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**Monitoring low adhesion on railways via the Internet of Things**

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**Abstract**

Adhesion refers to the ‘slipperiness’ of the rails due to surface contaminants such as leaves, rust, oil and grease, exacerbated by small amounts of atmospheric moisture from drizzle, dew or fog. Low adhesion is an issue on the railways because it reduces acceleration and braking efficiency. This leads to platform overruns and Signals Passed at Danger, putting the travelling public at risk as well as contributing significantly to service delays. In response, high resolution forecasting systems have been developed that takes into account site specific leaf fall forecasts, rail and dew-point temperature to estimate the occurrence of dew, frost, light rain and fog. However, in order to validate models, data is required from a high resolution monitoring network that is able to capture observations of rail moisture and leaf fall contamination. This paper investigates the feasibility of harnessing the emerging Internet of Things (IoT) to develop a high resolution, but low cost, rail moisture monitoring network. A low cost, self-contained sensor was developed and tested, with positive results, against existing, more expensive, sensors in both a lab and field setting. The paper concludes with a blueprint documenting an approach to improve the spatial resolution of moisture measurements across the network.

**Keywords:** Railway Tracks, Weather, Information Technology

**Notations**

IoT – Internet of Things

SPADS – Signals Passed At Danger

ACCAT - Adhesion Controllers Condition Assessment Tool

GSM – Global System for Mobile communications

PA – Percentage Agreement

**1. Introduction**

**1.1 Low Adhesion**

The presence of water significantly reduces the adhesion coefficient between the wheel and rail (Chen et al,. 2002, 2008; Wang et al., 2011), especially if present in conjunction with certain contaminants and environmental conditions, such as leaves, grease, high humidity and low temperatures (Hardwick et al., 2014; Wang et al., 2014, Wu et al., 2014). Low adhesion is an issue on the railways because it reduces braking efficiency and leads to station overruns and Signals Passed at Danger (SPADS), putting the travelling public and staff well-being at risk (AWG, 2004; Fulford, 2004). Furthermore, low adhesion can lead to wheel slides and spins which results in the train being unable to accelerate and decelerate normally, contributing to service delays. Poor adhesion also contributes to damaging wheels and tracks which are put under more pressure through harder brake rates (Baek et al., 2008; Chen et al., 2008; 2011). Dry leaf film also acts as an electrical insulator which can stop track circuits operating correctly and result in Wrong Side Track Circuit Failures.

To help mitigate the problem, high resolution low adhesion forecasting systems now exist that take into account site specific leaf fall forecasts, rail temperature and dew point temperatures to estimate the occurrence of dew, frost, light rain and fog (Met Office 2014). The use of such models can then be used to inform mitigation strategies on the network (e.g. targeted spreading of sandite to increase adhesion). However, in order to fully validate and improve the accuracy of the models, data is required from a high resolution monitoring network that is able to capture observations of wet rail syndrome and leaf fall contamination.

Moisture observations also have the potential to feed directly into Adhesion Management Systems such as the Adhesion Controllers Condition Assessment Tool (ACCAT) operational on the London Underground. Such management tools will be important in the future due to increasing service demand pressures on the mainline coupled with the need to reduce safety and performance issues during Autumn. There is also potential for future systems which alert drivers and route controllers to moisture observations using simple desk based interfaces or mobile devices.

This paper investigates the feasibility of harnessing the emerging Internet of Things (IoT) to develop a high resolution, but low cost, wet rail syndrome monitoring network. The results from such a network of sensors would enable improved validation and calibration of high resolution forecasting models and improve the accuracy of the low adhesion forecasts.

**1.2 Internet of Things**

The IoT quite literally means ‘things’ (e.g. sensors and other smart devices) which are connected to the internet (Atzori et al., 2010). This may seem insignificant, but ‘things’ represent a new, and increasingly, critical infrastructure requiring a dedicated technological ecosystem. Indeed, since 2008, the number of ‘things’ has outnumbered users online. The recent miniaturisation of technologies coupled with reducing costs of sensors of comparable accuracy to operational and scientific instrumentation has led to the growing feasibility of dense sensor networks. Central to the success of the IoT is the recent increased availability of Wi-Fi communications (e.g. smart cities and managed infrastructure corridors) (Chapman et al, 2014)

**1.3 Existing Approaches**

Measuring moisture on the railway is not new and dedicated sensors have been available for over a decade. Whilst there is potential in a number of approaches for measuring moisture on the railway, leaf wetness sensors are the most commonly used approach deployed at selected locations on the rail network. Leaf moisture sensors provide a potentially cheap and reliable means of alerting to dew formation and light rain at a selected location. They work simply by detecting electrical resistance based on moisture droplets that straddle conductors placed in a mesh on an insulating circuit board (typically fibreglass).

The Davis leaf wetness sensor is as close to the current standard currently commercially available. Consisting of a low voltage bi-polar excitation circuit, conductivity is measured across the 28cm2 grid and displayed as a moisture level (see <http://www.davisnet.com/product_documents/weather/spec_sheets/6420_spec_rev_e.pdf> for further details). This sensor is then incorporated into a monitoring solution of either a full weather station, or a scaled back solution such as SlipChex which was developed by AEA Technology in 2002 before being subsequently marketed by Delta Rail. A small number of these devices are present on the London Underground Central Line. However, despite the availability of such technology, there is a serious paucity of sites with the capability of measuring moisture across the UK’s railway network. This is mostly down to cost and the ability to use moisture observations in real time to inform decisions. Whilst moisture sensor heads are relatively cheap to procure, significant outlay is required to produce a final solution with hundreds of pounds also needing to be spent on data-logging equipment and GSM communications. The IoT approach can significantly reduce the cost of these by providing a low cost, low power, sensor embedded in an existing communications mesh (i.e. managed infrastructure corridors). Provided internet connectivity is available, moisture measurements could potentially be made at < £100 per site.

This paper outlines the development of a low-cost IoT sensor (Section 2) and subsequent testing of the sensor against standards in a laboratory (Section 3.1) and field setting (Section 3.2). It is worth highlighting that the innovation in this paper is in applying the Internet of Things to the problem and this paper demonstrates this by showing how existing ‘off the shelf’ components can now be readily assembled to do the same job as a much more expensive bespoke system.

**2 A Prototype Sensor**

Three bespoke low cost sensors were developed based on an existing commercial ‘off the shelf’ platform (Aginova Sentinel Aqua: http://www.aginova.com/docs/Sentinel\_Aqua\_Datasheet\_rev\_3.pdf). Although the sensor head is presently used for alternative applications (typically the sensing of moisture in internal environments such as computer server rooms), the sensor is actually similar to that used in the SlipChex system, albeit much smaller with a 10cm2 grid and is an order of magnitude cheaper to procure. For this project, this sensor head was adapted for use with the iCelsius wireless device (<http://www.icelsius.com/product/icelsius-wireless-summary-page>) which is a self-contained, Wi-Fi enabled unit with an internal 3.7V, 1000mAh, rechargeable, lithium-ion battery. The device can take observations at a temporal resolution of between 1 and 30 minutes, as well as upload data via remote mode to a cloud server (provided internet connectivity exists). In the absence of Wi-Fi, the sensor can be used in demonstration mode by communicating with a nearby smartphone. A standalone datalogging mode is also an intended future function of the iCelsius unit.

**3 Results**

**3.1 Laboratory Tests**

The purpose of the laboratory tests was to compare sensor performance against the Davis leaf wetness sensor (the closest comparable sensor on the market to that used in the SlipChex system). However, there are difficulties in making this comparison due to differences in scales used by the two sensors. The Davis leaf wetness sensor takes minute observations on an ordinal scale between 1 (dry) and 15 (wet) whilst the low-cost sensor expresses wetness as a percentage. Indeed, the use of either scale is questionable. A moisture sensor head simply consists of two conductors organised in a grid on the circuit board. A gap exists between the two conductors which is bridged by water droplets when moisture is present, thus completing the circuit (Miranda et al, 2010). Hence, the sensitivity of the sensor is ultimately determined by the size of the gap between the conductors which varies with sensor brand. Therefore, although these scales are set by effectively measuring changes in resistance, there is an argument for considering the output simply as a binary i.e. either wet or dry. This was particularly highlighted during early experiments where the sensitivity of each sensor was tested with a range of spraying / misting devices. During these tests, it became clear that both sensors instantly measured wet conditions with even the slightest of spray and that there was no discernible difference in sensor response at this level of moisture. Hence, further lab tests were redesigned to focus on detecting dew formation.

The lab tests were carried out in a climate chamber under controlled conditions, where the temperature and humidity could be freely changed. Air was de-ionised and heated before being pumped in and distilled water was injected to modify humidity. Both sensors were adhered to the head of a dummy rail using thermal paste, and a temperature/humidity logger was placed on top of the rail to monitor the ambient air (Figure 1).

In the experiments, the chamber was left to maintain a steady state of 0°C and 20% humidity. Once thermal equilibrium had been reached in the chamber, air was introduced containing condensation nuclei, in order to promote simultaneous condensation on both sensors. After 8 minutes, the chamber was sealed again so the chamber could return to the initial steady state and all instruments could return to thermal equilibrium and the dew could evaporate. An example plot from these tests is shown in Figure 2.

A marked similarity in sensor performance is clearly evident with both sensors instantly responding to the change in ambient conditions after the first minute of the experiment. The evaporation of the dew was also detected at the same time for both sensors. However, these experiments also highlight the increased sensitivity of the low-cost sensor which reacted rapidly to the formation of dew. This was expected as the spacing between conductors on this sensor is considerably smaller than the Davis sensor. Similarly, the low cost sensor reacts more quickly to the evaporation of dew. This is hypothesised to be a result of a small variation in heat capacity (i.e. thickness of the fibreglass circuit board upon which the conductors are mounted) between the sensors which will impact upon the duration of time that the sensor can ‘hold’ dew. Despite these minor variations, the performance of the two sensors in this experiment is judged to be largely comparable. However, it does highlight the need for caution when using manufacturer scales for operational purposes. A recommendation with respect to sensor design is to investigate optimising the sensor head for this particular application by varying the spacing of the conductors as well as the thickness of the board upon which they are mounted to more closely mimic the rail head.

**3.2 Field Trial**

The performance of the sensor was also tested during a 1 month field trial on the London Underground at Loughton. The site is an established location for monitoring of moisture via a SlipChex system attached to a dummy rail located approximately 3 metres from the live rail.

The low-cost sensor was adhered to a dummy rail using thermal paste and located in the proximity of the existing apparatus to enable a comparison of both systems (Figure 3). In a field setting, there is a need to collect data from the low cost sensor in remote mode where the sensor relays the data in real-time to the server. The existence of Wi-Fi is therefore a necessary prerequisite for this to occur. Unfortunately, Wi-Fi infrastructure was unavailable at Loughton and so there was a need for additional instrumentation to enable internet connectivity. A ZTE MF60 2.4GHz, mobile Wi-Fi hotspot (GSM enabled) was used and powered using a 75Ah leisure battery during the trial. All equipment was contained within a Campbell Scientific logger box for waterproofing and security. The equipment was deployed for a 4 week period between 28th October and 26th November 2014.

For the field test comparison, the pre-deployed sensor at Loughton used to measure moisture is slightly different to the Davis tested in the climate chamber. The sensor head is a Quartz 809-89 but is similar to the Davis in terms of size and specification. It produces minute based observations which are converted for operational use into an ordinal scale of 1 (dry) to 7 (wet). This provides an opportunity to calibrate the low-cost sensor by comparing percentage readings with the in-situ Quartz. The approach taken was to set the threshold at 2 on the quartz sensor (i.e. indicating the existence of some moisture) and to compare this binary wet / dry information with a range of thresholds for the low-cost device (e.g. Sentelhas et al., 2008). These thresholds were calculated by taking the median percentage value output by the low cost sensor over the study period based on the remaining outputs of the Quartz Sensor (Table 1).

Although the equipment was deployed for a 4 week period, continuous data collection proved challenging due to the Wi-Fi hotspot battery life restrictions (and not the low cost moisture sensor itself). Therefore, where Wi-Fi is available on the rail network, these restrictions will not apply.

The power requirements of the Wi-Fi hotspot meant that the battery needed changing every 9 to 10 days. The power supply proved to be very temperamental and despite 4 returning visits to ensure a month of data collection, the supply failed significantly on two occasions. This has resulted in large gaps in the dataset, the first between 9th and 13th November, the second at the end of the trial when the power failed on the 19th November. Despite two subsequent visits to the field site to restore power, this proved unsuccessful thus signalling the end of the trial period. Despite the technical difficulties, sufficient data was collected to draw a simple comparison between the low-cost sensor, the pre-deployed Quartz sensor, prevailing weather conditions recorded at Northolt weather station (Figure 4).

The sensors can be seen to react fairly consistently with changing weather conditions, as observed at Northolt (note the caveat that Northolt is approx. 20 miles west of Loughton and that localised variations in weather will mean that the data in Figure 4 can only provide an indication of the weather experienced at Loughton). As expected, each precipitation event during the study period was detected by both sensors, although the precipitation levels were insufficiently high to read more than 5 on the 7 point scale used on the Quartz sensor. Likewise, variations in wetness recorded by the sensors are largely consistent with variations in relative humidity (correlation coefficient = 0.495). Without a direct measurement of rail temperature it isn’t possible to calculate dew-point (i.e. the time of dew formation on the railway), but high relative humidity appears a reasonable indicator of surface moisture.

Although inspection of Figure 4 highlights large similarities between the sensor outputs, some differences are also clearly evident. The primary difference is that the low-cost sensor appears to over-estimate wetness compared to the Quartz sensor, to the extent that when the Quartz had fallen into category 1 (dry), the low-cost sensor often remained in the upper percentiles. This is most pronounced between the early 14th to the middle of the 18th November, where it consistently remained above 98%, despite variance across the entire observational range by the Quartz sensor. This higher sensitivity is consistent with the results from the laboratory trials, which hypothesised that the spacing between the conductors and the heat capacity are important for understanding differences in the sensitivity of readings. However, as there is no known certain ‘ground truth’ of when low levels of moisture were found on the railhead because there are uncertainties associated with the existing moisture sensor and the low cost sensor. Therefore, it was necessary to examine the prevailing weather to draw conclusions on the likely occurrence of moisture on the rail head during this period. Mid-November was an unusually benign period of weather for mid leaf fall season, characterised by high humidity (greater than 80%) and calm conditions, with occasional mist and fog (Figure 4). During this period, the increased sensitivity of the low-cost sensor is clearly demonstrated as humidity at this level is sufficient to register a wetness reading. In contrast, the Quartz sensor demonstrates more variation. To produce a quantitative comparison between the two sensors, contingency tables were produced for each previously determined moisture threshold for the low-cost sensor (Table 2).

Table 2 shows that regardless of threshold to define moisture on the low cost sensor, the percentage agreement (PA) between the two sensors is typically in the region of 75-80%. The oversensitivity of the low-cost sensor is also evident and expressed as a high quantity of Type 2 errors. It is demonstrated that this can be reduced by increasing the threshold used although this can be at the consequence of reducing the total percentage agreement. Figure 5 shows time series of Type 1 and Type 2 errors over the study period.

Overall, it was found that the low-cost sensor was able to differentiate wet periods to a greater extent than dry periods. All four low-cost sensor limits created a relatively high Type II error (false negative or false alarm) during dry periods but a low Type I error rate (false positive or missed rate) during wet periods. For most cases, Type II errors originated during times of high humidity further underlining the need to calibrate the low-cost sensor so that the sensitivity is suitable for the application. This could potentially be done in the future by locating the sensor at known areas of low adhesion and cross correlating incidents with sensor readings and a nearby weather station measuring relative humidity and precipitation (with more sensitive instrumentation such as a disdrometer or fog precipitation mesh). Potentially a temperature sensor probe located on a dummy rail could be used to model the dew point.

**4 Discussion**

Whilst models provide useful operational tools for low adhesion mitigation strategies, for output to be used to its full potential there is a need for additional monitoring on the network. This data provides a dual purpose:

1. Allows for the verification and improvement of high resolution models.

2. Enables real-time monitoring on the ground which could be fed directly into Adhesion Management Systems such as the Adhesion Controllers Condition Assessment Tool (ACCAT) operational on the London Underground.

Hence, high resolution data is crucial for both the prediction and real-time mitigation of low adhesion. The two approaches are complimentary, but however skilful a model is that can aid preparedness, there is no substitute for observations to back up those predictions and to enable low adhesion to be actively managed in real-time.

To achieve this, it is clear that such a moisture detection system needs to be of high resolution. Trace amounts of moisture are highly spatially variable and contrasts in railhead wetness will be present over even the smallest of distances. For example, dew formation is dependent on rail head temperature and so will vary depending on localised shading effects. The low cost IoT approach outlined in this paper is the only realistic solution capable of producing measurements at such a resolution.

However, there are currently some technological barriers. The availability of internet connectivity is presently not sufficient to enable a roll-out of sensors at this scale. Although this will be possible in the future, particularly with the advent of ‘sub-GHz’ (RSSB, 2015) which permits long-range internet connectivity, in the meantime a scaled deployment approach is required.

Sensors can be located at any critical point on the network by the establishment of a WiFi hotspot (although given the limitations identified in this study, this needs to be mains powered). Indeed, WiFi will already be available at many locations on the network (e.g. stations) to help facilitate this approach, where it is presently unavailable, temporary GSM communications can still be used. Connectivity can be further improved by using repeaters to extend the range of the WiFi network. This will enable high resolution monitoring along larger sections of line; an approach which may be particularly useful for problem locations where braking is frequently compromised. This data should then be sufficient to start to be used within adhesion management systems.

A phased deployment such as this is part of the vision of high resolution monitoring of the entire network. Gaps in coverage in critical areas will gradually be filled as and when long-range WiFi connectivity becomes available on the network.

Finally, moisture is only one component requiring measurement for model verification and improvement. Leaf fall quantities are equally challenging to measure at a high resolution and there is a need to investigate new methods to also measure this. Present methods such as lineside vegetation surveys lack the temporal resolution to be used effectively by high resolution models. There is a further need to investigate low cost imaging solutions which could be co-located with a moisture sensor. A high resolution deployment of both devices would be a very powerful component of an adhesion management system.

**5. Conclusions**

This paper has assumed that leaf wetness sensors remain the most feasible way to detect moisture on the railways. The low-cost sensor was able to successfully identify wet and dry periods under both lab and field conditions, but possessed a high Type II error rate, indicating over sensitivity to high humidity. Such differences between the sensors are partially attributed to the different conductor spacing and thickness of the fibreglass circuit board which acts as an insulator between the conductors and the rail. Indeed, the thickness of ‘off the shelf’ sensors are designed to provide a heat capacity which closely matches a leaf and hence there is a need to investigate different constructions more appropriate for the application. This could be done in a ‘live’ setting so that incidents can be directly related to measured conditions. On site weather data would also need to be collected. Presently, a high Type II error could lead to biases in adhesion models towards simulating wetter conditions. However, given the nature of the application, a negative bias is probably preferable to ensure safety on the network (saving resources is considered of secondary importance).

This feasibility study has assumed that the current state of the art in sensing technology is the most appropriate for an IoT moisture detection system. However, this approach is limited as it relies on indirect measurement moisture formation on a fibreglass circuit board attached to a piece of dummy rail. Hence, alternative approaches should also be investigated that will permit non-contact approaches to measuring moisture. Such methods would permit real time monitoring of the live rail and would also reveal information pertaining to the presence of contaminants on the rail head such as leaf fall contamination. It also has potential for direct mounting on rolling stock for mobile measurements.

Overall, this study has demonstrated that low cost sensing of moisture is more than plausible, but there is now a need to scale up the study into a demonstration network to test the practicality over spatial and temporal scales. However, the barriers to consistent data collection highlighted in this study have clearly indicated that, whilst IoT sensing technology is low power (internal lithium batteries can last for up to 3 years at a suitable data resolution), the use of battery powered Wi-Fi hotspots are impractical. For an extended trial, mains or solar power will be needed for internet connectivity via a hotspot or ideally the availability of an alternative hardwired Wi-Fi network. The use of an extended trial will also permit sensor performance to be assessed over an extended time period. It is accepted that a major disadvantage of low cost sensors is that whilst accuracy can initially be very promising, long term consistency (e.g. sensor drift) can be an issue. This can only be thoroughly tested over an extended timescale. If significant issues are identified then a sensor redesign may be required. However, an alternative means for dealing with this issue is that as the price of sensors is so low (<£100 per node), then the entire unit should be viewed as a consumable and replaced periodically (e.g. a biannual maintenance schedule to fit around battery life expectancy).

Finally, given the prerequisite of available Wi-Fi for an IoT moisture detection system, medium term plans for improved trackside wireless coverage on the railway network are essential. It is now common place to see Wi-Fi technologies with access points deployed along road corridors (e.g. on managed sections of the UK motorway network). The presence of such a mesh ensures that IoT sensors can now be located at a high resolution on major roads (Chapman et al, 2014). Such technology is presently at the proof of concept stage for the railway network (RSSB, 2015) which is assessing the potential of trackside 900MHz wireless internet protocol connectivity. Whilst ‘sub GHz’ Wi-Fi is presently not compatible with the sensors used in this feasibility study, it is increasingly emerging as a new standard in the industry. Conversely, should internet connectivity not improve in the medium term, then alternative technologies operating on a line of sight communications mesh (e.g. Zigbee) provide an alternative approach without the need for investment in trackside Wi-Fi. However, this will ultimately be more expensive than the low cost IoT approach outlined in this study. Furthermore, given the lead times in research and development of such systems, the conclusion is that Wi-Fi connectivity will improve regardless over the next 5-10 years and systems should be designed to take advantage of the opportunities which that offers.

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Figure 3: Loughton fieldsite showing various items of monitoring equipment showing low-cost sensor (front) and SlipChex system (rear)

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|  |  |  |
| --- | --- | --- |
| Quartz (wet) | Quartz (dry) | Low-cost (median) |
| 2-5 | 1 | 90.5 |
| 3-5 | 1-2 | 95.0 |
| 4-5 | 1-3 | 97.1 |
| 5 | 1-4 | 99.6 |

Table 2: Contingency tables of the low-cost and Quartz sensor wet and dry counts for the four previously determined thresholds (2>assumed wet for Quartz). Type 1 error: Quartz wet, low-cost dry; Type 2 error: Quartz dry, low-cost wet. PA=Percentage Agreement

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Threshold=95.1%  (PA: 76.4%) | | Quartz | |  | Threshold=97.35%  (PA=78.1%) | | Quartz | |
| Dry | Wet | Dry | Wet |
| Low-cost | Wet | 23.3% | 48.6% | Low-cost | Wet | 20.7% | 47.8% |
| Dry | 27.8% | 0.3% | Dry | 30.3% | 1.2% |
|  | | | |  | | | |
| Threshold=98.4% (PA=77.8%) | | Quartz | | Threshold=99.7% (PA=67.6%) | | Quartz | |
| Dry | Wet | Dry | Wet |
| Low-cost | Wet | 19.8% | 46.6% | Low-cost | Wet | 14.3% | 30.8% |
| Dry | 31.2% | 2.4% | Dry | 36.8% | 18.1% |