Research on Integrated System for Condition Monitoring of Rolling Stock (ICMRS)

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ABSTRACT

Integrated System for Condition Monitoring of Rolling Stock (ICMRS)is sub-categories into three different problem statement as given below:-

1. **Hot Axle & Hot Wheel:** Based on Automatic Detection of rise in Temperature of Axle and Wheel at a speed from 5 to 100Kmph.
2. **Wheel Impact Load:** Toinvestigate the wheel-rail impact responses to minimize the wheel/rail failure.
3. **Broken/Hanging Part:** The system should be so designed that it can detect any hanging object from the wagon running at a speed of 100Kmph.

The comprehensive analysis of all these problem statement leads to the proper development of complete system which will recognize all the given constraints based on Artificial Intelligence, image processing, IoT system and data processing.

Keywords: Hot Box, Pyrometer, Proximity ,Optris, Lidar, image processing, Cloud Computing, IoT.
PROBLEM STATEMENT 1.

HOT AXLE HOT WHEEL

I. INTRODUCTION:

Temperature of rolling stock axle-box & wheel bodies are one of the most important parameters of diagnostics, upon exceeding thereof it is stated that the axle-box is in technical disorder. The normal operation of the axle-box is characterized by heat exchange balance between axle-box elements, wheel-set and ambient air temperature, i.e. when the released amount of heat equals the amount of heat dissipated in the environment by the axle-box and wheel-set.Rise in Axletemperature depends upon when, the train is running at the uninterrupted regime:1) Depends on the type and dimensionsof bearings, 2) Anti-frictional and hydrodynamic properties of the lubricant 3)Spaces between the bearing rollers and rings 4) Static and dynamical loads of the bearing,5)Train running speedduration of travel without stops 6)Ambient air temperatureand the road curves.

Friction of axle-box node partsresults in the heating of their surfaces. Upon reaching the limit values this heating may cause the structural changes in the upper surfaces of the bearing parts, due to which the rollers may become clogged. Axle fracture may occur after 25 min (or if the train is moving, on the average, at60 km/h after 25 km) from the moment when the inner ring of the bearing spins on the axle, therefore of special importance it is to locate the Hot Axle-Box Detectors (HABD) at a properdistance. With the inner bearing ring spinning on the axle journal (one of the most dangerous axle-boxbreakdowns), the temperature increase variation reaches from 8ºC/min to 38ºC/min. Therefore, after 25 min (or if the train is moving, on the average, at 60 km/h after 25 km) the temperature of the axle of the wheel-set at the place of ring spinning may reach from plus 266ºC to plus 800ºC. For this reason, it is very important to locate HABD at a proper distance. It is set in modernrequirements that a distance between two HABD should not exceed 35 km.

HABD should ensure that axle-boxes of all impermissibly hot rolling stocks should bediagnosed. HABD danger levels are identified, which with account taken ofthe axle heat flow temperature may be plus 100ºC, 120ºC or 140ºC.

Axle-box breakdowns may be subdivided into four main groups: 1) Poor lubrication, 2) Fatigue, 3) Notqualitative mounting and 4) Contamination (with metal admixtures, water). Bearing damage occurs due toimproper lubrication, excessive load, excessive rotation speed, inadequate mechanical propertiesinsufficient operating clearance, radial stress caused by an external heat source, obstructed run due tothe breaking of the cage, initial damage of the bearing. The damage of box-axle bearingmechanisms could be classified into two types: brinelling and spalling. Brinelling consists of oneor more indentations distributed over the entire raceway circumference that is subjected to staticoverloading. Each indentation acts as a small fatigue site, producing sharp impacts with thepassage of the rolling element, eventually leading to the development of spalling at the indentationsites as the bearing continues to operate. Under normal loading conditions, the bearing will formminute cracks due to material fatigue after certain duration of usage. With an increase in size duringcyclic loading, the cracks progress to the surface and are manifested as spalling in the contact areas.

Considering all the above parameters a non-contact device is required with a response time of 4milli second to detect the Hot Box and Hot Wheel at a Train running speed up to 100Kmph.

I. BLOCK DIAGRAM:

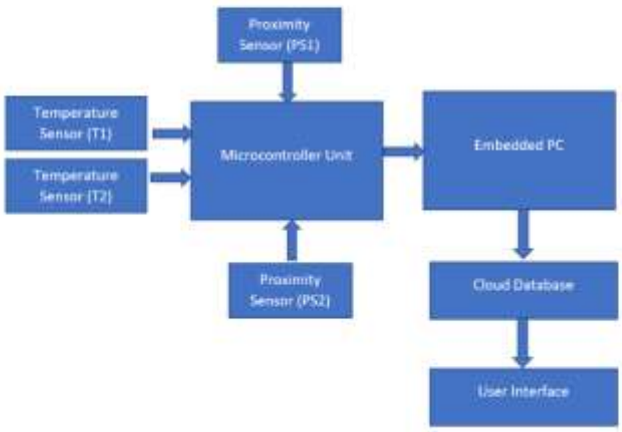


Fig: 1 Block Diagram of the System

II.WORKING

The system should contain two temperature sensors for left and right axle temperature measurement, with wheel temperature detection where as two proximity sensors will be used for counting the Axle Box and the number of wheels.

As per the block diagram it is clear that the Temperature1(T1) and Temperature2(T2) will be directly connected to the Microcontroller unit for analogue data processing whereas proximity sensor connected with the MCU will send digital signal for data processing, further the data will be processed into serial format as per the algorithm design. The serial data will be recorded in the Embedded PC in the form of

Excel format which will be further send to the cloud database via internet connection for online monitoring of the system.

III. SPECIFICATIONS: (For 1 Set of Hot Box and Hot Wheel)

1. Two numbers of Non-Contact Infrared Thermometer along with communication box & power supply unit. Model No. CT Fast LT 25 F (Optris Make- Germany)

- Temperature range :- 50 to 975 degree C
- Optical resolution : 25.1
- Spectral Range : 8-14 µm
- System accuracy (at ambient temperature 23±5◦C) : ±1 % or ± 2◦C whichever is better.
- Response Time :

Analog output (90%): 6 ms or better sensitive sensor less than 6ms. Digital output (50%): 3ms or better sensitive sensor less than 3ms.

- Environmental rating
- Sensing head : IP 65 (NEMA-4)
- Electronic box : IP 65 (NEMA-4)
- Cable length : 15m
- Power Supply 8 – 36 VDC

2. Two numbers of Electronic Rectangular inductive proximity sensor with 50 mm sensing range (Flush mountable) with PNP Function with MX Terminal cable of 4m length. Operating voltage 10 to 30 VDC, Make- Q80-3.
3. One number of Embedded PC system with dual core processor having HDMI interface, with 8GB RAM, with 2 COM Port, 3.5" SATA HDD with Dongle card for 4G Connectivity and 4 USB connector, Model Name–Fujistu.
4. One number of Grey Color powder coated metal box (2 feet x 3 feet) for automatic computerized axle box temperature recorder with

- Micro controller board with power supply.
- Proximity sensor interface board with power supply.
- 6A MCB-1 with 15A sockets box

5. The system will measure LH & RH axle box & wheel temperature of moving train along with axle number.
6. The system will be capable to measure axle box temperature of train running at a speed of 110 kmph.
7. The system will be capable of storing the measured data in field unit.
8. At the end of the train the saved data will be transferred to centralized web server within 2 minutes.
9. Tier-III level secured data center-based cloud application with domain name & web hosting with dedicated IP & internet (With 4G SIM or any mode of communication channel)will be required for online processing of data.
10. The web application also have forms for viewing:

- Train wise details of all location with minimum & maximum temperature recorded on each train.
- Train wise form should also have facilities to update actual train number, train name & remarks of the train examiner.

- If the maximum temperature of the train is higher than defined temperature & difference between adjacent axles is more than 20◦C then the row will be highlighted with pink color. Also the system will generate an alarm & SMS to phone numbers included in the system.
- A button will be provided on each row of the train to access a web page to display RH & LH temperature with axle number of the train.
- A report generation form will be developed for online database record.

IV. LIVE WORK:

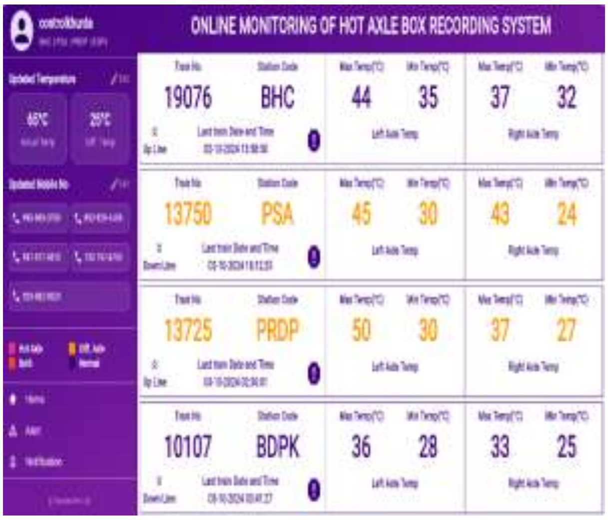
We have successfully compiled& installed a complete set of HDB system for Indian Railways whichcan measure the HOT AXLE BOX and number of AXLE of the train at a speed of 110Kmph.
Taking in action all the parameters as per the norms of Indian Railways, we have successfullyachieve the targetwith a data uploading speed @ of 1min per train, after crossing from the HBD System.

V. LIVE SITE IMPLETED OF HOT BOX DETECTOR

Fig.2: Site of Implementation

Fig: 3 – Control Panel

VI. LIVE REPORT OF HBD:



PROBLEM STATEMENT 2.

WHEEL IMPACT LOAD

II.INTRODUCTION:

The Wheel Impact Load Detector is a set of rails instrumented with strain gauges. The system uses strain gauges stuck on the web of the rail to measure the shear strain from which the corresponding shearing load (the wheel load) is determined. The strain gauges are connected to a data acquisition system which acquires data, computes the values and relays these to the internet based servers.

I. NEED:

- Defective rolling stock produces high impact loads.
- These loads over a prolonged period of time, leads to Rail/Wagon failure, wheel bearing failure etc.
- WILD measures impact load independent of the cause.
- WILD system assists railway engineers to attend to the defective rolling stock immediately.
- WILD reduces Service Failures and Unplanned Maintenance Cost of Rolling Stocks & Tracks.
- WILD is used to catch the defects in the early stage and thereby protecting Rail Infrastructure & avoids Catastrophic Failures

II. DEFECTS THAT CAUSE HIGH IMPACT LOAD:

1. **Wheel Flat**
2. **Broken Spring**
3. **Dashpot Oil Leak**
4. **Unevenness in Side Bearer**
5. **Cone Defect**
6. **(a) PU Pad / (b) EM Pad**
7. **CC Housing**
8. **Axle Bolt Cant**
9. **Friction Liner**
10. **Bolster**
11. **Uneven Loading**

12. **Coil Spring Weak**
13. **Shell Tread**
14. **Snubber Spring Broken**
15. Defect in Suspension
16. Skid mark, etc
17. Loose/Compacted Ballast
18. Track Twist
19. Track Geometry Defects
20. Welding Defects in Welded Rails
21. Expansion Joint Defects
22. Broken/Damaged Sleepers
23. Fractured Rails

III. WORKING OF WILD

The space between sleepers is instrumented using strain gauges and any load that appears in the effective zone is considered, in which the maximum load treated as the impact load. The instrumented portions can be determined and prepositioned to give best coverage for the wheel of interest and each channel produces a portion of load profile for all the wheels.

Fig:4.Transducer Mounting Zone

IV. BLOCK DIAGRAM:

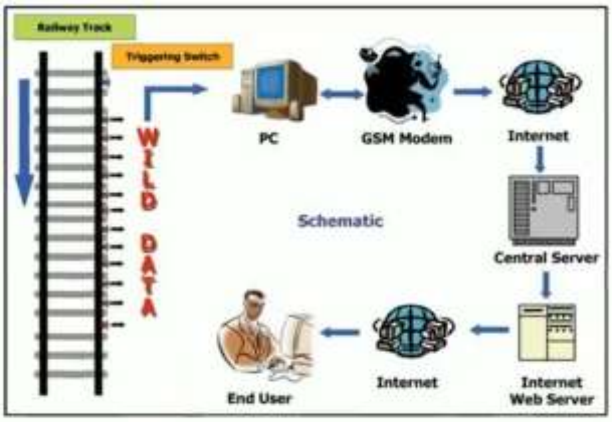


Fig: 5 Block diagram of WILD system

2nd Approach of Development

The finite element method (FEM)-based wheel-rail rolling contact model with a fresh wheel flat was built to investigate the wheel-rail impact responses, where a comprehensive dynamic explicit algorithm was employed. Two basic dynamic effects (i.e., inertia effect and strain-rate effect) and temperature effect during the wheel-rail sliding process were considered. Influences of train speed, flat length and axle load on the wheel-rail impact responses were discussed in terms of wheel-rail impact force.

The wheel-rail interaction has become increasingly one of the most attractive and important topics in the field of rail transportation, since the serious wheel/rail failure will surely lead to a series of disasters. The wheel flat is a main type of potential dangerous factors of inducing the wheel/rail failure, which is usually generated by the two following factors: (i) the sudden lock of a running wheel during the braking process, resulting that the braking force exceeds temporarily the available wheel-rail friction force; and (ii) the sliding of the wheel on the rail under the circumstance of a local reduction of the wheel-rail adhesion force. Figure 6 shows a typical photograph of a wheel flat formed by wheel-rail sliding.

Fig: 6 Wheel Defect

PROBLEM STATEMENT 3.

HANGING PART DETECTION SYSTEM (HPDS)

HPDS is basically based on detecting any object detecting above the rail up to 150mm will be treated as hanging object barring.

Fig: 7 Hanging part detection

I. WORKING:

The system will be equipped with an extremely sensitive camera which will capture the video stream of moving train and stored in the HDD for its frame wise finite processing based on image processing and Artificial Intelligence (AI) software. As soon any hanging bodies detected, it will generate a message and send it to the registered mobile number with its captured frame.

II. BLOCK DIAGRAM OF PROCESS FLOW

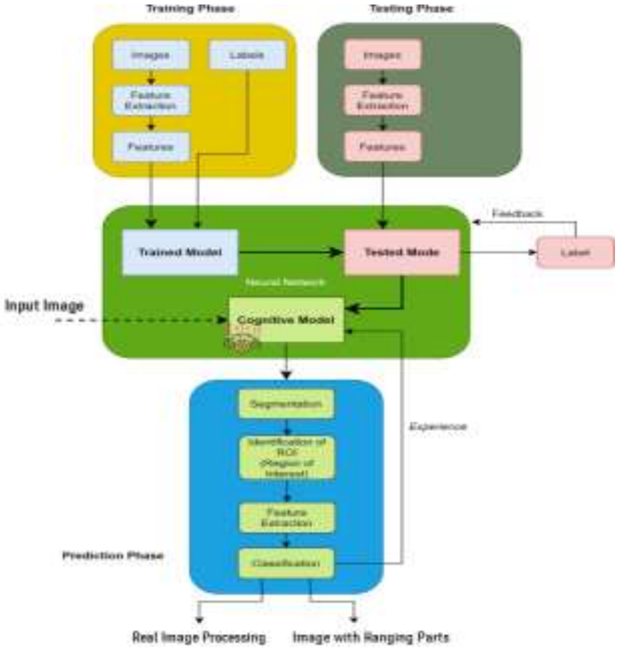


Fig: 8 Methodology

Identifying and classifying of hanging part detection is considered to be a more challenging task. For pattern recognition, AI procedures such as the least square support vector machine (LS-SVM) were used. It has yet to be determined how they are used to isolate hanging parts from trained images.

The alternative techniques have been developed by using different AI strategies. It incorporates the use of texture features derived fromimages by applying pattern recognition techniques to various standardimages, it is possible to effectively segmentimages, remove texture-based characteristics, and eventually identify the hanging object.

Fig. 8 shows the cognitive-based proposed model to classify images. In this approach, during training phase the neural network was trained with a large number of datasets.In this phase, the model is properly trained with associated labels. The performance as well as accuracy is based on the number of training datasets used during training.

2nd Approach for Hanging Part Detection:

Lidar Point Clouds

In this section, first, we review the dataset as the most popular benchmark for lidar 3d object detection task. Then, we explain the lidar coordinate frame used in the dataset. Finally, the data format of returned lidar points is processed.

Each training example is a 10 milliseconds snapshot of the 3d world around the train and is formed by a lidar point cloud (you can think of a lidar point cloud as a 360-degree photo that is captured over a period of 10 milliseconds) and two tycamera images synchronized with the scanning lidar sensor. The synchronization of the two cameras with the lidar sensor is essential for the perception methods that rely on the fusion of camera images and lidar point clouds. Such synchronization requires the cameras to capture images when the lidar scan is at the centre of their field of views.

The 3d object detection background section with formally defining 3d object detection task as well as reviewing the 6 degrees of freedom to encode each predicted oriented 3d box. Then, we present the focal loss and hard negative mining as the common methods to address the background class-imbalance in classification loss of 3d object detection networks, and smoothas a robust regression loss against outliers. Also, we compare the regression targets of 3d object detection networks with and without anchor boxes. Moreover, data augmentation is discussed as an essential part of training pipelines of 3d object detection networks in order to ensure better generalization, and two search-based methods that solve finding optimal data augmentation policies using Reinforcement learning (RL) and evolutionary algorithms, will be provided.

In the 3d object detection neural networks section, first, we discuss the challenges of processing lidar points by neural networks caused by the permutation invariance property of point clouds as unordered sets of points. Then, we divide 3d object detection networks into two categories of networks with input-wise permutation invariance and networks with point cloud ordered grid representations. Regarding 3d object detection networks with input-wise permutation invariance, PointNet which is a permutation invariance architecture for lidar-based classification and segmentation.

Finally, we focus on 2d voxelization representation as an alternative to 3d voxelization representation, which demonstrates better computational efficiency via using 2d convolutional layers instead of 3d convolutional layers. Also, we compare hand-engineered and machine-learned feature encoders as part of 3d object detection networks that rely on 2d voxelization representation as their inputs.

REFERENCES

1. Gerdun, V. & Sedmak, T. &Sinkovec, V. &Kovse, I. & Cene, B. Failures of bearings and axles in railway freight wagons. Engineering Failure Analysis. 2007. Vol. 14(5). P. 884-894.
2. Hoeprich, M.R. Rolling-element bearing internal temperatures. Tribology Transactions. 1996. Vol. 39. P. 855-858.
3. Li, Y.F.; Liu, J.X.; Wang, Y. Railway Wheel Flat Detection Based on Improved Empirical Mode Decomposition. Shock Vib. 2016, 2016. [Google Scholar] [CrossRef]
4. Ling, L.; Cao, Y.B.; Xiao, X.B.; Wen, Z.F.; Jin, X.S. Effect of Wheel Flats on the High-speed Wheel-Rail Contact Behavior. J. China Railw. Soc. 2015, 37, 32–39. [Google Scholar]
5. Schneider, A. Railway Safety Research–A Cross-Disciplinary Literature Review; Universität Koblenz, Universitätsbibliothek: Koblenz, Germany, 2020. [Google Scholar]
6. Gao, N.; Touran, A. Cost overruns and formal risk assessment program in US rail transit projects. J. Constr. Eng. Manag. 2020, 146, 05020004. [Google Scholar] [CrossRef]