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HIGH-RESOLUTION MONITORING OF WEATHER IMPACTS ON INFRASTRUCTURE NETWORKS USING THE INTERNET OF THINGS

Lee Chapman and Simon J. Bell

Two use cases are presented for winter road maintenance and seasonal resilience on the railways to showcase the potentially transformative impact of the Internet of Things on observations and forecasting.

T he impacts of weather and climate on infrastructure are numerous. Whereas extreme events clearly pose the biggest challenges, significant opportunities to improve the resilience of infrastructure exist in the prediction of smaller "everyday" impacts where preventative action can be taken by operators to reduce the severity of the impacts. There are many examples where such actions are taken by industries to reduce the impact of weather on infrastructure, for example, winter road maintenance (Mahoney and Myers 2003), railway buckling (Ferranti et al. 2016), leaves on the line (Chapman et al. 2016), and wind impacts on power cabling (McColl et al. 2012).

Over the last two decades, developments in modeling [e.g., route-based forecasting for winter road maintenance (Chapman and Thornes 2006)] and decision support systems [e.g., maintenance decision support system (MDSS); Petty and Mahoney 2008] mean that weather impacts can now be predicted at high resolution so that mitigation activities can be specifically targeted at vulnerable sections of infrastructure. This helps to minimize the cost of interventions while reducing disruption but, more importantly, secures the networks for continued use. The importance of this is not to be underestimated. It is not uncommon to encounter a range in surface temperatures of 30°C on the railway network in high summer (Chapman et al. 2006) or 10°C on the road network in winter (Shao et al. 1997). Such large

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ranges of temperature can mean that while most of the infrastructure is safe, small sections could be potentially lethal if left untreated. Likewise, blanket treatments are wasteful, often unnecessary, and can have negative environmental impacts.

However, while decision support systems have been in operational use for the last decade, in an environment of increasing litigation, practitioners remain nervous about making decisions solely based on largely unverified high-resolution model output. This means that forecast validation is now needed on a scale previously not required. It is only with such forecast validation that end users will become responsive to using methods that save money without compromising infrastructure safety: for example, selective salting for winter road maintenance where only the coldest sections of road are treated (Handa et al. 2006) or localized rail speed restrictions in hot weather as opposed to the blanket restrictions currently used (Ferranti et al. 2016). However, to date, existing measurement techniques do not meet this need (Hammond et al. 2010). Traditional point measurements using sensors are expensive to install in the numbers required and therefore lack the spatial resolution. Mobile measurements provide an alternative, but these lack the temporal resolution to provide the full picture and are of limited value for model initialization (Gustavsson 1999). Hence, there is a need to consider new innovative techniques to provide high-resolution data to unlock the potential of high-resolution models. This paper discusses the role of the emerging Internet of Things (IoT) in fulfilling this need.

THE INTERNET OF THINGS. IoT quite literally means "things" (e.g., sensors and other smart devices) that are connected to the Internet. Since 2008, the number of things has outnumbered users online. Technological developments in the field are rapid and now mean that low-cost sensors can be produced and deployed in dense networks to monitor weather and climate (Young et al. 2014). The miniaturization and reduced cost of electronics is one key factor driving this change; however, the enabling technologies are improvements in batteries, communications, and cloud-based data storage.

Lithium batteries are already proving transformative across a range of applications (e.g., electric vehicles; Lu et al. 2013), but they are also playing a key role in the IoT. It is now possible to power a meteorological sensor (e.g., to measure temperature; Young et al. 2014) for several years from a single small cell. This step alone vastly reduces the cost of making a measurement, as a connection to a mains supply or the inclusion of an energy-harvesting solution is no longer required.

Communications are traditionally one of the largest drains on energy, as significant power is needed to transmit the data. This can be overcome (where available) by using a hardwired solution, but many weather outstations presently rely on the Global System for Mobile Communications (GSM). These are power hungry, draining a small lithium battery in a matter of hours. The IoT now has a vast array of low-power wireless options to overcome this. These include Bluetooth, Wi-Fi, and ZigBee over short distances (i.e., meters/line of sight), but the latest developments

Fig. 1. Prototype road surface temperature sensor mounted, as operationally, on street furniture adjacent to a road. The small black hole is the thermopile aperture, which is aimed at the road surface.

LABORATORY TESTING OF A LOW-COST RST SENSOR

The RST sensor uses the Melexis infrared thermopile model MLX90614. It has a 5° field-of-view sensor and is small (~4-mm diameter). It has a range from −40° to 125°C for sensor temperature and from –70° to 380°C for object temperature with a resolution of 0.1°C or better and a reported accuracy between 0.5° and 1°C. A number of sensors have been tested using a Weiss series WKL 34 climatic chamber capable of generating reproducible and stable temperature conditions from −40° to +180°C within a 34-L chamber. Temperature constancy in time is ±0.3°C with cooling and heating rates of 6° and 4°C min⁻¹, respectively. Humidity can also be controlled in the range 10%–98% with a built-in humidification–dehumidification system (Fig. 2). To simulate operational conditions, test sensors were aimed at a slab of asphalt (22-cm width, 3-cm depth). As is customary for infrared road temperature sensors, sensors were configured to assume the asphalt surface has an emissivity of 0.95 at nadir. A reference platinum resistance thermometer was embedded in the center at a depth of 2 mm [precalibrated at a United Kingdom Accreditation Service (UKAS)-approved laboratory]. Figure 2 shows the configuration of the four prototype sensors in the chamber (referred to as S1, S2, S3, and S4). Each sensor was mounted vertically with a 3-cm gap between the MLX90614 aperture and the asphalt. Each test took a total of 12 h to complete (comprising three 4-hourly periods). The temperature of the chamber was set differently for each period: +10°, 0°, and −10°C. To ensure stability within the chamber, only data from the last hour of each 4-h period were used. Results of the test are shown in Fig. 3 and Table 1.

The variance of the reference thermistor (black box plot in Fig. 3) is small, confirming that the asphalt slab reaches a stable state of equilibrium. While the median and mean of the prototype sensors rarely agree exactly with that of the reference thermistor, they do fall within acceptable limits of ±0.7°C. If greater accuracies are required, bias correction per sensor can then be performed before deployment either within the firmware or on the cloud server.

are seeing a rapid deployment of low-power wide area networks (LPWANs). These are specifically designed for the IoT (i.e., battery-operated sensors) and permit long-range communications (i.e., ≥30 km—effectively a whole city) with a single antenna. There presently exists a range of competing standards such as Long Range (LoRa), Sigfox, Long-Term Evolution (LTE), and Narrowband IoT (NB-IoT); however, all operate on the same low-power–low-bit-rate principle to maximize battery life on the device. As such, a stand-alone sensor can now be located anywhere within a wide area where it will periodically relay data over the Internet to a server or "cloud."

Cloud-based storage has now become the standard means to store data, and this development has also facilitated the rapid growth in the IoT by providing a stable and reliable means to store the vast amounts of data produced by potentially millions of devices. Cloud server and storage solutions are low cost, scalable, and bespoke, allowing for platforms to be easily developed to display large datasets in real time or indeed to push (or pull) data via application programming interfaces (APIs) to end users to ingest into forecasting models. While devices themselves can be intelligent, enabling processing tasks within firmware, the cloud allows for a "smart server–dumb sensor/client" approach, which is preferable to mitigate against security threats (Weiss and Lockhart 2012).

Fig. 2. The Weiss series WKL 34 climate chamber. Inside are four test sensors mounted above the slab of asphalt into which the reference thermistor is embedded.
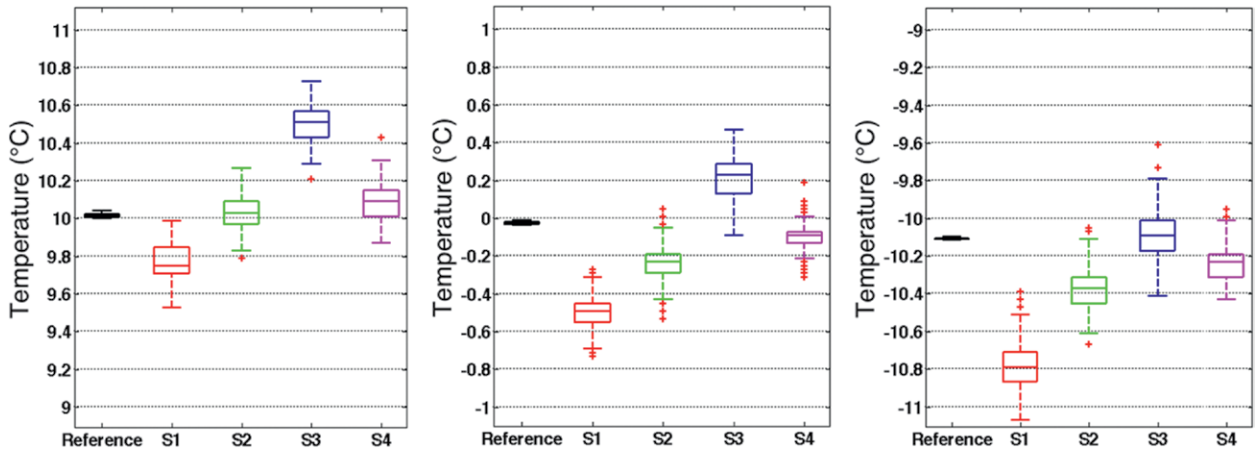
FIG. 3. Box-and-whisker plot summary of temperature readings at three different chamber temperatures: (left) +10°, (center) 0°, and (right) −10°C by the reference thermistor and four prototype sensors. Each box represents data collected over 1 h.

As a direct result of these technological changes, the emergence of the IoT has been rapid and is already creating a significant presence in weather and climate. Recent years have seen an upsurge in scientific literature looking at opportunistic sensing (i.e., crowdsourcing), which harvests data from the growing number of low-cost consumer weather monitoring devices taking advantage of the abovementioned developments [see Muller et al. (2015) for a full review]. For example, the Netatmo personal weather station has become prolific, with tens of thousands of devices situated around the world. This means that in places where there has been a previous paucity of weather data (e.g., cities), dense networks are now available for climatological analyses and, potentially, weather services (e.g., Meier et al. 2017; Chapman et al. 2017; De Vos et al. 2017). Similar developments have also occurred obtaining data from vehicles (Mahoney and O'Sullivan 2013), where data can be filtered before

use to improve data quality control using vehicle data translators (Drobot et al. 2010). Despite these studies and indeed considerable interest in the road weather sector, the discipline remains broadly wary of the opportunistic sensing approach. There are clearly issues in devolving the siting and maintenance of equipment to the crowd, and these concerns will remain until data quality control and assurance are satisfactorily dealt with. In contrast, the key operating principles actually underpinning the IoT are sound and as the following use cases demonstrate, when bespoke sensors are built for dedicated applications and managed by professional meteorologists, there is potential for the approach to be truly transformative.

USE CASES. *Winter resilience on highways.* Highway engineers consult Road Weather Information System (RWIS) observations and weather forecasts to make a daily decision as to whether the road network needs treatment. There have been significant developments in all components of RWIS over the last two decades. The range of techniques available to make observations has increased significantly, notably with a large range of noncontact devices to measure road surface temperature (RST) and condition. However, equipment costs have remained high, and there is still a paucity of measurement devices. Forecasting and decision support systems have also developed significantly. Bolstered by increasing computer power, high-resolution mesoscale models, and improved downscaling techniques, route-based forecasts now contain detailed forecasts for every stretch of road (most of which is unmonitored). If the IoT approach can improve confidence in these forecasts, then selective salting (where treatment is only actioned on

TABLE 1. Mean temperature bias for four sensors (S1, S2, S3, and S4) at each of the three test temperatures relative to observations made by the reference thermistor (only reference observations within 3 s of infrared sensor observations are used). The sample size for each cell is ~240, with the value in parentheses denoting the standard deviation of the bias.

	Reference (°C)		
Sensor	**10.02**	**−0.02**	**−10.11**
S1	−0.24 (0.09)	−0.47 (0.10)	−0.67 (0.12)
S2	0.01 (0.09)	−0.21 (0.10)	−0.27 (0.11)
S3	0.49 (0.09)	0.24 (0.11)	0.02 (0.13)
S4	0.07 (0.09)	−0.07 (0.08)	−0.13 (0.09)
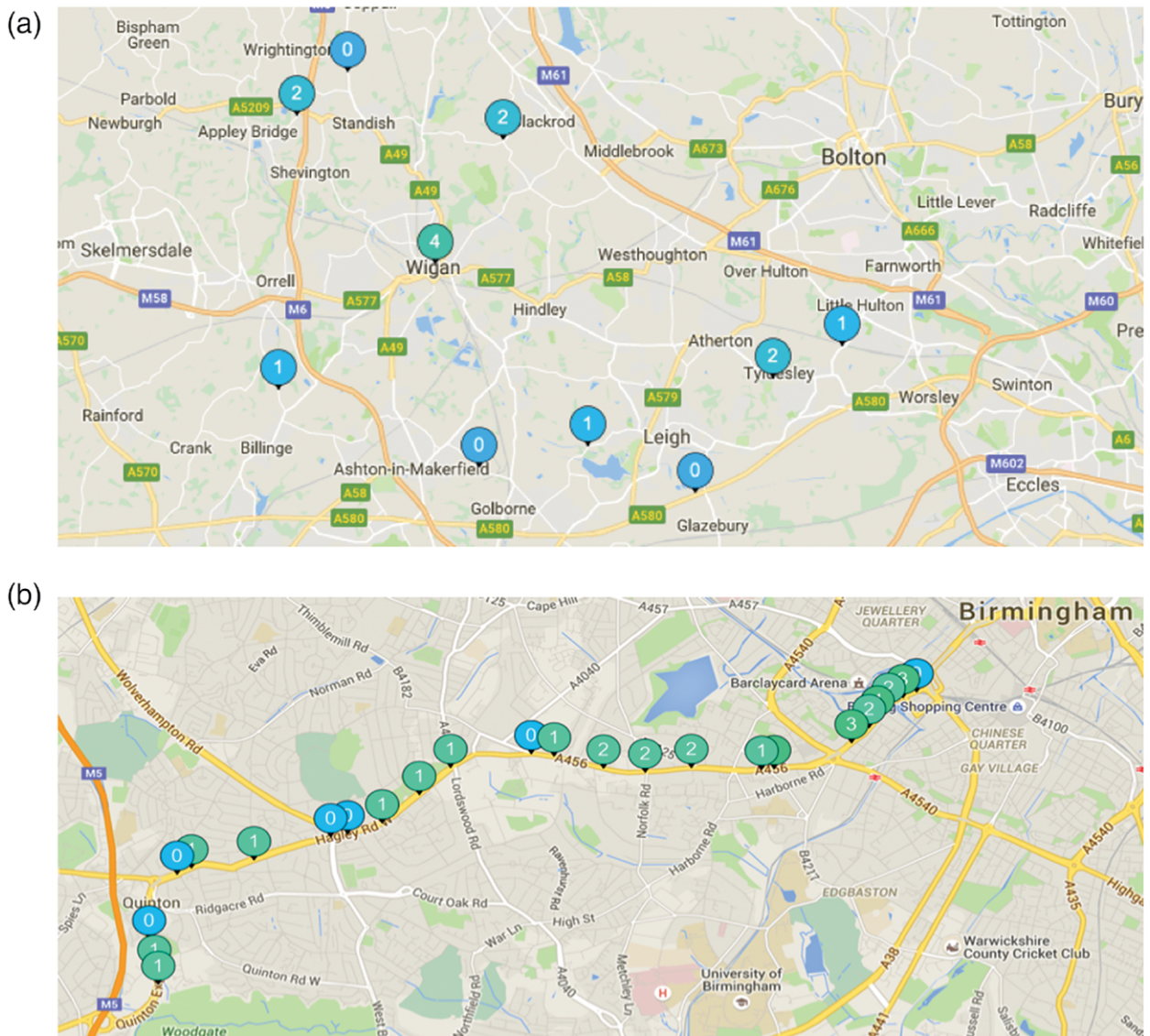
FIG. 4. Screenshots of the web application used to visualize sensor data. Live networks are shown to illustrate (a) network-scale deployment and (b) high-resolution deployment at the scale required to validate a route-based forecast (copyright Google, Inc.).

sections forecast to freeze) would result in large cost savings. The infrastructure (e.g., maintenance decision support systems; Petty and Mahoney 2008) to achieve this has been in place for over a decade, but a paucity of observations remains a significant barrier to implementation.

To fill this need, a low-cost road surface temperature sensor using a thermopile has been developed (Fig. 1). Based on the full set of IoT principles, it consumes minimal energy and can be powered for a full winter season using two standard, off-the-shelf, AA alkaline batteries. Communication options are based around LPWAN (where available), with Wi-Fi as a backup option. The accuracy of observations remains crucial for road weather applications, so it

is important to determine whether low-cost sensors are sufficiently accurate. Laboratory testing can be used to increase confidence in this approach (Fig. 2), and the results indicate that accurate observations of road surface temperature now appear to be possible using low-cost IoT sensors (Fig. 3 and Table 1; details in the sidebar). In the field, data are relayed in real time to the cloud, where it undergoes quality-control processing (e.g., bias correction/filtering to remove traffic effects) before being displayed to the end user.

Overall, the sensor is portable and self-contained within a weatherproof enclosure and requires no external power or communications. The low price of this approach compared to traditional sensors (virtually two orders of magnitude cheaper) now means

FIG. 5. Low-cost rail moisture sensor on trial using a dummy rail next to a live railway (image courtesy of Elliott Warren).

that the IoT can provide a complimentary observation module within RWIS. A simple network could involve locating a single sensor on each salting route (Fig. 4a). This in itself would provide a step change in granularity or observations, but the potential remains to instrument the network at the same resolution of a route-based forecast, for example, every 100 m (Fig. 4b), potentially transforming current winter resilience practices via selective salting or even dynamic routing (Handa et al. 2006).

Summer and autumn resilience on the railways. While railways represent one of the most efficient modes of transportation, day-to-day weather can cause challenges. In summer, heat-related delays on the railway are a consequence of the buckling of railway tracks

and the overheating of lineside equipment (Palin et al. 2013; Ferranti et al. 2016). In autumn, leaves on the line are a perennial problem. Leaves that fall onto the track and are accompanied by a small amount of moisture (e.g., dew) compact and create a Teflon-type coating on the top of the rail. This coating has a negative impact on braking performance, which leads to delays due to platform overruns and, worse still, signals passed at danger (Fulford 2004). Again, forecasts are provided to help mitigate the problem. These forecasts are used to impose speed restrictions to reduce safety impacts of buckling during spells of hot weather (Palin et al. 2013) or support spreading sandite onto the tracks to improve adhesion at problem locations in the autumn (Chapman et al. 2016). Such problems are localized, and these actions can be better targeted to reduce costs and delays. To this end, high-resolution forecasts are starting to be produced for the rail industry, but as per winter road maintenance, adequate verification data will be required before such products are used to maximum benefit.

Again, the IoT can provide a solution. As far as monitoring of summer heat is concerned, a thermopile sensor (i.e., Fig. 1) can again be used to provide a noncontact means of measuring rail temperature. These would be deployed in a network at known "hot spots." Autumn resilience is more challenging and requires estimates of daily leaf fall along with observations from a suite of sensors to measure rail temperature, air temperature (e.g., Young et al. 2014), and moisture. The latter is the most important variable, as it has been shown that the smallest amounts of water on the track (i.e., dew or drizzle) are the most problematic and suggests that a sensor needs to have the capability of detecting these trace amounts. Recent research has shown that this is possible using IoT leaf wetness sensors located on a "dummy rail" at the side of the live track (Fig. 5). Again, climate chamber tests and field deployments have yielded positive results, and the potential of the approach to densely instrument known sections of poor adhesion is evident [see Chapman et al. (2016) for full details]. However, existing approaches are dependent on the use of dummy rails, so further research is required to facilitate measurements by noncontact means.

DISCUSSION AND CONCLUSIONS. This paper has highlighted the need for high-resolution sensor networks and indeed the transformative potential of the IoT for the infrastructure sector and weather forecasting more generally. However, both scientific and technological challenges still exist.

Scientifically, there is a need to provide sensors of comparable quality to existing standards. As this paper and others (Young et al. 2014; Chapman et al. 2017; Meier et al. 2017) suggest, despite the low-cost nature of IoT sensors, performance in both laboratory and field trials appear positive. One frequent concern with low-cost sensors is sensor drift, and given the age of the technology, this has been impossible to fully ascertain to date. A further challenge as networks mature is to consider how annual maintenance and calibration regimes fit into this new paradigm. Low-cost devices are essentially consumables, and a rotational deployment–calibration strategy could be an option here.

Technologically, the IoT continues to develop at a tremendous rate, tackling challenges that were significant hurdles just a couple of years ago. LPWAN access remains a barrier in many parts of the world, but this is rapidly changing. Similarly, battery and energy-harvesting technologies continue to improve year on year.

Given the pace of developments, and assuming increasing adoption of the IoT is inevitable in the industry, it is worth considering the broader implications of high-resolution observation data. For example, current forecasts are largely built to cope with a paucity of data. Data could soon be available at an unprecedented scale and in turn may lead to a new generation of forecasting products in the statistical and nowcasting arenas (e.g., Shao and Lister 1996). A potential move to more open data would also free up innovation within the sector in this regard. In the commercial sector, there could also be significant changes, causing the traditional lines between instrumentation manufacturers and forecast providers to become increasingly blurred. Likewise, the industry could see technologists increasingly marketing meteorological products. This would be a concern, as the integrity of the measurement is of paramount importance. However, the conservative nature of the infrastructure sector, and broader meteorological community, should ensure this remains the case. For example, atmospheric scientists have been quick to highlight issues with low-cost air quality sensors (Lewis and Edwards 2016).

In summary, the IoT has the potential to completely change decision-making and operations on infrastructure. It will unlock the potential of high-resolution models as well as stimulate further innovation, increasing the weather resilience of infrastructure. Aside from infrastructure improvements, the IoT will promote new developments in the weather industry, including open data and opportunistic sensing.

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