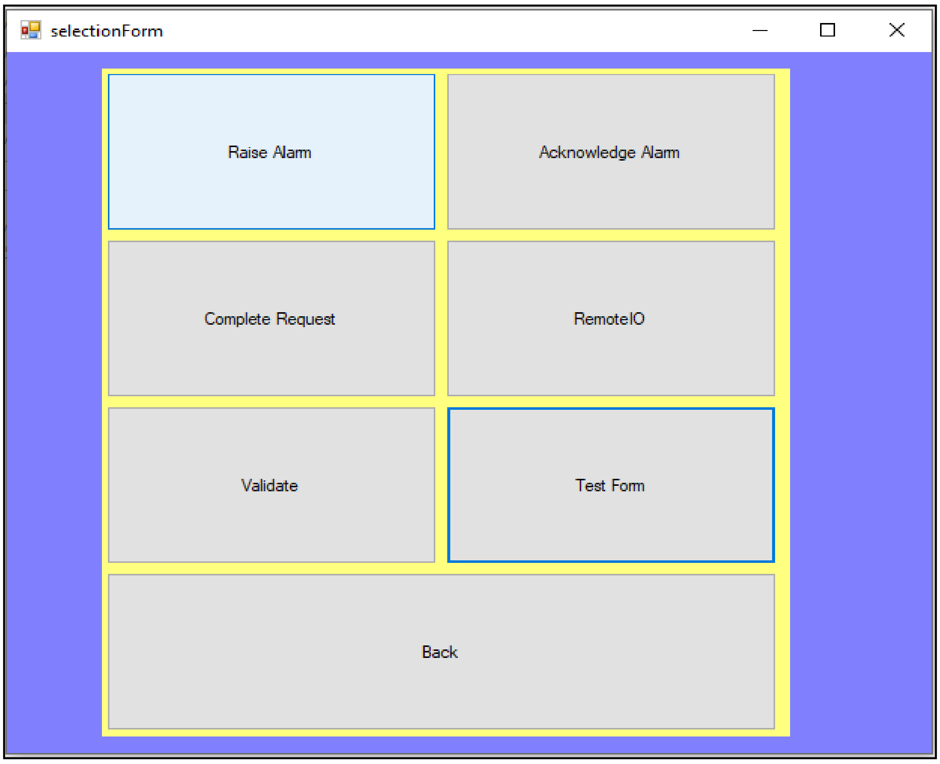

Figure 16: A view of the selection form

- Raise Alarm

  This links the interface for raising alarms of machine related breakdowns with the operators

- Acknowledge Alarm

  This links the interface for acknowledging the raised alarms with troubleshooting assistance.

- Complete Request

  This links the interface for completing the acknowledged request with the actual corrective action taken by the maintenance member. This is an interface dedicated for the maintenance crew.

- Remote IO

  This links the interface with the remote ADAM modules to get the current status and configuration.

- Validate

  This links the interface with the interface which is used to do the high level validation of the knowledge base. This is mainly designed for the engineers. Beside this, this shows up-to-date maturity as a percentage.

3.4.2 Process flow of the breakdown expert.

The following describes the process flow charts for the activities that are taken place inside the expert system of the breakdown expert.

Process of a breakdown request

- **Breakdown alarm generation**

  Relevant machine related breakdown has to be raised by the machine operator. For the alarm generation, the interface mentioned in the appendix B should be used.

- **Acknowledge breakdown alarm request**

  When a breakdown alarm is raised in the system, a buzzer will sound via ADAM module and the raised issue is listed in the table in the main screen. Trouble shooting assistance facility is available in this step. Based on the maturity of the knowledge base, possible root causes and corrective actions are presented to the technician. Technician can do a forward chaining root cause analysis by simply clicking on the issue. Non validated causes and corrective actions are highlighted in red colour and validated items are highlighted in white colour. Non validated items are also shown because they are capable of giving some kind of helpful hints to the technician for trouble shooting. After the acknowledgement of the breakdown request, this alarm is added to the acknowledged breakdown list. Then this breakdown request vanishes from the acknowledge breakdown window and signals the ADAM module to turn off. Besides, this is added to the list of the completed breakdown alarms. Figure 17 shows the detailed explanation of the acknowledging procedure of a breakdown alarm.

- **Complete breakdown alarm request**
  This step can be applied for a breakdown request only if the breakdown request is successfully acknowledged. In this step, the technician can give his feedback regarding the breakdown assistance. A self-evolution is carried out for the proposed causes and corrective actions and real causes and corrective actions. If the new corrective actions are added these are listed under validation screen for the engineer to examine the accuracy of the proposed causes and breakdowns. Figure 18 shows the process flow chart in the complete request interface.

- **Validate breakdown alarm request**
  This screen belongs to the engineers. Newly added breakdowns, type of breakdowns and corrective actions added to the system are shown as a list in this interface. Engineer can add them into knowledgebase after a proper evaluation for using them in the troubleshooting assistance.

Process flow chart for acknowledging a breakdown request is shown in figure 17.

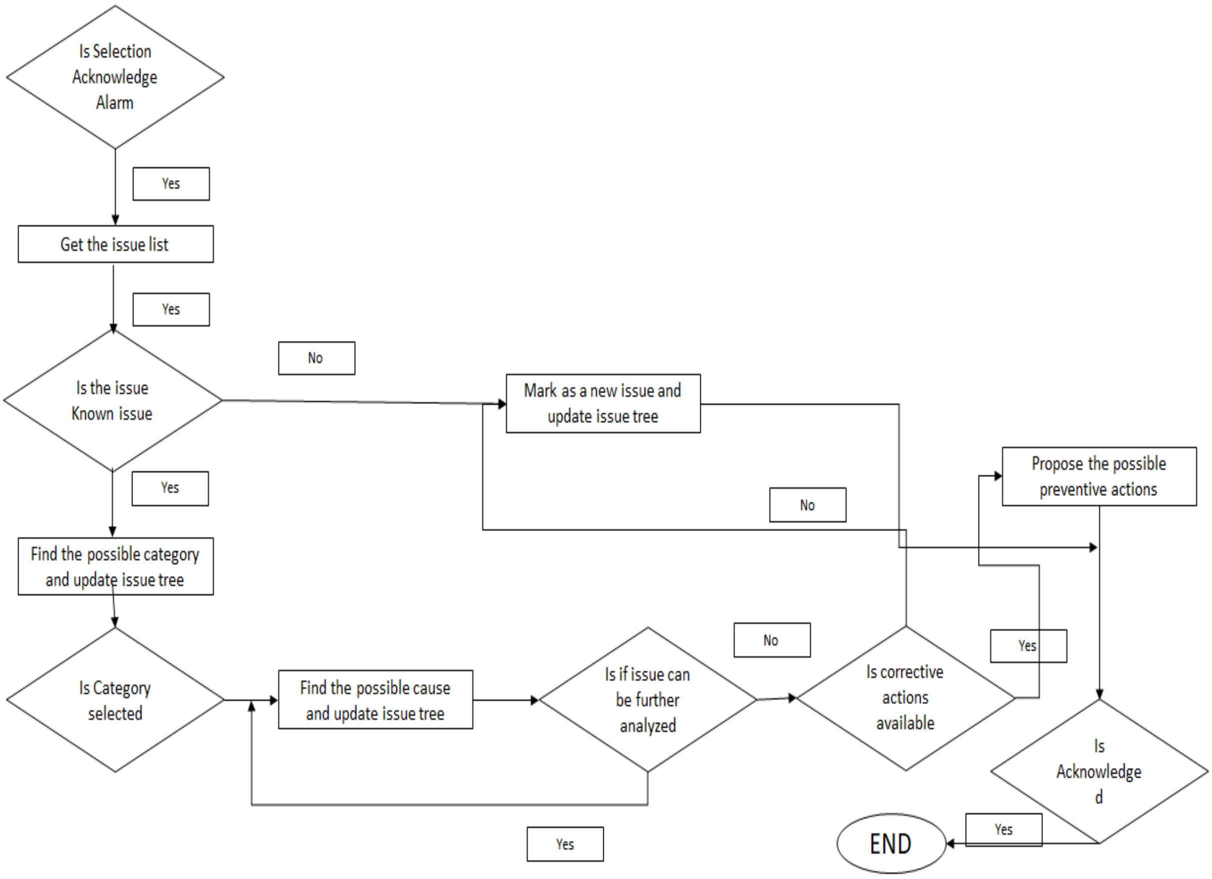

Figure 17: Process flow chart for acknowledging a breakdown request

Process flow chart for completing a breakdown request is shown in figure 18.

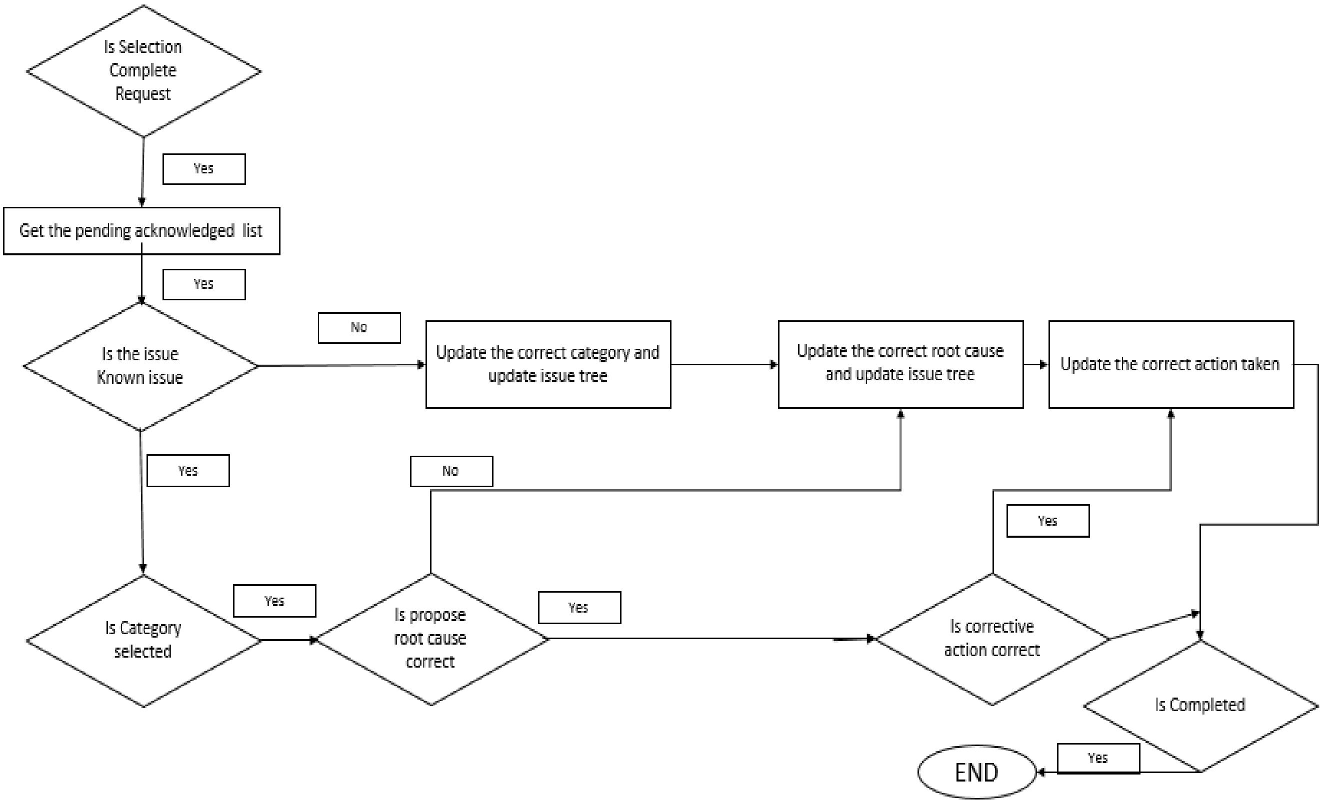

Figure 18: Process flow chart for completing an acknowledged request

3.4.3 Maturity calculation for the knowledge base

This parameter has been introduced to use as a measure to get the current maturity level of the system. For each of the breakdown that is raised in the system, a comparison procedure is followed for the causes, root cause and corrective actions proposed by the system at the acknowledgement stage against the actual actions that are performed by the technician during the rectification of the breakdown.

These causes and corrective actions are compared at the acknowledged stage and the completed stage in step wise. Step wise means the cause, root causes and corrective actions that are proposed by system in forward chaining is compared with those at the completed stage. Base on the step wise matching, following proposed algorithm gives a percentage mark to a completed breakdown. Total maturity is obtained by averaging the percentage marks of the overall breakdowns. Special precautions have been introduced to the system to avoid feeding the faulty percentages into the system due to the mistakes of the machine operator such as entering wrong machine breakdown descriptions. If that kind of scenario happened it is given minus marks and not considered in the maturity evaluation. Though such mistakes are made by the machine operator, they are tracked in acknowledging and completing steps of the machine operator and the validation step of the engineer. Due to this, correct information can be fed again to the system. Further, these types of mistakes done by the operators can be clearly filtered and inform the relevant supervisor to give the required awareness to operators and to assure that the same mistake is not repeated.

Following figure shows a typical comparison of a proposed issue with a real issue at the complete request stage of the breakdown expert.

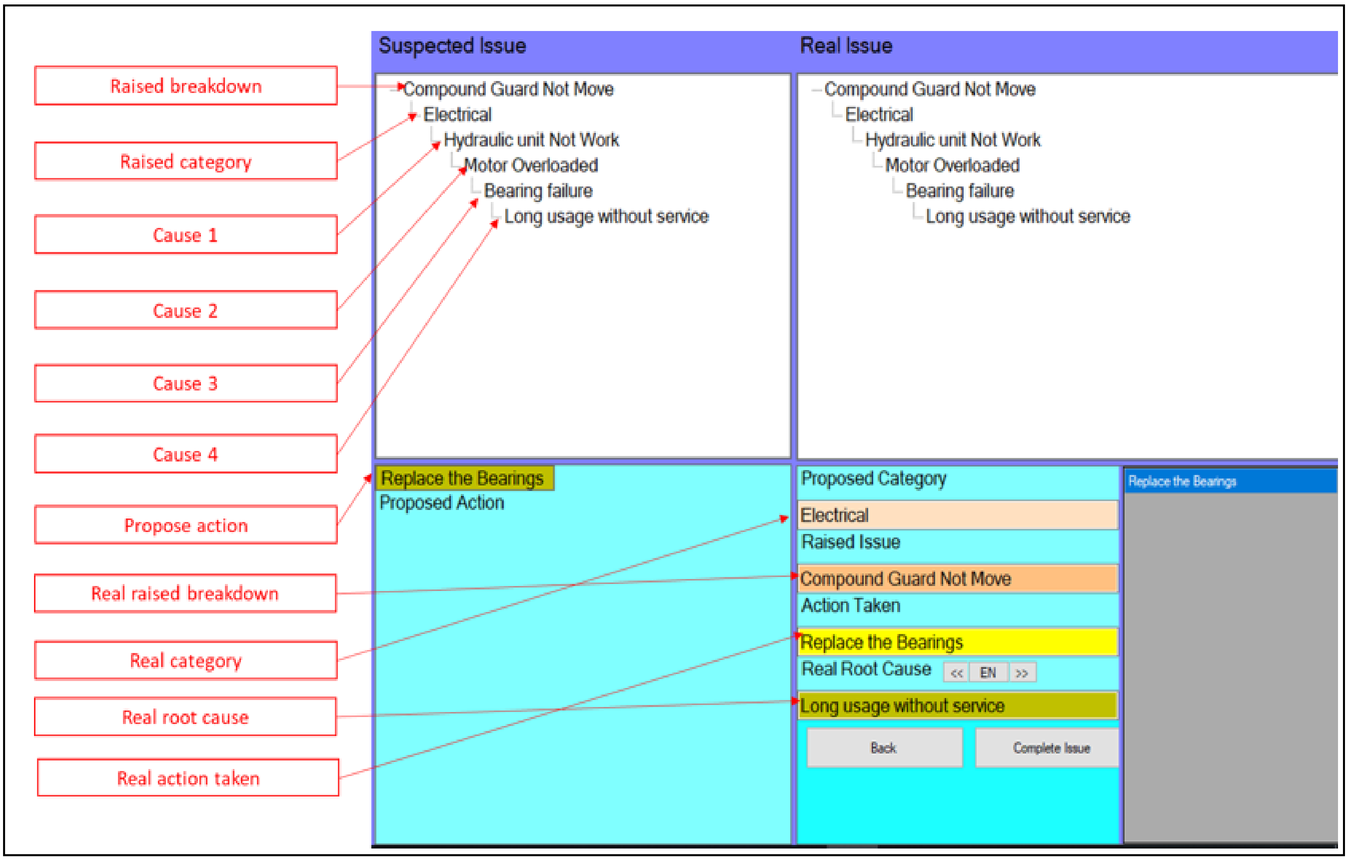

Figure 19: Comparison of proposed actions and completed actions of a breakdown during the complete stage

The algorithm for calculating the maturity level of a breakdown is shown below.

Table 4: Marking scheme for the maturity calculation

Raw Index	**Comparison parameter to compare the real against the proposed**	**Marks when comparison is ok**	**Marks when comparison is not ok**	**Marking criteria explanation**
1	Raised breakdown and real breakdown	0	-1000	This is used to identify whether the machine operator has given the correct alarm issue. If the issue is wrong entry system will give -1000 marks to identify the wrong entry in maturity calculation
2	Proposed category and real category	20	0	20 marks are given if the proposed category and real category are exactly matching
3	Proposed cause 1 and real cause 1	30/(n-2)	0	Sub level causes are compared with real issue tree and give the marks accordingly
4	Proposed cause 2 and real cause 2	30/(n-2)	0	Sub level causes are compared with real issue tree and give the marks accordingly
5	Proposed cause 3 and real cause 3	30/(n-2)	0	Sub level causes are compared with real issue tree and give the marks accordingly
6	Proposed cause *i* and real cause *i*	30/(n-2)	0	Sub level causes are compared with real issue tree and give the marks accordingly
7	Proposed cause (n-1) (propose root cause) and real root cause	30	0	30 marks will be given if the real root cause and the proposed root cause are matching
8	Proposed action taken and real action taken	20	0	20 marks will be given if the proposed action taken and real action taken are matching

Here n= number of steps and it should be always greater than 2 since every breakdown should contain a proper breakdown description, breakdown category and at least one cause.

$$\begin{aligned} &Maturity\ level\ mark \\ &= (Raised\ Breakdown\ and\ Real\ Breakdown\ comparison\ mark) \\ &+ (Proposed\ category\ and\ Real\ category\ mark) \\ &+ \sum_{i=3}^{i=n-1} Proposed\ cause\ i\ and\ real\ cause\ i\ comparison\ mark \\ &+ (Proposed\ action\ to\ take\ and\ real\ action\ taken\ comparison\ mark \end{aligned}$$

Alarms and displays

3.4.4 Architecture for remote outputs

To have a proper communication between the production floor and the breakdown expert, it is required to maintain a proper communication methodology. For this, alarms, buzzers and remote displays are introduced to the system. These alarms, buzzers and displays are installed in the optimum locations to ensure that the proper communication is established continuously.

For this, the following architecture is proposed for remote outputs.

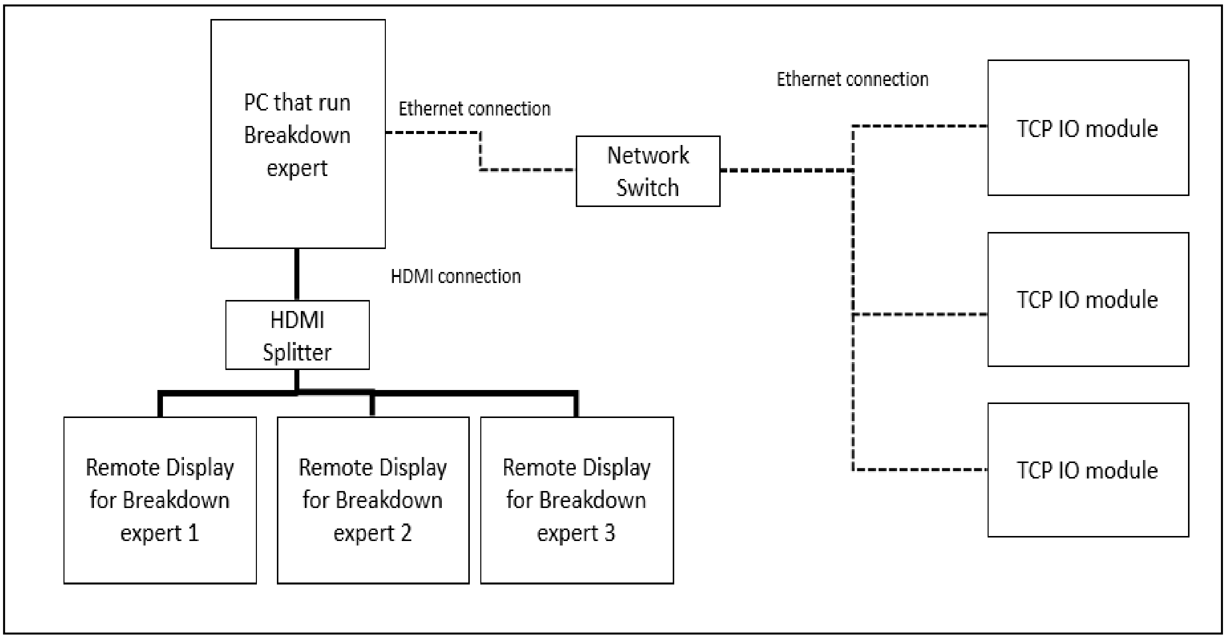

Figure 20 : The architecture for remote outputs.

As can be seen in figure 20 , there are five major components in the proposed architecture of the remote outputs.

- PC that runs the breakdown expert
- Network switch

- HDMI splitter
- Remote display
- TCP IO module

A detailed description about the hardware is as follows.

3.4.5 Minimum requirement of the PC that runs the breakdown expert software.

For this, a normal personal computer is used with the following specifications.

processor :Intel i3 3.3 Ghz dual Core

RAM:4 GB DDR3

Storage drive capacity: 500 GB

Ethernet ports: 2 (speed compatibility 10/100/1000 MB per second)

Operating system: Windows 7

In the floor, this pc has to be installed with a proper UPS backup power system to ensure a trouble free operation of the breakdown manager.

3.4.6 TCP IO module.

This module is used to communicate with the breakdown manager by means of the Ethernet connection. TCP is used as the communication technique for this device. Reasons for the selection of this module are as follows.

- Easiness of the integration to C# with socket programming.
- Minimizes the cost of wiring for long distance.
  Since this can be easily connected to the system via Ethernet ports, a considerable amount of the wiring cost is reduced.
- Long life time (average life time is at least 5 years)
- Compatibility to the industrial environment.

3.4.7 Design of the remote alarm controlling unit

This module is used to communicate with the buzzers and alarm indicators. With this device, the breakdown expert can provide dry relay outputs to the alarm indicators and buzzers based on the user inputs. The following figure shows the basic installation architecture for an installed TCP IO module unit.

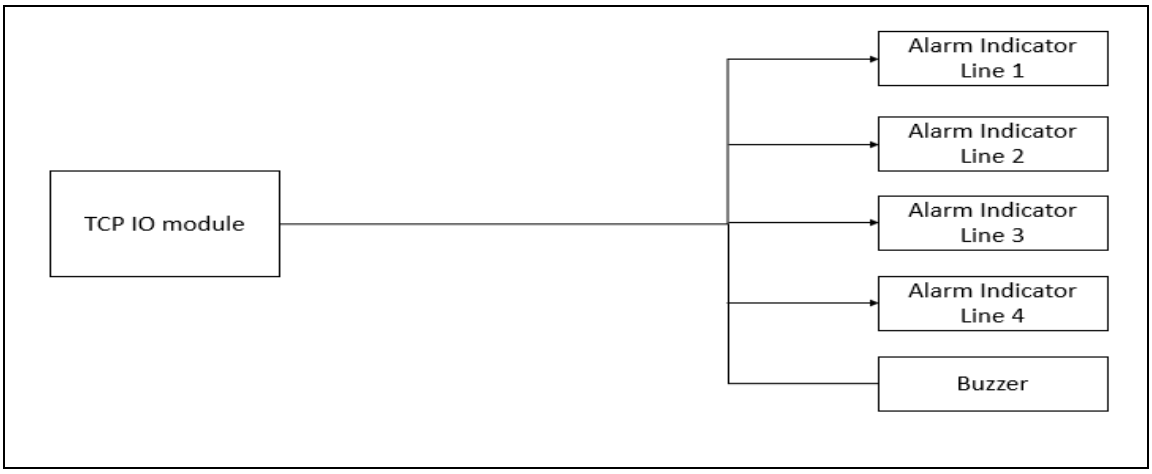

Figure 21 : TCP IO module and control wiring for outputs

There are dry output relay points in the TCP IO module used in this application. Relevant alarms and buzzers are activated via socket programming by the breakdown expert. In the breakdown expert, it has been provided the facility to integrate additional TCP IO modules easily via IP addresses.

3.4.8 Remote display unit

These are 40” displays that are installed in the production floor at locations where the optimum visibility to floor members can be achieved. These displays are connected to HDMI port of the PC via HDMI splitter.

Chapter 4

4. PERFORMANCE OF THE OVERALL SYSTEM

4.1 The Methodology for the analysis of results

As discussed in the previous chapter the main objectives of this research is to provide a dynamically updating PM schedule based on the machine condition data and breakdown history, and troubleshooting assistance for the maintenance crew. For this task two subsystems have been designed namely the maintenance planner which is a system based on artificial neural networks and the expert system, respectively. So the result and analysis is conducted separately for the system.

4.2 Analyzing the results of the maintenance planner

In the Camso Loadstar, there is a KPI for allowable loss pieces for the production lines. Based on that, the allowable tire loss for a particular period (allowable tire loss till next PM) of a critical machine can be obtained. This value is considered as the allowable loss pieces for the critical machines that is taken into consideration.

In the solid tire manufacturing plant which is taken into consideration, there are ten process critical machines. These are basically mill machines.

Table 5 : Test results obtained with the Maintenance planner.

Machine Name	Last PM date	Allowable Loss(PCs) {Target Loss PCs}	Real Loss PCs	No of Days PM should conduct after last PM(Calculated via NN)	Date the machine should release for Pm according to NN	Date the machine release for PM by production	Delay days	Expected Loss from NN considering the pm conduct day	difference (PCs) real loss and expected Loss with pm conducting delay
ML0031	6/5/2019	295	290	88	9/1/2019	9/1/2019	0	295	5
ML0030	6/4/2019	300	338	101	9/14/2019	9/28/2019	14	343	5
ML0029	6/3/2019	150	164	104	9/15/2019	9/25/2019	10	164.2	0.2
ML0033	6/5/2019	60	58	117	9/30/2019	9/30/2019	0	58	0
ML0034	8/8/2019	100	116	37	9/14/2019	9/20/2019	6	119	3
MI0035	8/21/2019	85	81	32	9/22/2019	9/22/2019	0	85	4
ML0036	7/31/2019	30	28	64	9/28/2019	9/28/2019	0	30	2
MI0037	6/14/2019	200	203	69	8/22/2019	8/22/2019	0	200	-3
ML0126	6/24/2019	150	153	101	10/3/2019	10/3/2019	0	150	-3
ML0127	6/22/2019	150	156	105	10/5/2019	10/5/2019	0	150	-6

At the time of implementing the system, the allowable loss PCs error for a critical machine is 10. This is given by the management of the Camso Loadstar. Based on that value and the results shown in table 5, the allowable error percentage and the achieved error percentage are obtained.

Note:
The error percentage is defined as follows.

$$Error\ percentage = \frac{(Real\ loss\ pieces - Expected\ loss\ pieces\ to\ PM\ conducted\ date) X\ 100}{(Expected\ loss\ pieces\ to\ PM\ conducted\ date)}$$

The percentage error of the real and actual loss pieces is shown in the following table.

Table 6 : Percentage error of the real and target loss pieces

Machine Name	Allowable error percentage +/-	Actual error percentage +/-
ML0031	3.39%	-1.69%
ML0030	3.33%	-1.46%
ML0029	6.67%	-0.12%
ML0033	16.67%	0.00%
ML0034	10.00%	-2.52%
Ml0035	11.76%	-4.71%
ML0036	33.33%	-6.67%
Ml0037	5.00%	1.50%
ML0126	6.67%	2.00%
ML0127	6.67%	4.00%

When the above test results are taken into consideration, all of the results obtained for these critical machines are at a satisfactory level relative to the targets given by the management.

4.3 Analyzing the results of the breakdown expert

When the breakdown expert is taken into consideration, a self-evaluation mechanism is available in the expert system. Direction of the Camso Loadstar management is to provide a system for trouble shooting with an overall maturity of 85% at initial stage. At the startup, the maturity was at a level of nearly 50%. Currently it has reached to a level of 90%.

Figure 22 shows the up–to-date validation results of the Breakdown expert.

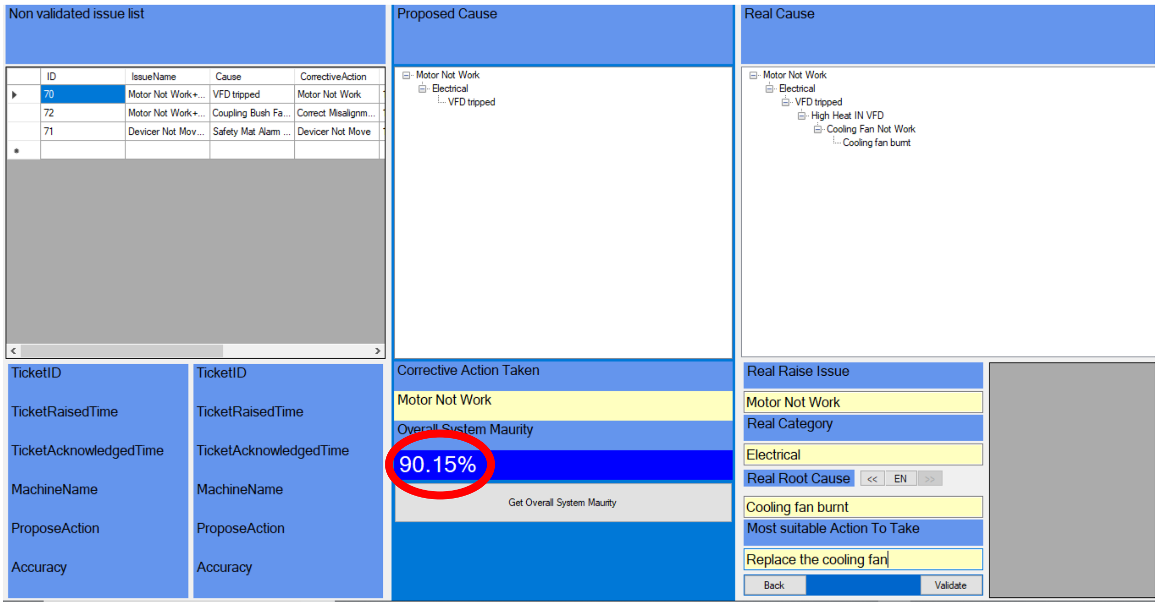

Figure 22 : The validation results from the validation screen in the breakdown expert.

Figure 23 shows the daily maturity percentage variation from 1/9/2019 to 11/10/2019.

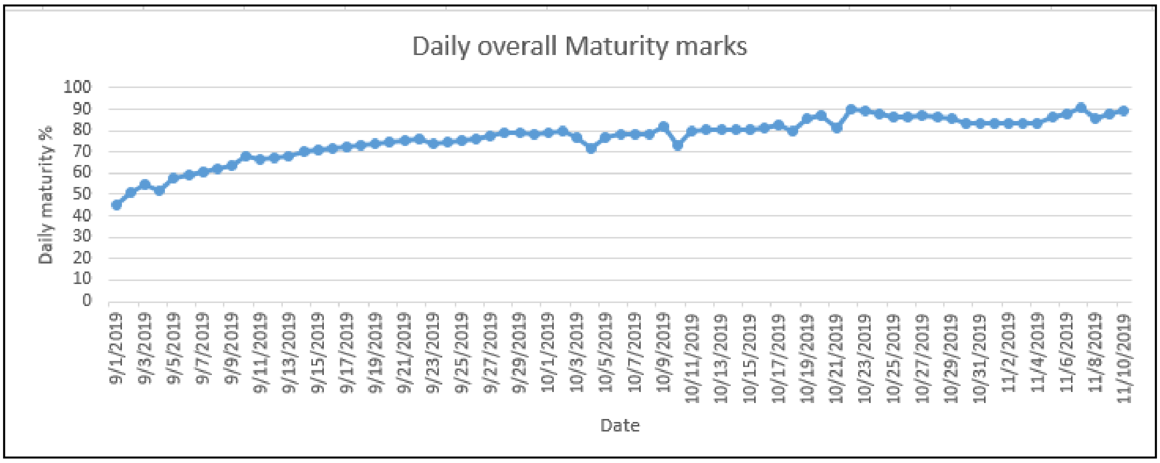

Figure 23: Daily maturity variation from 1/9/2019 to 11/10/2019

Chapter 5

5. CONCLUSION

5.1 Discussion and conclusion

In this thesis, a system is proposed and implemented to find the optimum time frame to plan the PMs for the critical machines of a solid tire manufacturing plant based on the conditional monitoring data and production data. In addition, a system is introduced as a trouble shooting assistance tool. Since both of these systems are developed using AI technologies, these systems are capable of continuously learning.

Testing and trials of the proposed systems are conducted based on the data and targets obtained from the Camso Loadstar management. Through the long time observation of the test results, it may be possible to further narrow down the targets.

With the features of the interface of the maintenance planner, it is easy to predict the future results based on the current situation. This is a great advantage for the maintenance planner to plan the PMs exactly on relevant dates. Besides that, this tool helps maintenance planners to present the production loss and cost in a quantified manner and justify the losses due to not releasing the machines for maintenance on the due date.

Breakdown expert is a great tool for both the maintenance team and the production team to minimize the down times. For each breakdown, this tool monitors the time points at which the breakdown is raised, the breakdown is acknowledged and the breakdown is completed. In addition to that, alarms and buzzers are tuned on till the breakdown in properly acknowledged. Due to these features, time taken by the maintenance crew to correct the breakdown will be significantly reduced. In addition, due to the availability of the trouble shooting facility, it is easy to conduct the trouble shooting. This contributes to further reduce the downtime.

All the breakdowns are recorded in the knowledge base. These can be used later for further analysis. Since root cause analysis and the corrective actions are present in this database, it is possible to take permanent corrective actions for the repetitive breakdowns. By doing that, it is possible to extend the time span of the PMs causing a reduction of the maintenance cost. At the same time, it is possible to identify the lack of spare parts, if there is any. Identifying weak and low quality spare parts is a great glory for a maintenance team in a 24 hour running production facility, since it is possible to plan and find a correct solution for that by clearly identifying the problem . With the data recorded in the breakdown expert, by monitoring the time taken for acknowledging and completing the request, assessments regarding the competency levels of technicians in respective areas can be easily identified. These findings may be useful when designing the training plans for technicians.

At the current situation, all the breakdowns are done via breakdown sheets. These sheets are to be evaluated by the technicians and the engineers. However, the efficiency of the usage of these breakdown sheets is not at a satisfactory level due to insufficient user friendliness of these documents. This paper work can be completely eliminated from the process after properly establishing the breakdown expert, since the each breakdown is properly evaluated by technicians and engineers, systematically.

5.2 Future work

It is important to improve the system reliability in this maintenance management model. For that it is important to maintain relevant databases in a separate server which has a better back up facilities and redundancies. Data centers are one of the best places to maintain the database systems that are relevant to this maintenance management model. With this architecture, it is possible to use the maintenance planner and breakdown expert system in different locations. As a result, this system would be very much compatible with the client and server application architecture. This allows administrative users and engineers to remotely connect to the system.

Further to that it is better to maintain a separate server for the breakdown expert instead of maintaining one tool for all the user interfaces and remote IO interface. By separating these two units, a failure in one PC that maintain one system does not cause to stop the whole process of the other system.

In the proposed architecture in this thesis, the consideration is only on the computer based applications. However, there is a feasibility to convert some of the proposed applications/interfaces (such as validation and completed interfaces of the breakdown expert) to mobile phone based applications.

As mentioned in this thesis, with the breakdown expert it is possible to obtain the time consumed by the technicians to acknowledge the breakdowns. As a further improvement, it is possible to develop this system to give the information regarding the delays in acknowledgements to high management levels in real time. For example sending sms or email messages by the technicians to relevant maintenance supervisors and engineers regarding the delayings in acknowledgements for the breakdowns.

In this thesis, the prime focus is on solving the machine maintenance related issues. However, the logic and features discussed in this thesis can be applied for the issues that are arisen in the plant premises. For example, after establishing a proper knowledge base, the breakdown expert can be introduced to quality control department to conduct problem solving for the quality related matters.

Currently, the parameters used for the maintenance planner application is manually fed into the system after storing them in a data file by the technicians who conduct the condition monitoring. This process can be more user-friendly and convenient, if a database server and a user friendly interface can be proposed for the technicians. Some of the condition monitoring data can be uploaded to servers in real time, if the relevant sensors for temperature monitoring and vibration analyzing are installed in the machine itself permanently. When the sensors are used with the system, it is essential to introduce relevant error filtering mechanisms. This can be achieved by introducing relevant threshold levels for the sensors to detect the faulty operations. This may be somewhat costly, but beneficial, since this helps to increase the accuracy level of ANNs maintained in the maintenance planner. Besides this, it can be used to obtain a real time picture of the machines, so that the accuracy of the results obtained from the maintenance planner will be significantly increased.

When this system is developed further with interfaces and servers, it is recommended to use the same type of database servers and the same programming language to minimize the additional efforts and unnecessary troubles in connecting the developments. Further, if this is used in a location with controlling devices such as Programming Logic Controllers (PLCs) which also connect with the databases etc, it is recommended to use the same type of database for both PLCs and the proposed intelligent system. If this kind of infrastructure is maintained with the total system, this system can be easily developed to send necessary messages for PLCs to get precautions when machine related abnormalities are observed through the break down expert. This will be a greatly reduce the downtime by taking correct actions to avoid breakdowns which are going to happen.

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APPENDIX-A

GENERALIZED ANN MATLAB CODE FOR CRITICAL MACHINES

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
% Created 28-Jul-2019 22:57:15
% Author: R.P.S.K. Jayasuriya
%
% This script assumes these variables are defined:
%
%   Input - input data.
%   output - target data.

%x = Input';
%x=importdata('Input.txt');
%t = importdata('output.txt');

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt backpropagation.

% Create a Fitting Network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
```

```
% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean Squared Error
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
   'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)
% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
%if (false)
   % Generate MATLAB function for neural network for application
   % deployment in MATLAB scripts or with MATLAB Compiler and Builder
   % tools, or simply to examine the calculations your trained neural
   % network performs.
   %genFunction(net,'myNeuralNetworkFunction');
  % y = myNeuralNetworkFunction(x);
%end
%if (false)
   % Generate a matrix-only MATLAB function for neural network code
   % generation with MATLAB Coder tools.
   %genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
  % y = myNeuralNetworkFunction(x);
```

```
%end
%if (false)
   % Generate a Simulink diagram for simulation or deployment with.
   % Simulink Coder tools.
   %gensim(net);
%end
```

APPENDIX-B

INTERFACE FOR ALARM GENERATION FOR THE MACHINE OPERATORS

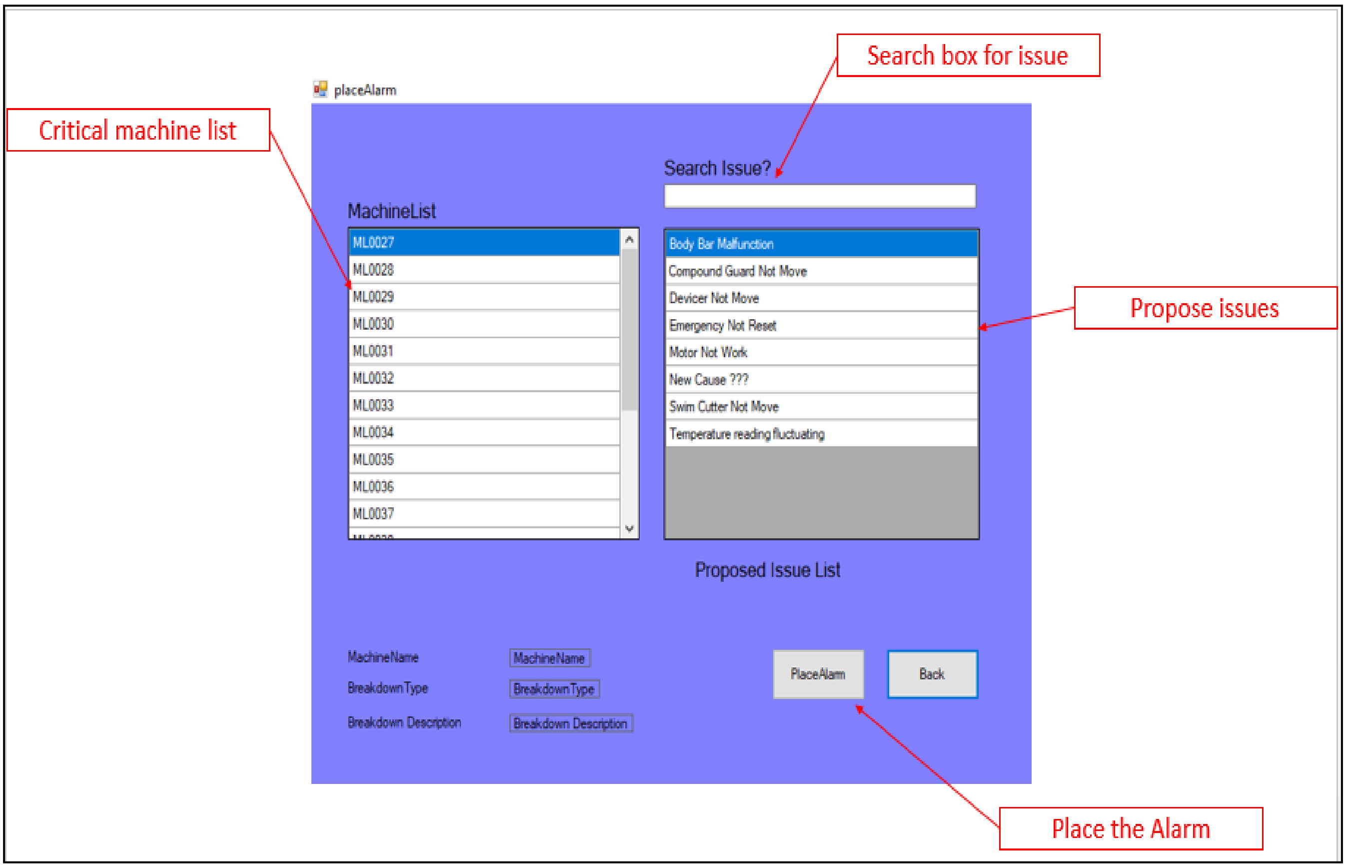

Figure 24: Place Alarm interface