Detection and clustering of an Neutral Section faults using machine learning techniques for SMART railways

Kennedy Phala
Department of Electrical and Electronic Engineering
University of Johannesburg
Johannesburg, South Africa
kmphala@webmail.co.za

Wesley Doorsamy
Department of Electrical and Electronic Engineering
University of Johannesburg
Johannesburg, South Africa
wdoorsamy@uj.ac.za

Babu Sena Paul
Institute fot Intelligence Systems
University of Johannesburg
Johannesburg, South Africa
babusenapaul@gmail.com

***Abstract*— Fault detection and diagnosis plays an important role particularly in railways were abnormal events are detected and a detailed root causes analysis is performed to prevent similar occurrence. The current method used to detect immediate and long-term faults is through foot inspections and inspection trolleys fitted with cameras proving to be inefficient and time consuming when analyzing the data. This paper examines the smart fault detection system on the overhead wires by applying machine learning techniques for accurate assessment of the neutral section before and after failure thereby grouping the events into fault bins. Modern computational intelligence has enabled the fault diagnostic and fault detection to be accurate from the data generated from the sensors. The interaction between the pantograph and contact wire will be monitored using accelerometers and non-contact infrared thermometer sensors were should there be a deviation from the normal signal spectrum it will be detected. The measured data from onsite will be conveyed to ThingSpeak for cloud computation thereby providing notifications in real-time which allows the end user to visualize, analyze and act on data online. A prototype has been built and tested which shows that the system works reasonably with data collected from sensors.**

Keywords- fault diagnostic; neutral section; machine learning; accelerometer; k-means, data aggregation

1. Introduction

Railways have played a phenomenal role in moving both passengers and freight to their destinations which leads to the need to automate some of the systems used for transportation to improve safety, operation and lowering the cost of maintenance. In South Africa, the railway industry is still regarded as a main core for the large transportation of passengers and freight within the metropolitan cities and from mines to the harbour. Railway infrastructure consist of multi-disciplinary departments such overhead wires, track, signalling, bridges, telecommunication and technical support where each of these multi-disciplinary departments interact with one another during train operation. The railway industry is faced with a challenge of doing maintenance since the network spans out to 30 400km outdoor for electrified and non-electrified section. Foot patrols and trolley inspections are proving to be labour intensive and inefficient to some extent of human fatigue. Currently the method used to detect failures on the Neutral Section (NS) it is through foot inspection where a depot technical personnel walk to inspect the condition of the NS using stagger gauge (under live condition) and trolley car (under work occupation) to check if the asset is in good condition. In between the NS the overhead system is protected from fault currents and insulation failure using protection scheme (voltage & current transformer, distance relays etc.). Conventional wired sensors could still be deployed but due to the long sections of catenary wire the wireless system offers attractive alternative [1]. Precise fault diagnosis system requires both historical data and continuous monitoring for accurate assessment to prevent ultimate failure on the railway network. There are many thriving developed model-based fault monitoring and diagnosis devices embedded with artificial intelligence algorithms that provide accurate data interpretation. Smart fault monitoring and diagnosis system will assist in providing the overview of the entire overhead infrastructure which leads to reducing human inspection requests through automated monitoring and correct interpretation of events before and after the incident. The infrastructure assets will be embedded with sensors for detecting abnormal events and should transmit the data to cloud wireless for alerts and storage. The NS will be continuously monitored to predict component failures and to prevent future failures as well by detecting anomalies in real time [2]. Continuous monitoring and fault detection of infrastructure is important solely because it identifies the emerging defects from the stage of origin before leading trains accidents such as hook-ups and huge flashes. The quick response from the maintenance personnel makes it easy to prevent the failures from occurring. The fault monitoring system will detect failures arising from unbalanced arc runners, breakage of balancing droppers and wires, trains not switching off from the generated fault current heat dissipation thereby grouping the similar events into clusters using k-means.

The prompt increase in research and technological development on Internet of Things (IoT) and Wireless Sensor Networks (WSN) have both enabled the infrastructure to be continuously monitored wirelessly thereby storing the live data into cloud to improve costs, productivity and accuracy of fault diagnostic [3]. There are three most useful topologies (star, tree and mesh) utilised and these topologies are efficient and reliable for fault detection and condition monitoring processes due to that they can withstand severe environmental condition [4]. Star topology communication, each end nodes connects directly to the gate way were a single gateway may send and receive data. On this type of system, the end node is not permitted to send message to one another. Tree topology end node is connected to the router node were all the nodes are feeding into gateway. The end node and router node always check for communication signal between the two before transmitting to the gateway. Lastly the mesh topology enables data to be send from one node to the other that is within the range. Global system for mobile communication/general packet radio service (gsm/gprs) provides one of the advantages for long range of data transmission and short message sent capability in real time. This is one of the complex systems that enable vigorous communication and flexible network. These large amounts of data require flexible, efficient and cost-effective tools for storage and analysis. The discovery of Wi-Fi IEEE802.11, ZigBee IEEE 802.15.4 and Bluetooth 802.15.2 yielded the foundation for machine to machine communication. The process allows machines to communicate, interpret and analyse the data autonomous without human intervention [5].

Benefits of smart infrastructure

- Improve asset productivity
- Improve turnaround time
- Reduced operational costs
- Increases network availability and efficiency
- Predict asset failure and proper fault diagnostic
- Improve customer/passenger satisfaction

2. RELATED WORK

In our proposed design, two sensors namely accelerometer (ADXL345) and non-contact infrared thermometer sensor (MLX90614) shall be used to detect any anomaly. GSM/GPRS is used to transmit data to ThingSpeak for cloud computing. Data analytics will be executed online via ThingSpeak Matlab analysis app, ThingSpeak is compactable with Matlab and it allows Matlab commands to be executed online as the data trickles in.

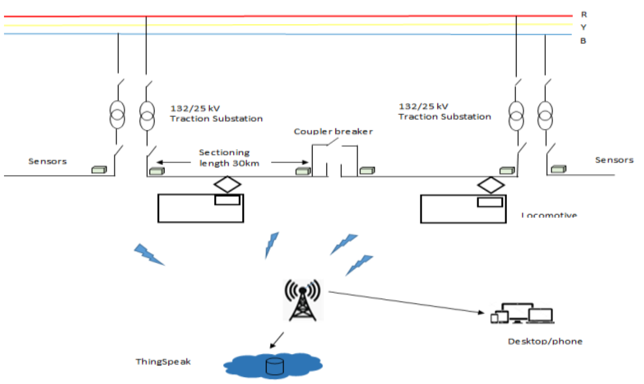

Fig. 1 Block diagram of fault detection system

A. Hardware

Micro electromechanical systems accelerometer

Micro electromechanical systems (MEMS) accelerometer is formally known as a device that measures both acceleration (vibrations or motions) and static force (gravity). These devices are widely used for example on infrastructure monitoring (buildings/bridges), rotation, train tilting, earthquakes, disaster management and airplanes to mention a few [4]. MEMS acceleration measures in terms ‘g’ gravitational force, which is rated 9,81m/s² and it also a vector quantity which has both direction and magnitude. Recent advancement of electronics has enabled the deployment of accelerometers to measure the vibrations, shock and tilt angles on the railways through wireless communication. These devices are small in size, consumes low power, cost effectively and easy to install. The accelerometer will detect any abnormal shock vibrations and tilt angles resulting from failures.

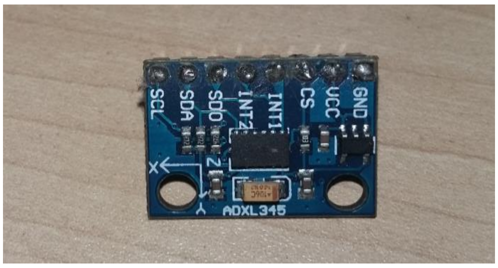

Fig. 2 MEMS accelerometer ADXL345

ADXL345 features [7]

- Free fall detection
- Activity/inactivity monitoring
- Single/double tap detection
- Tilt sensing application
- Very small and easy to install
- Dynamic acceleration from vibrations and motion
- Ultra-low power; 0,3mA standard mode consumption, 40µA in economic consumption mode and 0,1µA in standby mode

Non-contact infrared thermometer sensor

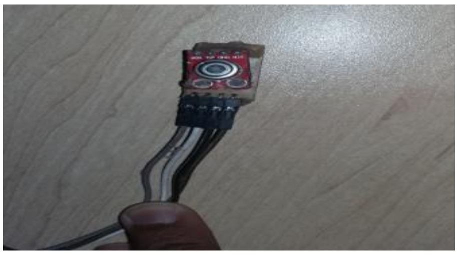

Fig. 3 Non-contact infrared thermometer sensor MLX90614

The non-contact infrared thermometer sensor has dual measurement were ambient (Ta) and object (To) temperature can be measured simultaneously from a distance. The sensor is intended to measure the temperature of the NS component under normal and abnormal conditions. The object temperature under abnormal condition will be differ from ambient should there be a spark/flash generated from the trains failing to switch-off or when the NS is unbalanced. The high precision of the measurements largely depends on the distance from the object tested, angle (field of view) of the surface and the environmental temperature. The distance between the object and the sensor shall be 50mm apart.

Non-contact infrared thermometer sensor features [8]

- Small in size
- Temperature range -40º C to +125º C for Ta
- Temperature range -70º C to +380º C for To
- High accuracy of 0,5º C for both Ta and To
- Measurement resolution of 0,02º C
- Customizable PWM output for continuous reading
- Operating voltage 5V direct current (DC)
- DC source current serial data (SDA), serial clock (SCL), pulse-width modulation (PWM) pin 25mA

Arduino Pro Mini

Arduino Pro Mini is a microcontroller board with ATmega328P that has 14 digital input/output pins using pinMode, digitalRead and digitalWrite. Each pin can receive and provide 40mA. This board is suitable for this experiment because of its low current consumption, smaller in size (34mmx18mm) and can be installed as a permanent installation. The Future Technology Devices International (FDTI) Universal Serial BUS (USB) to serial will be used to upload the code and power the pro mini. The microcontroller board will be interfaced with accelerometer and thermometer sensors to gather data then convert it from analog to digital. The collect data will then be transmitted via gsm to cloud.

Arduino Pro Mini features [9]

- Microcontroller ATmega328P 8bit AVR controller
- Flash memory 32KB (2KB used by bootloader)
- Operating temperature -40º C to +150ºC
- Max current through each input/output (I/O) pin 40mA
- Sleep mode current consumption 4.89mA
- Clock frequency 8MHz (3.3V)
- Pulse-Width Modulation pin 6
- Transmitter (TX) used to transmit transistor-transistor logic (TTL) serial data
- Receiver (RX) used to receive TTL serial data

Mini A6 GSM/GPRS module

The mini A6 module shall be interfaced with arduino pro mini to transmit the measured data to cloud. The mini A6 gsm/gprs module supports quad-band frequencies and a whole lot of features such making and receiving calls, SMS messages and data transfer application for Internet of Things projects.

Fig. 4 A6 gsm/gprs module

Mini A6 gsm/gprs features [10]

- Operating frequency 850/900/1800/1900MHz
- Operating voltage 4.5V to 5.2V DC
- Operating max current 2A
- Sleep mode current 5mA
- Communication interface TTl serial port
- On board IPX and spring antenna pad
- AT commands support the standard AT and transmission control protocol/internet protocol (TCP/IP) command interface

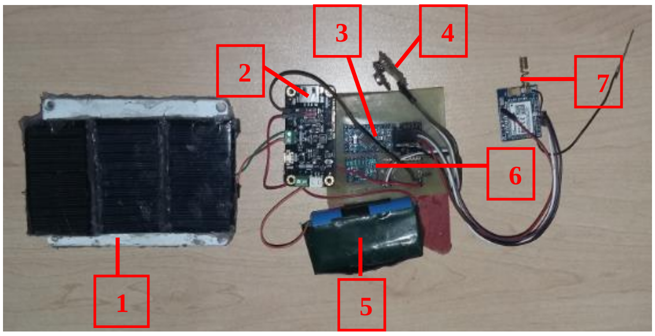

Fig. 5 Hardware of fault detection circuit

1 – 3x 0.3W/5V Solar panels
2 – Solar Power Manager
3 – Arduino Pro mini
4 – Non-contact infrared thermometer sensor
5 – Lithium ion batteries
6 – ADXL345 accelerometer
7 – A6 gsm/gprs module

The system will be powered by two lithium-ion batteries rated 3.7V/2600mAH each during at night or when there is no enough irradiance during the day. Solar charge controller connected embedded with maximum power point tracking (MPPT) is used to charge the batteries and power the power the arduino pro mini. 3 solar panels rated 0.3W/5V shall be connected to the charge controller to power and charge the li-ion batteries.

B. Software

Matlab and ThingSpeak

Data generated from the interaction between the overhead machine vehicle pantograph and NS will be transmitted to ThingSpeak for cloud computing and storage. Thingspeak allows the user to perform data aggregation, visualize and perform data analytics while live data in the cloud trickles in [11]. The data will be stored privately online and it will be imported to Matlab for further data processing.

Machine learning

Unsupervised learning a subsequent of machine learning that aims to automatically extract features from data sets generated from the sensor devices without prior training (12). K-means clustering will be employed to group the observations of the measured data from sensor devices into distintive groups were groups of similarities are part of one cluster while those that are not similar are grouped different from each other. Below is the k-means applied to ThingSpeak for cloud computing while data triggers in from the NS system and pantograph interaction.

d- euclidean distance
n-number of data set in a cluster
x,y- distance between to sets
k- clusters number

K-means algorithm [13]

- **Starting point**
  - Put K randomly where the measured data to be clustered
    $y_1^{(0)}; y_2^{(0)}; \ldots .\, y_K^{(0)};$

– Allocate each measured data to the group which has the closest centroid

$$x \in l_i^{(k)} \, if \; d(x, z_i^{(k)}) < d(x z_j^{(k)})$$
$$i = 1,2 \ldots, k; i \neq j$$

- **Learning**

  *Clustering algorithm

  – Calculate the distance to each cluster k centroid

$$d(x_j, y_i) = \left(\sum_{j=1}^{n} (x_j - y_j) \right)^{1/2} \quad (1)$$

  – Recalculate all the data points of the cluster
- **Application**
  – Repeat the process up until the data points do not converge anymore

Once k-means has been implemented, silhouette plot will be applied to determine the degree of separation between the clusters. The plot graphical shows how close each data point from neighbouring cluster.

Silhouette plot of one data can be defined as follows [14];

I = data sets in the cluster , i=1,2, 3,……
a = average distance of i to the points in the same cluster
b = minimum average distance of i to points in another cluster

$$S_{(i)} = \frac{b_{(i)} - a_{(i)}}{\max\{a_{(i)}, b_{(i)}\}} \quad \text{if } |c_i| > 1 \quad (2)$$

$$s_{(i)} = 0, \text{if } |c_i| = 1$$

$$S_{(i)} =$$

$$1 \quad - \frac{a_{(i)}}{b_{(i)}} \quad \text{if } a_{(i)} < b_{(i)}$$

$$0 \quad \text{if } a_{(i)} = b_{(i)}$$

$$-1 \quad - \frac{b_{(i)}}{a_{(i)}} \quad \text{if } a_{(i)} > b_{(i)} \quad (3)$$

Silhouette coefficients
1≤ S(i) ≤ -1
+1: indicating points that are very far from neighbouring cluster

0: indicating points not distinctly in one cluster or another cluster

-1: indicating points that are assigned to wrong cluster

Once after the k-means has been implemented and performance evaluated on Matlab then the code shall be uploaded onto ThingSpeak for cloud computing.

3. METHODOLOGY

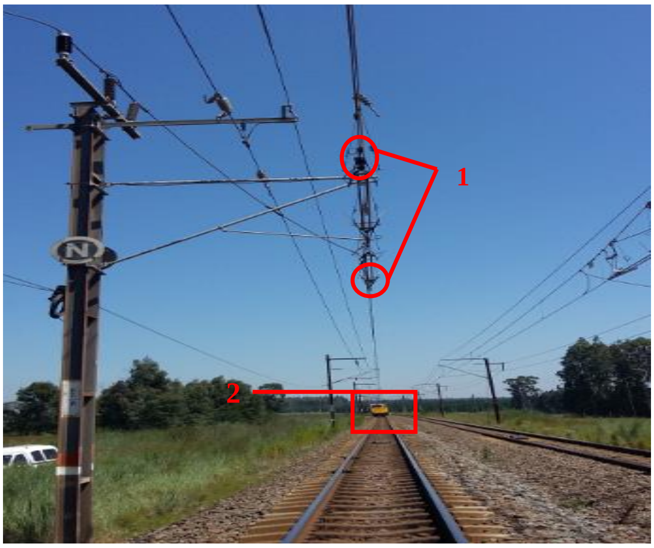

Fig. 6 Proposed detection system on the Neutral Section

1 – Two enclosures housing sensors installed on NS

2 – Overhead machine vehicle

Before the first phase of the experiment, two enclosures housing the sensors were installed as shown in figure 8 on the NS to detect any anomaly. An overhead machine vehicle fitted with standard pantograph was used to generate data between the pantograph and NS system to be recorded by the accelerometers and non-contact infrared thermometer sensors.

First phase of the experiment: Install the device and let it run and measure without any external influence to see the behaviour of accelerometer readings (X, Y, Z) and temperature sensor.

Second phase of the experiment: Allow the overhead machine vehicle to run at different speeds 15km/h, 30km/h, 60km/h, 80km/h to check the behaviour pattern of the accelerometer (X, Y, Z). As the overhead machine vehicle runs at different intervals, all the data will be recorded and stored to cloud wirelessly. Once the phases of the onsite simulations are executed, a csv from ThingSpeak is imported to Matlab to perform k-means clustering.

4. EXPERIMENTAL RESULTS AND ANALYSIS

Error analysis

External influences such track cant, wind and rain; is evident as false alarms from generated data. It is seen that accelerometer behaviour is influenced by the following parameters;

- Overhead machine vehicle speed
- Contact wire height/ruling height
- Contact wire force
- Pantograph position
- Pantograph upliftment force
- Condition of track
- Wind speed

Thingspeak online analysis and visualisation

Below are the results for both ambient and return wire clamp object measured by the non-contact infrared thermometer sensor. The x,y,z axis were recorded from different speed intervals to observe the pattern of the NS responding to the contact pantograph interaction. There amplitude for vibration was greater at 80km/h as compared to 15km/h. Also the tilt positions before and after, there was a magnificent change where x-axis was above 4 degrees.

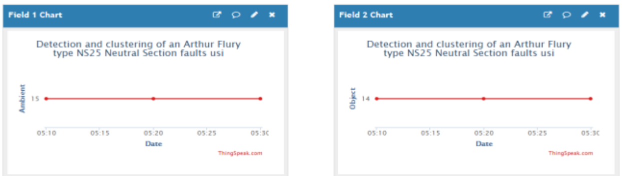

Fig. 7 Ambient and Object temperature readings

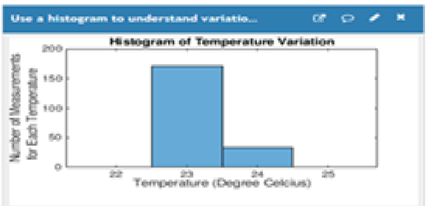

Fig. 8 Online analysis histogram temperature variations

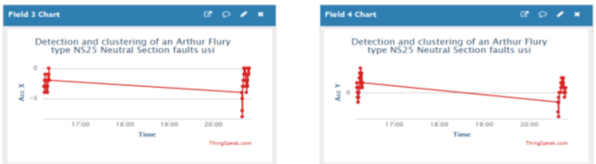

Fig. 9 Vibration acceleration for X, Y, Z when the pantograph touches the NS

Fig. 10 Tilt angles for X, Y, Z before the pantograph passed the NS

Fig. 11 Tilt angles for X, Y, Z after the pantograph passed the NS

Fig. 12 Real-time alerts for detected failures via Twitter and SMS

Applying K-means model

K-means algorithm was implemented and tested via Matlab software.

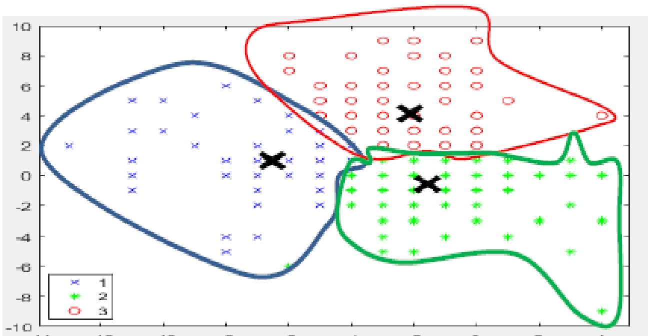

Fig. 13 Clustered vibration acceleration for X,Y,Z axis

Silhouette plot to determine the degree of separation between the cluster peformed on Matlab software.

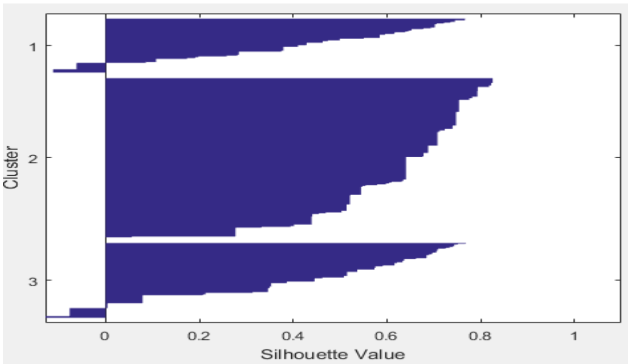

Fig. 14 Silhouette plot for k-means clustering (k=3)

5. FUTURE WORK

Classify train types based on the vibrations detected, measure the train speeds and fault currents to provide accurate fault diagnosis on the type of each event. Develop a system that will reduce the electrical magnetic interference generated from the 25kV AC overhead lines. Develop an algorithm that will detect and remove outliers form the data since k-means is sensitive to outliers.

6. ACKNOWLEDGEMENT

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7. CONCLUSION

The design, building, testing and simulation was achieved were the system was able to collect and send data to cloud using wireless communication, receiving triggered events in real-time via twitter/SMS and group the data into faulty bins from the collected data sets of sensors. The chosen number of clusters was validated using silhouette plot were k=3. The IoT and WSN has enabled the NS to be monitored remotely with accurate fault diagnostic results. It is evident from the onsite simulations that the system is highly reliable and can continuously operate without interruption all day where it will assist with fault detection and diagnosis from the state of occurrence thus reducing the cost of monitoring.

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