Robust Sensor Suite Combined with Predictive Analytics Enabled Anomaly Detection Model for Smart Monitoring of Concrete Sewer Pipe Surface Moisture Conditions

Karthick Thiyagarajan, *Member, IEEE,* Sarath Kodagoda, *Member, IEEE,* Ravindra Ranasinghe, *Member, IEEE,* Dammika Vitanage and Gino Iori

***Abstract*—Globally, the water industry considers microbial induced corrosion of concrete sewer pipes as a serious problem. There are reported analytical models and data analytic models that are used to predict the rate of corrosion throughout the sewer network. Those models incorporate surface moisture conditions of concrete sewer pipes as observations. Due to the unavailability of sensors to monitor concrete sewer surface moisture conditions, water utilities use surrogate measures such as relative humidity of the air as an observation for the model. Hence, the corrosion predictions are often hampered and associated with prediction uncertainties. In this context, this paper presents the development and successful evaluation of an electrical resistivity based sensor suite for estimating the surface moisture conditions of concrete sewer pipes. The sensor was deployed inside a municipal sewer pipe of Sydney city, Australia to carry out field measurements. The post-deployment study revealed the survival of the sensing system under hostile sewer conditions and demonstrated their suitability for long-term monitoring inside sewer pipes. Besides sensor development, a predictive analytics model was proposed for anomaly detection. The model incorporates a forecasting approach using a seasonal autoregressive integrated moving average technique for anomaly detection. The model was evaluated using the sensor data and results demonstrated its effective performance. Overall, the proposed sensor suite can ameliorate the way water utilities monitor sewer pipe corrosion.**

***Index Terms*—anomaly detection, concrete corrosion, concrete moisture, electrical resistivity, forecasting, SARIMA, smart monitoring, sewer pipe, surface moisture sensor, Wenner probe.**

I. Introduction

UNDERGROUND sewer systems are an important infrastructure requirement of any country. They protect our public societies from the perils of sewerage borne diseases and unhygienic conditions [1]. Currently, the concrete sewer pipes are undergoing significant levels of degradation due to hydrogen sulphide (H_2S) induced concrete corrosion [2]. This corrosion is well known to be caused by the microbial activities, which convert the H_2S present in sewer air into sulphuric acid (H_2SO_4) on the concrete sewer walls [3]. The micro-biologically generated H_2SO_4 penetrates the pores of the concrete and starts to chemically react with the cementitious material of the sewer pipe and finally, corrodes the concrete reinforcement bars (rebars) [4]. Failure to restrict the concrete sewer pipe corrosion will expedite the process of structural failure.

On a global scale, the concrete sewer pipe corrosion causes a major problem for the water utilities as they incur losses that are estimated to be billions of dollars every year [5]. In Australia, the total value of sewer pipe assets is appraised to be over \$100 billion [6] with the annual maintenance cost for sewer pipe renewals mostly due to concrete corrosion is almost AU\$ 100 million [7], where the Sydney city alone spends more than AU\$ 40 million [8]. This cost is expected to upsurge as the ageing sewer pipe continues to deteriorate [9]. It is expensive to replace concrete sewer pipes [3].

In the interest of managing the sewer assets effectively, there is a need for water utilities to directly measure concrete corrosion at discrete geographical areas to determine the remaining useful life of the sewer pipes. Unfortunately, there are no reliable and robust sensors available in the current technologies to measure the level of corrosion throughout the sewer network cost-effectively. So, water utilities lookout for the factors that leverage corrosion. In this regard, concrete corrosion in sewers is largely influenced by the microbial activities [10], [11]. Therefore, quantifying their activity could shed light on concrete corrosion. However, due to sensing limitations in hostile sewer conditions, it is highly challenging to identify and monitor the liable microbial activity. Alternatively, water utilities focus on monitoring the H_2S concentration levels in sewer air, temperature and moisture of the concrete surface as they provide favourable conditions for the microbes to live and reproduce [7], [12]. Presently, there are industry-proven sensors for monitoring H_2S levels in sewer air e.g. [13], and sensors to monitor sewer concrete surface temperature conditions e.g. [14]. However, there have been

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no proven technologies to monitor surface moisture conditions without damaging the concrete structure under hostile sewer environments for a long-term period. This sensing limitation has led utilities to use surrogate measures like relative humidity of the sewer air as an observation to predictive models for estimating the concrete sewer pipe corrosion [15]. As a result, the corrosion predictions throughout the sewer network is largely associated with prediction uncertainties due to the inadequacy of needed data [16].

Recent studies have mainly focused on monitoring the specific parameters to investigate the ambient conditions of the sewer by using commercially available sensors [17]–[19]. For instance, few studies have demonstrated the feasibility of monitoring relative humidity levels inside the corrosive sewer pipes in different cities of Australia, where the researchers have reported the varying daily conditions [7], [15]. Humidity sensors were developed by using advanced sensing methods such as fibre optic technology for sewer applications like detecting leakages in sewer tunnels [20]. Recently, humidity measurements near the concrete surface were measured using Fibre Bragg Grating based sensors for in-sewer applications [4]. However, the functional relationship between moisture content and relative humidity illustrates higher humidity levels inside confined sewers do not necessarily imply higher moisture on sewer walls [15]. Although there are several kinds of literature pertain to monitoring the relative humidity in sewers, there are no reports to date on measuring concrete surface moisture conditions reliably inside sewers.

For addressing the sewer pipe corrosion problem, this research collaborates with four Australian water utilities led by Sydney Water (New South Wales Government-owned statutory corporation) to develop a robust sensing system to estimate surface moisture conditions in sewers. Since the sewers in Australia are categorized as Zone-II hazardous areas [21], the sewer operators defined several requirements in developing the sensor as there are no systems available in the market to readily measure surface moisture conditions in sewers. The main requirements are: a) sensing method should not cause any alterations or damages to the exposed concrete sewer surface, b) no flammable substances inside sewers, c) easy access to sensor data, d) sensor enclosure should accommodate other sensors like temperature sensor, e) enclosure should be light-weight and robust to hostile sewer conditions, f) easy to carry and mount design of the enclosure, (g) easily replaceable direct current (DC) battery pack for supplying power to the sensor suite, and (f) moisture sensor should indicate wet and dry conditions.

There are several embedded sensing technologies available in the literature to measure moisture by installing the sensors inside the concrete through chiselling or drilling in a few civil infrastructures other than sewer pipes [22]–[26]. However, the embedded sensors can be degraded over time due to acid permeation in concrete sewers. Various non-invasive technologies [27]–[38] and invasive method [39] were reported. None of those technologies were proven to work in sewer conditions. After a comprehensive scoping study [6], [40], several laboratory investigations were performed to identify electrical resistivity based moisture measurements as a promising solution to tackle the challenges arising from the sewer environments [41]–[43]. However, the sensors can produce anomalies [44]–[46], which can be random and momentary [47]. Removal of such anomaly is crucial for efficient sensor monitoring applications [48], [49].

This article elucidates the development and evaluation of the sensing system for real-time estimation of surface moisture conditions in sewers. Once the sensing system was tested and packaged in the laboratory, it was deployed in the hostile gaseous sewer environment for investigating the feasibility and examining sensing performance. From the field-testing campaign, electrical resistivity measurements were obtained from the surface of interest. Then, on-site calibration was carried out to determine the surface moisture conditions of the measured sewer surface. After completing the field testing, the sensing system was evaluated in the laboratory conditions to examine its sensing capabilities after exposure to the aggressive sewer conditions for about three months. Further, in the off-line analysis, temporal dynamics of moisture and the effects of ambient temperature and surface temperature were investigated. Besides the sensor suite development, a predicitive analytics model leveraging the Seasonal Autoregressive Integrated Moving Average (SARIMA) approach was developed to detect sensor anomaly. The performance of the proposed model was evaluated with the real-time surface moisture sensor data obtained from the hostile sewer pipe.

This paper is distinct from those existing in the current literature in a form that it supplies the needed data about the surface conditions of the concrete sewer rather than the ambient gaseous variable such as relative humidity. To the extent of our knowledge, this is the first paper to report the non-invasive method of surface moisture estimation from concrete sewers with the motive of accurately predicting the propagation of sewer corrosion.

The remainder of this article is structured as follows: Section II describes the methodology for the sensor suite development and field deployment whereas Section III details the formulation of predictive analytics enabled anomaly detection model. Section IV presents the results followed by a discussion in Section V. Finally, Section VI concludes the paper with the prospects.

II. Sensor Suite Development and Field Deployment

A. Sensing System

The surface resistivity of the concrete material can be measured by placing the resistivity meter on the surface of interest. In this work, commercially available resistivity meter was utilized (Resipod, Proceq) [50]. The sensing principle of the resistivity meter used in sensor development is based on the Wenner method [51]. This technique uses four electrodes positioned in a straight line with an equidistant space between the electrodes. A current is applied to the outer two electrodes that are in contact with the concrete

TABLE I: Specifications of the Surface Resistivity Meter

Measurement Range	0 - 2000 kΩcm
Operating Temperature Range	0°C to +50°C
Input Power	± 5V 100mA
Frequency	40 Hertz

surface and the resultant potential difference is measured across the two inner electrodes. Based on the ratio of the injected current and the measured voltage, the electrical surface resistivity can be determined. However, the measured resistivity is dependent on the distance between the electrodes. Mathematically, the resistivity can be computed by using equation (1):

$$\rho = 2\pi a\left(\frac{V}{I}\right) \tag{1}$$

where ρ is the resistivity of the concrete material expressed in terms of kΩcm, a=50mm is the distance between the electrodes, V is the electrical potential difference measured by the inner two electrodes and I is the current injected by the outer two electrodes. Based on the resistance of the concrete material, the resistivity meter automatically changes its current injection mode through outer electrodes. The resistivity meter (Resipod, Proceq) has two current ranges. When the contact resistance of the outer two electrodes and the resistance of the concrete is not too high, the resistivity meter injects a nominal current of 200μA. The outer two electrodes inject a nominal current of 50μA when the contact resistance of the outer two electrodes and the concrete resistance is too high. This is due to the reason that the concrete behaves similar to an insulator when its resistance is too high. Hence, the nominal current of 50μA is injected to measure resistivity. For more information, readers can refer to [52].

For long-term sewer monitoring application, the ODROID-XU4 based Single Board Computer (SBC) was utilized as a data logger. It is a 16GB embedded multimedia controller module with pre-installed Linux computing and small form factor having a dimension of 82×58×22 mm^3. The electrodes of the resistivity meter protrude out of the sensor enclosure to establish contact with the concrete surface for measurements. They use spring mechanism so that the electrodes can touch the concrete surface even in case of the concrete surface is not flat (rough). The key specifications of the resistivity meter are shown in Table I.

Although the resistivity meter has its application for infrastructure monitoring, it is not proclaimed to use in confined sewer systems. Therefore, pre-deployment evaluation was conducted before deploying it inside the sewer pipe. The pre-deployment evaluation focuses on the measurement capabilities of the resistivity meter to determine the reproducibility and limit of detection. The evaluation was carried out by placing the resistivity meter on the benchmark and taking repeated measurements. The temperature sensor used to measure surface temperature and the ambient temperature of the sewer is an epoxy coated thermistor sensor (THERM-EP, ICT International). This sensor has the accuracy of ±0.05°C for the operating temperature range -40°C to +80°C.

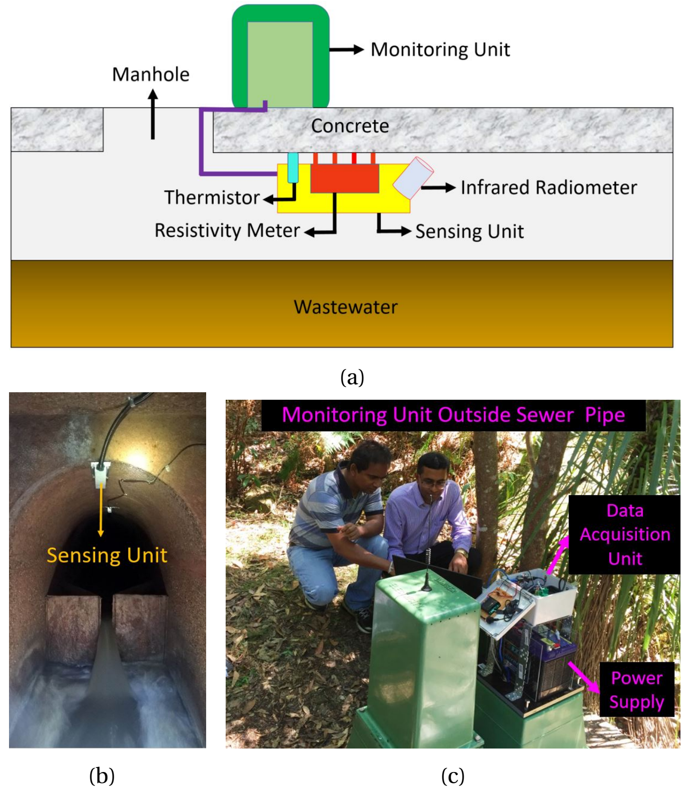


Fig. 1: Field deployment. (a) Illustration, (b) Sensing unit inside the sewer pipe, (c) Monitoring unit constructed outside the sewer pipe.

B. Field Application

After developing the sensor suite in the laboratory, it was deployed inside the Sydney Water based sewer pipe at Thornleigh suburb of Sydney city, Australia during the summer season. The sensor suite consists of two main units: sensing and monitoring unit as illustrated in Fig. 1a. The sensing unit was installed near the crown of the confined concrete sewer pipe as shown in Fig. 1b on 3rd November 2016 and the monitoring unit was constructed outside the sewer pipe to set up the access station as in Fig. 1c. Besides the electrical resistivity meter, the sensing unit accommodates an infrared radiometer and a thermistor sensor for measuring the surface temperature variations on the concrete sewer. The resistivity meter was activated to measure the surface resistivity variations of the concrete sewer pipe on 10th November 2016. The sensing unit was mounted on the sewer pipe in a way such that the electrodes are in contact with the concrete surface, so that surface measurement is attained. From the sensing unit, the data signals from the resistivity meter were transmitted to the access station by using a 20-meter-long Ethernet cable.

In the access station, the transmitted data signal from the resistivity meter was processed and data logged by the ODROID based data logger. The incoming digitalized signals from the sensing unit were decoded from binary format to hexadecimal format. The on-board operating system of the SBC in the access station was programmed using Python programming language to perform surface resistivity measurements at regular intervals. From the SBC at the access station, the logged surface resistivity measurements with the time-stamp can be downloaded in the form of a text file (.txt).

The field site used for sensor evaluation was located in a remote area, where there is no access to the electrical mains power supply. To overcome this issue, the access station was developed to operate by using battery power. The SBC in the access station was powered by using a 12V 100Ah rechargeable heavy-duty battery. The constructed access station was not equipped to communicate the measured data remotely and so, once in a week an operator goes to the access station to check the operating conditions of the sensing system and data logging facilities whilst swapping the battery with a fully charged one. Every time, the operator swaps the DC battery, the SBC was rebooted and restarted to perform the data acquisition at desired time intervals.

Other sensors that measure the surface temperature of the concrete sewer pipe and the ambient temperature of the sewer atmosphere were also powered by the DC battery in the access station. The data from those sensors were stored using a data logger (TSM-1, ICT International). All the temperature sensors were monitored from the access station and were programmed to perform measurements at hour boundaries. All the cables transmitting measured data signals were protected from the sewer vermins by enclosing with an electrical conduit from the sensing unit to the access station. This field deployment application was carried out for about three months and both the sensing unit and monitoring unit in the access station was removed from the site on 7th February 2017. During the field testing period, the gas phase H_2S levels were between 2ppm and 5ppm. It was monitored by using a Thermo Fisher OdaLog®L2 Hydrogen Sulphide Logger. The concrete sewer pipe surface had a pH of 5. This was measured by using a pH indicator strip.

C. On-site Calibration

The free water retained on the surface of the aggregate particles, which considered to be part of mixing water in the concrete is known as surface moisture [53]. Depending on the moisture content, the concrete material behaves either as an insulator or a conductor. From various studies [41], [54], it has been proven that the electrical resistivity of the concrete decreases when the moisture increases and vice-versa. Therefore, the surface electrical resistivity measurement is said to have a strong correlation with surface moisture. In this study, we aim to estimate the moisture conditions on the concrete surface of the sewer pipe. The sensor suite employed in this study was calibrated on the field site by placing the sensing unit and taking resistivity measurements in dry and wet surface areas. By using the surface resistivity measurements, the surface moisture conditions can be mathematically determined by using equation (2):

$$SM = 100 - \left(\frac{SR_S - SR_W}{SR_D} \right) \times 100 \tag{2}$$

where SM is the surface moisture condition of the concrete sewer pipe, SR_S is the surface resistivity value measured from the resistivity meter, SR_W is the surface resistivity value measured at the wet area of the concrete sewer pipe and SR_D is the surface resistivity value measured at the dry area of the concrete sewer pipe. All the surface resistivity measurements are expressed in terms of kΩcm and the surface moisture conditions are expressed in terms of %. The resistivity of the completely dried concrete sample is approximately 10^6 Ωm (MΩcm) [55]. In sewers, most of the pipe surfaces are wet. However, the sewer surface near the manhole was observed to be touch dry, where the resistivity value was observed to be 364 kΩcm. The wet area concrete surface resistivity value was measured near the tidal region. The value was observed to be 16 kΩcm. The surface resistivity ranging from 364 kΩcm to 16 kΩcm was considered to be the range of surface moisture conditions.

D. Post-deployment Study

A post-deployment study was conducted in the laboratory conditions following the three months of field evaluation under hostile sewer environments. In this study, the sensing capabilities of the moisture sensor and the robustness of the enclosure were investigated. By using the benchmark, the sensing capabilities of the moisture sensor was evaluated by taking repetitive measurements. Further, the sensor enclosure and the sensor electrodes were examined through a careful visual inspection to identify any damages that occurred during the field evaluation.

III. Predictive Analytics Enabled Anomaly Detection Model

This section presents the development of the Predictive Analytics Enabled Anomaly Detection (PAE-AD) model for the surface moisture sensor suite. The proposed PAE-AD model uses Seasonal Auto-regressive Integrated Moving Average (SARIMA) process $SARIMA(p,d,q)(P,D,Q)_{R_p}$ for forecasting. The SARIMA process is defined in (3):

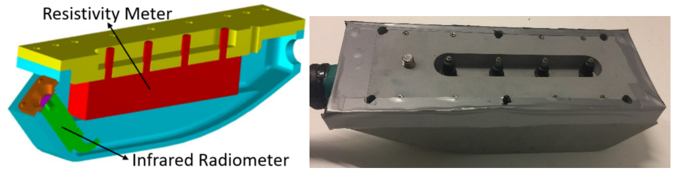
$$\begin{aligned} \left(1 - \sum_{x=1}^{p} \phi_x \beta^x\right)\left(1 - \sum_{x=1}^{P} \Phi_x \beta^{R_p}\right)(\Delta)^d (\Delta^{R_p})^D \widetilde{R_t} \\ = \left(1 + \sum_{y=1}^{q} \theta_y \beta^y\right)\left(1 + \sum_{y=1}^{Q} \Theta_y \beta^{R_p}\right)\varepsilon_t \end{aligned} \tag{3}$$

where β is the backshift operator, p is the autoregressive process order, P is the seasonal autoregressive parameter, d is the differencing level, D is the seasonal differencing parameter degree, q is the moving average process order, Q is the seasonal moving average parameter, $\widetilde{R}_t$ is the mean deviation, ε_t is the white noise and R_p is the seasonal period. The terms ϕ and θ are the autoregressive process weight parameter and moving average process weight parameter respectively. The terms Φ and Θ are the weight parameters of the seasonal autoregressive process and seasonal moving average process respectively. The Hyndman and Khandakar algorithm [56] is utilized in the development of the PAE-AD model for automatically fitting the optimal values of p, d, q, P, D and Q in (3). Let σ_g be the standard deviation of the Gaussian distribution with weights ψ_j, then the probability distribution $(R_{t+f}|R_t, R_{t-1}, R_{t-2}, ...)$ of a future value R_{t+f} of the $SARIMA(p,d,q)(P,D,Q)_{R_p}$ process will be normal with mean $\hat{R}(f)$. Then, the prediction bounds for the $SARIMA(p,d,q)(P,D,Q)_{R_p}$ forecast is computed by (4).

$$\hat{R}_{t+f}(\pm) = \hat{R}_t(f) \pm \mu_{\lambda/2}\left(1 + \sum_{j=1}^{f-1} \psi_j^2\right)^{1/2} \sigma_g \tag{4}$$

where $\hat{R}_{t+f}$ is the $SARIMA(p,d,q)(P,D,Q)_{R_p}$ process forecast value that lies between the upper bound $\hat{R}_{t+f}(+)$ and lower bound $\hat{R}_{t+f}(-)$. The $\mu_{\lambda/2} = 95$ is the percentile of the probability distribution $(R_{t+f}|R_t, R_{t-1}, R_{t-2}, ...)$

By using the actual sensor measurements from 11th November 2016 to 20th November 2016, the PAE-AD model is trained to forecast one day ahead i.e. 24 data points with $\hat{R}_{t+f}(+)$ and $\hat{R}_{t+f}(-)$. The forecast data $\hat{R}_{t+f}$ of that particular day is compared with the actual sensor measurements R_t of that respective day. A sliding window approach [57] is incorporated in the PAE-AD model development. Let $SW_s = k$ be the size of the sliding window. Then, the sliding window will have k data points of $\hat{R}_{t+f}$ and R_t in a frame. Then, Pearson's chi-squared statistical hypothesis testing is performed for k data points inside the sliding window to compute p-value for the sliding window frame dataset. Here, the critical significance level α for p-value is set as 5% i.e. $\alpha = 0.05$. In this work, $k = 6$. This value is chosen based on the heuristic knowledge of sensor data characteristics. If the p-value of the sliding window is more than 0.95, the window moves one step ahead to compute the p-value of the new frame that contains 6 data points. In the case of p-value being less than 0.95, the PAE-AD model checks each sensor data of the sliding window is between the upper bound $\hat{R}_{t+f}(+)$ and lower bound $\hat{R}_{t+f}(-)$. If the value does not lie between the bounds, it is treated as an anomaly. The detected anomaly is removed and the respective $\hat{R}_{t+f}$ value is replaced in the PAE-AD model. This sliding window process continues until all the 24 data points of the day are evaluated. The PAE-AD model runs for each day. The previous day sensor measurements after isolating detected anomalies are added to the PAE-AD model training framework to forecast next day.



(a) (b)

Fig. 2: (a) CAD model of the sensing unit illustrating the accommodation of resistivity meter inside the sensor enclosure. (b) The physical enclosure of the sensing unit displaying the electrodes of the resistivity meter.

IV. Experimental Results

A. Sensor Suite Development and Pre-deployment Evaluation

The sensor enclosure was made up of Polyvinyl Chloride (PVC) material. Figure 2a shows the 3D CAD design of the sensor enclosure, where the resistivity meter and infrared radiometer are placed inside the enclosure. Figure 2b shows the physical prototype of the sensing unit and displays the protruding electrodes of the resistivity meter. Pre-deployment evaluation was conducted in laboratory conditions. In this evaluation, the resistivity meter was placed on the benchmark measures of 16 kΩcm and 120 kΩcm to determine the reproducibility. As an outcome of this evaluation, all the measurements were identical to the benchmark measures and therefore, the data reproducibility was 100%. However, it was observed that if any of the electrodes are not properly in contact with the concrete surface, the measurements were recorded as 0 kΩcm or error. Further, the resistivity meter has the limit of detection, which is between 0 kΩcm to 2000 kΩcm. Overall, from the pre-deployment evaluation, it can be concluded that the resistivity meter can be deployed inside sewer pipes for measuring the surface electrical resistivity variations of the concrete with the manufacturer settings.

B. Field Deployment and Real-time Measurements of Concrete Surface Electrical Resistivity Variations

The surface electrical resistivity variations measured by the resistivity meter inside the concrete sewer pipe is presented in Fig. 3. The measurement data were obtained from 10th November 2016 to 20th December 2016 and from 28th December 2016 to 7th February 2017. From Fig. 3, it can be observed that there are no drastic differences in surface resistivity measurements between the days. However, it can be noticed that the diurnal variation pattern relatively varies less than 2 kΩcm. Overall, the surface resistivity data from the resistivity meter displayed a decreasing trend for the summer season of Sydney, Australia from November 2016 to February 2017.

C. Effects of Surface Temperature and Ambient Temperature Inside Concrete Sewer Pipe

Figure 3 presents the profiles of surface resistivity measurements, surface temperature measurements of the con-

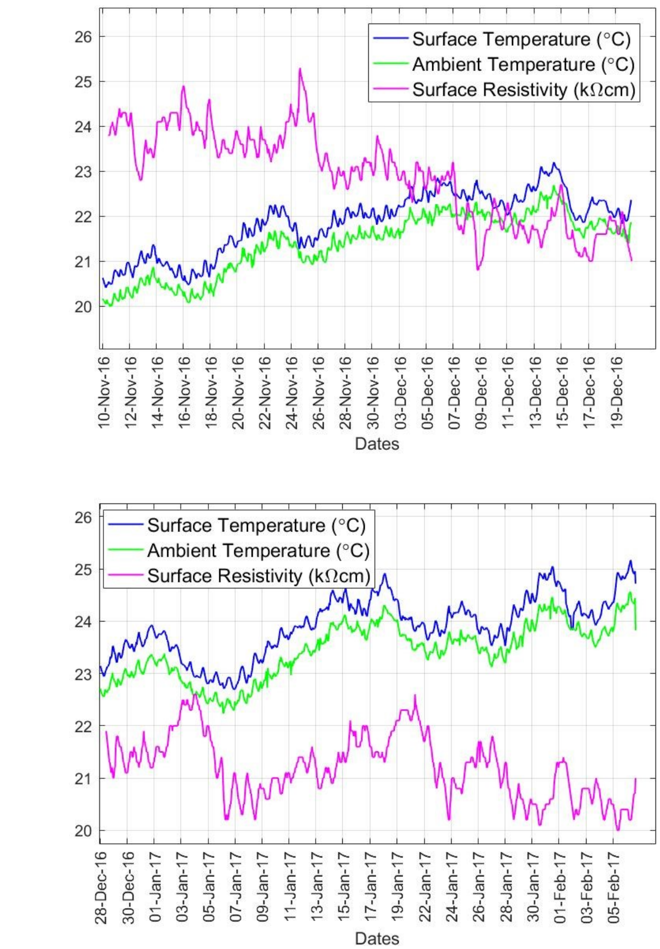


Fig. 3: Profiles of surface resistivity, surface temperature, and ambient temperature.

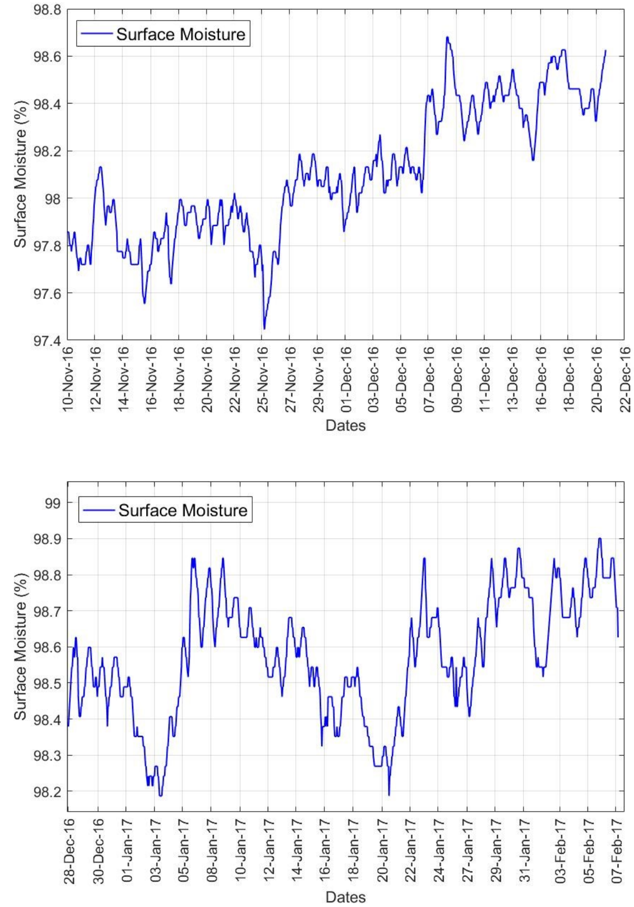


Fig. 4: Estimated surface moisture profiles of the concrete sewer pipe.

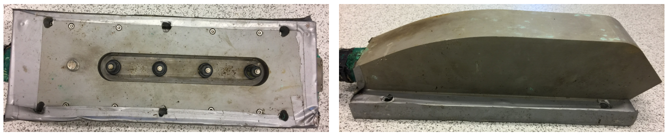
crete sewer pipe and ambient temperature measurements of the sewer atmosphere for comparative analysis. From Fig. 3, it can be observed that the surface temperature has increased approximately from 21°C to 25°C between early November 2016 and early February 2017. Similarly, the ambient temperature has increased approximately from 20°C to 24°C. During the field tests, the maximum surface resistivity of 25 kΩcm was observed in November 2016 and nearly 20 kΩcm was observed in February 2017. Between 7th January 2017 and 17th January 2017, an increasing trend in surface temperature and surface resistivity measurements were observed. The behaviour of surface resistivity and surface temperature variations needs to be investigated comprehensively by taking data throughout the year for detailed analysis.

D. On-site Calibration and Surface Moisture Interpretation

To determine the surface moisture conditions of the concrete sewer pipe, an on-site calibration was conducted at the end of the field evaluation by placing the resistivity meter in wet and dry areas of the concrete sewer pipe and measuring the concrete surface resistivity. Figure 4 presents the profiles of surface moisture condition estimates, where it can be observed that the surface moisture condition of the concrete sewer pipe is showing an increasing trend from November 2016 to February 2017, which is the summer season of the Sydney city of Australia. Overall, it can be concluded that the surface moisture conditions of the concrete sewer pipe were high during the field evaluation.

E. Post-deployment Study

In this post-deployment study, the sensing performance of the system was evaluated along with careful visual inspection of the sensor enclosure. Sensor measurements were taken after the field evaluation, where the sensing system has produced continuously 16 kΩcm and 120 kΩcm against the benchmark measure of 16 kΩcm and 120 kΩcm respectively. This demonstrates that the measurements from the resistivity meter are produced without any bias and therefore, it implies that the measurements obtained from the sewer were reliable. Figure 5a shows the electrode conditions of the sensing unit whereas Fig. 5b



(a) (b)

Fig. 5: (a) Top view of the sensor enclosure displaying the sensor electrodes after exposure to hostile sewer conditions for about three months. (b) Side view of the enclosure displaying the de-colouration occurred during the field evaluation.

shows the post-exposure condition of the sensor enclosure to a hostile sewer environment, where no visual degradation barring slight de-colouration on the enclosure material was observed. From this post-deployment study, it can be concluded that the sensing system operates as desired without any apparent bias and the tailor-made sensor enclosure demonstrated robustness to sewer conditions after three months of exposure.

F. Comparative Analysis of Forecasting Models

The forecasting performance of different time series models such as SARIMA [58], Exponential Smoothing State Space (ETS) model [59] and Bagged Model [60] was evaluated for univariate data coming from the surface moisture sensor suite. The statistical performance metrics such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square (RMSE) were used for evaluating the forecasting performance, which are defined in (5), (6) and (7) respectively.

$$MAE = \frac{1}{n}\sum_{t=1}^{t=n} |F_D - S_D| \tag{5}$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{t=n} \left|\frac{F_D - S_D}{S_D}\right| \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{t=n} (F_D - S_D)^2} \tag{7}$$

where the F_D is the data forecast from different univariate forecasting models such as SARIMA, ETS model and Bagged model respectively, S_D is the data obtained from the sensor measurements, t is the instantaneous time and n is the number of forecast values. For the aforementioned models, forecasting performance evaluation was done by training the model using the data from 11th November 2016 to 20th November 2016. The data from 21st November 2016 to 27th November 2016 were used for testing the forecasting performance of each model. Table II presents the computed forecast errors for different models, where it can be observed that the MAE, MAPE and RMSE were higher for Bagged model relative to ETS and SARIMA. For the ETS model, the three aforesaid metrics has lower forecast error relative to the Bagged model. However, those values for the ETS model were higher than the SARIMA. This implies

TABLE II: Comparative Analysis

Statistical Metrics	SARIMA	ETS	Bagged Model
MAE (kΩcm)	0.6516	0.7204	0.7544
MAPE (%)	0.0282	0.0312	0.0327
RMSE (kΩcm)	0.8432	0.8933	0.9249

that the forecasting performance of the SARIMA model is better than the ETS and Bagged model. Hence, SARIMA forecasting technique is employed in this work to develop the PAE-AD algorithm.

G. Performance Evaluation of the PAE-AD Model

This subsection presents the results of the PAE-AD model's performance evaluation. Figures 6 and 7 shows the implementation of PAE-AD model for anomaly detection, where the first plot shows the forecasts of the model and the second plot shows the actual sensor measurements with anomalies and the third plot shows the p-value less than 0.95 critical value for the anomalous data.

The Successful Detection Rate (SDR) [61] defined in equation (8) is used as a performance metric to evaluate the PAE-AD model's anomaly detection capability.

$$SDR = \left[\frac{SD}{AM}\right] \times 100 \tag{8}$$

where SD is the total number of successful anomaly detections and AM is the total number of anomalies. The SDR is expressed in terms of %. The SDR for the periods from 21st November 2016 to 20th December 2016 and from 29th December 2016 to 7th February 2017 is 100% and 96.77% respectively. Overall, the PAE-AD model detected 97.82% of 46 anomalies contained in the sensor measurement data.

The forecasting performance of the PAE-AD model was evaluated by comparing the forecast data of two different periods with the anomaly free sensor measurements of those respective periods. Figure 8 shows the temporal profile of forecast data and actual sensor measurements, where it can be observed that the PAE-AD model's forecasts follow a similar pattern to the actual sensor measures. This implies that the forecasted data generates a reasonable alternative to the sensor data. Also, MAE, MAPE and RMSE were used as statistical metrics to evaluate the proposed model's forecasting performance. Table III presents the computed statistical values for the PAE-AD model's forecast, where all the error metrics indicates high accuracy.

V. Discussion

In spite of the fact that there are various sensor technologies available off-the-shelf for estimating concrete moisture conditions, their adaptability to sewer environments has not been studied until now. This research study has utilized an electrical resistivity meter for determining the surface moisture conditions of the concrete sewer pipe. Although the sensing system has shown physical robustness to deployed sewer conditions, the measurements were found to

TABLE III: Evaluation of PAE-AD Model Forecasting

Period	MAE (kΩcm)	MAPE (%)	RMSE (kΩcm)
26th November to 1st Dec. 2016	0.3214	0.0138	0.4543
12th to 17th January 2017	0.2258	0.0105	0.2713

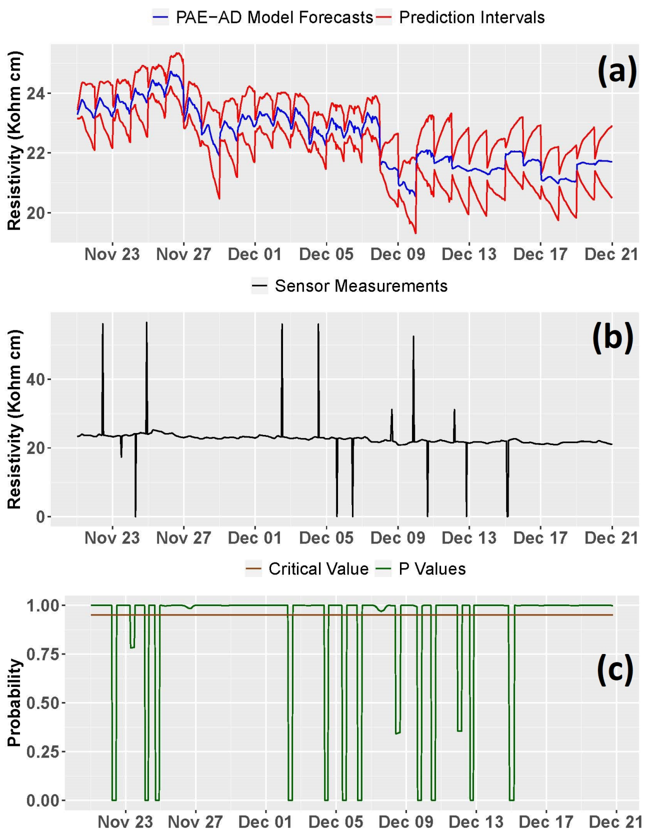


Fig. 6: Illustrating the PAE-AD model's anomaly detection. (a) PAE-AD model's forecasts and prediction intervals, (b) Sensor data with anomalies and (c) p-values corresponding to the sensor measurements from early November 2016 to the third week of December 2016.

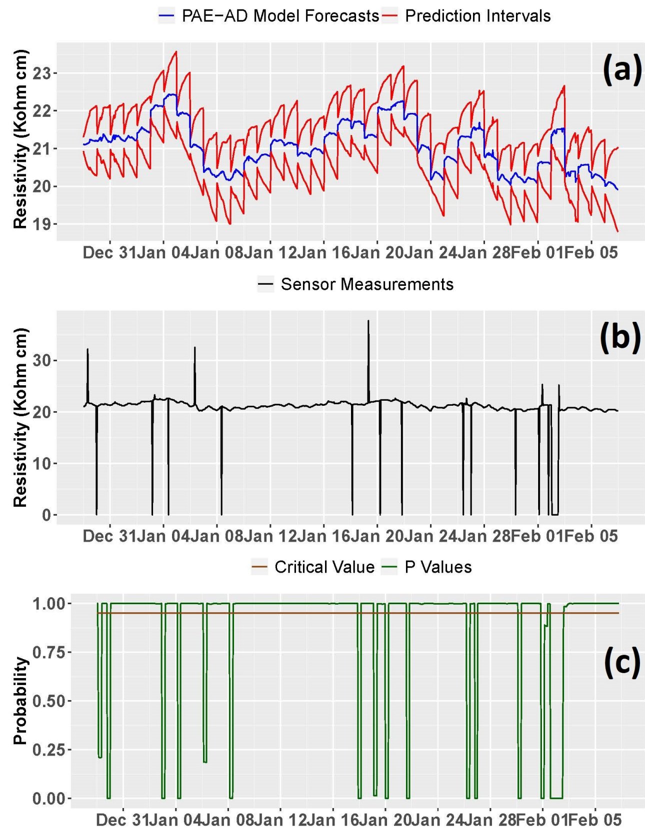


Fig. 7: Illustrating the PAE-AD model's anomaly detection. (a) PAE-AD model's forecasts and prediction intervals, (b) Sensor data with anomalies and (c) p-values corresponding to the sensor measurements from late December 2016 to the first week of February 2017.

be influenced by nearby metals (rebar). Therefore, it needs an on-site calibration for estimating the surface moisture conditions based on the electrical resistivity values. The in-situ evaluation was conducted in a Sydney suburban area of Australia, where there is no access to electrical mains power. So, a DC car battery was used to operate the sensing system. An ODROID based data-logger was used for storing the surface resistivity measurements from the sewer pipe. This data-logger was power-hungry and so, the DC battery was swapped with the recharged one. After swapping the battery, the operating system of the data-logger was restarted to perform measurements and logging at desired time intervals. To address the issue of high-power consumption by the data-logger, we are presently investigating the use of a micro-controller based data logging system.

The effect of rebar position on electrical resistivity measurements was studied by the authors. As detailed in [62], it was observed that sensor measurements taken perpendicular to the rebar has less influence compared to measurements taken by placing the electrodes on the top of the rebar. The ideal place for sensor measurements is at an area where the rebar is not in close proximity to the sensor electrodes. The effects of H_2S could be attributed to the surface pH conditions. It is still under investigation and will be published in a future publication. This is now mentioned in the manuscript [41].

From the post-deployment validation study, it can be concluded that the sensing system was in working conditions after three months of exposure to sewer conditions and therefore, the surface resistivity measurements from the sewer concrete surface were legitimate. Nevertheless, the surface resistivity data contained 2.36% of anomalies. They were manually removed for computations and in plots shown in Figs. 3 and 4. The sensor enclosure made up of PVC material exhibited durability to withstand corrosive sewer conditions. However, de-colouration of the PVC material was observed in a few areas.

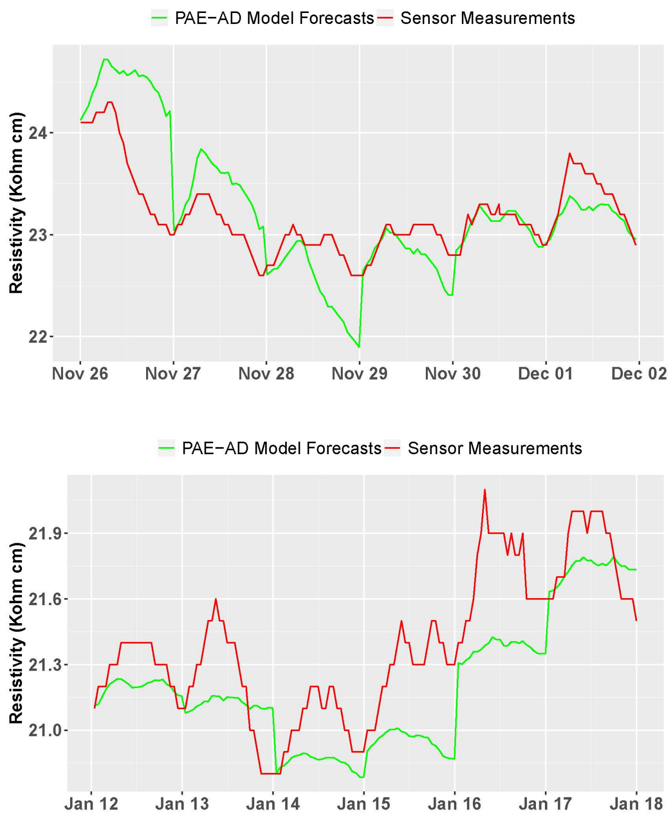


Fig. 8: PAE-AD model's surface resistivity forecasts.

This study mainly focused on developing surface moisture sensor suite and evaluating its suitability for monitoring inside harsh sewer environmental conditions. In this study, the humidity sensor was not installed in the pipe section where the surface moisture measurements were taken as there are no humidity sensors, which can operate long-term in sewer conditions. However, at the time of installing and removing the sensor unit, relative humidity was measured by using a hand-held relative humidity sensor (RH511, Omega). The reported scientific studies suggest that when the relative humidity of sewer air is over 95%, the concrete surface moisture conditions tend to be higher [15]. In this study, it was observed that the concrete moisture conditions were over 97% during the field testing. This could be because of the higher humidity conditions prevailed in the sewer pipe section, where the sensor was tested. However, the link between the concrete moisture and relative humidity cycling needs to be studied in detail, as even in the previous study it was poorly understood [63]. Detailed investigation of the effects of relative humidity conditions on surface moisture measurements in the long-term will be investigated in a future study.

During the field tests, the temperature difference between the gas phase temperature and the sewer wall temperature was less than 1°C. This may have negligible effects on surface moisture. However, in areas where the sewer pipe is above-ground, the difference in the gas phase and sewer wall temperature can be larger, which can influence surface moisture conditions. This needs to be studied comprehensively in the future to gain more insights on the influence of temperature parameters on surface moisture conditions.

From the field-testing campaign, it was observed that the surface moisture variations during the summer (November to February) period in Sydney, Australia is over 97% and the variations are less than 1.5%. This is a finding, which was not reported in previous studies. In this study, a small variation in moisture conditions was observed. This observation needs to be extended throughout the year to assess the moisture variations. Highly moist environmental conditions on the concrete sewer wall favours the growth of corrosion causing bacteria, which induces the corrosion rate significantly. However, this needs to be further investigated by a corrosion expert or a microbiologist to understand the significance of the corrosion potential.

While computing the statistical metrics for different forecasting models, four anomalies were present in the actual sensor measurements. Those anomalies were removed manually to compute the metrics to display the forecasting performances. However, even with those four anomalies, the SARIMA model has the lowest values for all the metrics. In the statistical comparative analysis, the SARIMA based model prediction between 21st November 2016 and 27th November 2016 has lower accuracy compared to the PAE-AD model prediction from 26th November 2016 to 1st December 2016 and from 12th January 2017 to 17th January 2017. This is mainly due to the reason that in the comparative analysis, we trained the SARIMA based model and predicted for seven continuous days whereas, in the PAE-AD model, we have predicted one day ahead by updating the PAE-AD model's training data with the previous day sensor measurements.

Surface moisture sensor measurements can produce anomalies for several reasons. They can be momentary or long-lasting. A momentary anomaly can occur randomly. Long-lasting anomalies are continuous and may lead to sensor failure. One possible cause for the anomaly is when the electrodes of the sensor are not touching the surface properly. It can be due to the failure of the spring mechanism in the sensor electrode or damages that occurred on the surface of the concrete sewer wall. In this circumstance, the sensor tends to produce 0 kΩcm. Another possible cause is when there is a fluctuation in the input signal or low power supply to the sensor system. In this scenario, the sensor produces random values. Identifying anomalies is crucial for sensors monitoring inside the harsh sewer environment. It can be detected by a simple statistical method. However, the PAE-AD model includes a forecasting module, which enables temporal forecasting of sensor data. Besides anomaly detection, the PAE-AD model can utilize temporal forecasts to detect early sensor failure based on the continuity of abnormal sensor data. In addition, the forecast data caters reliable estimates of sensor measurements on abnormal events such as anomaly occurrence, sensor faults and during the scheduled maintenance period. Thus, the estimated data can be a replacement for the faulty sensor data. Also, the PAE-AD model allows the operators to manage sewer pipes by foreseeing the trends of sensor measurements for appropriate decision-making whilst monitoring the sensor health conditions.

Currently, there is a predictive analytics model for predicting sewer concrete corrosion. However, the uncertainty in predictions is high in certain areas. In such areas, the developed sensor will be deployed to monitor surface moisture conditions. Primarily, it is important to know whether the concrete sewer wall is wet or dry because the corrosion causing bacteria grows on the highly moist concrete surface. This information will be fed as an additional input to the predictive model for improving corrosion prediction. However, concrete sewer surface moisture condition is not the only parameter that influences corrosion or it does not have a linear correlation with the corrosion rate. Some of the parameters that can influence the corrosion process are temperature and relative humidity of the sewer air, concrete sewer surface temperature and gaseous H_2S content in sewer air. The electrical resistivity measurements can relatively indicate whether the concrete surface is wet or dry. For this reason, calibration was done by taking measurements in wet and dry areas of the pipe section.

VI. Conclusions and Further Work

This article reports the development of a sensor suite and predictive analytics enabled anomaly detection model for smart monitoring of surface moisture conditions inside the concrete sewer pipe. The main highlights are:

- A sensor suite based on electrical resistivity measurements was developed for real-time continuous monitoring of concrete sewer pipe surface moisture conditions under corrosive sewer conditions.
- The competence of the developed sensing system to survive the hostile environmental conditions of the sewer atmosphere for about three months demonstrated its suitability for long-term sewer monitoring applications.
- A PAE-AD model was proposed and evaluated with the surface resistivity data obtained through the developed sensing system. The model detected 97.82% of the anomalies contained in the sensor data and statistical evaluation indicated the high accuracy in the model's forecasting performance.

Our industry partner Sydney Water in Australia currently uses a predictive analytics toolkit for predicting corrosion on the entire sewer network. The toolkit's prediction is based on the Bayesian non-parametric method. It means that each prediction at an unknown point in the sewer network is a Gaussian distribution with mean and variance. Higher the variance implies higher prediction uncertainty in the geodesic distances from the predicted point and to the observed point. In the future, the developed sensor unit will be deployed for real-time monitoring at a location where there is a high prediction uncertainty in the sewer network. Then, the surface moisture data will be fed as an input to the corrosion predicting model for minimizing the prediction uncertainty and thereby, improving the prediction accuracy. This allows the water utilities like Sydney Water to efficiently manage their sewer assets and enables operational cost savings through targeted sewer pipe renewals and chemical dosing.

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References

[1] I. Pikaar, K. R. Sharma, S. Hu, W. Gernjak, J. Keller, and Z. Yuan, "Reducing sewer corrosion through integrated urban water management," *Science*, vol. 345, no. 6198, pp. 812–814, 2014.

[2] G. Jiang, J. Keller, P. L. Bond, and Z. Yuan, "Predicting concrete corrosion of sewers using artificial neural network," *Water research*, vol. 92, pp. 52–60, 2016.

[3] L. Zhang, P. De Schryver, B. De Gusseme, W. De Muynck, N. Boon, and W. Verstraete, "Chemical and biological technologies for hydrogen sulfide emission control in sewer systems: a review," *Water research*, vol. 42, no. 1, pp. 1–12, 2008.

[4] L. S. M. Alwis, H. Bustamante, K. Bremer, B. Roth, T. Sun, and K. Grattan, "Evaluation of the durability and performance of FBG-based sensors for monitoring moisture in an aggressive gaseous waste sewer environment," *Journal of Lightwave Technology*, vol. PP, no. 99, p. 1, 2016.

[5] M. P. H. Brongers, P. Y. Virmani, and J. H. Payer, "Drinking water and sewer systems in corrosion costs and preventative strategies in the United States," *United States Department of Transportation Federal Highway Administration*, 2002.

[6] K. Thiyagarajan, "Robust Sensor Technologies Combined with Smart Predictive Analytics for Hostile Sewer Infrastructures," Ph.D. dissertation, University of Technology Sydney, 2018.

[7] P. Wells and R. E. Melchers, "Microbial Corrosion of Sewer Pipe in Australia Initial Field Results," in *18th International Corrosion Congress Proceedings November*. Citeseer, 2011.

[8] A. Romanova, M. Mahmoodian, and M. A. Alani, "Influence and interaction of temperature, H2S and pH on concrete sewer pipe corrosion," *International Journal of Civil, Architectural, Structural, Urban Science and Engineering*, vol. 8, no. 6, pp. 592–595, 2014.

[9] P. F. Boulos and A. T. Walker, "Fixing the Future of Wastewater Systems With Smart Water Network Modeling (PDF)," *Journal-American Water Works Association*, vol. 107, no. 4, pp. 72–80, 2015.

[10] A. G. Boon, "Septicity in sewers: causes, consequences and containment," *Water Science and Technology*, vol. 31, no. 7, pp. 237–253, 1995.

[11] A. P. Joseph, J. Keller, H. Bustamante, and P. L. Bond, "Surface neutralization and H 2 S oxidation at early stages of sewer corrosion: Influence of temperature, relative humidity and H 2 S concentration," *Water research*, vol. 46, no. 13, pp. 4235–4245, 2012.

[12] T. Wells, R. Melchers, A. Joseph, P. Bond, D. Vitanage, H. Bustamante, J. De Grazia, T. Kuen, J. Nazimek, and T. Evans, "A collaborative investigation of the microbial corrosion of concrete sewer pipe in Australia," in *OzWater-12 Australia's National Water Conference and Exhibition, May*, 2012, pp. 8–10.

[13] Y. Liu, K. R. Sharma, S. Murthy, I. Johnson, T. Evans, and Z. Yuan, "On-line monitoring of methane in sewer air," *Scientific reports*, vol. 4, 2014.

[14] K. Thiyagarajan, S. Kodagoda, R. Ranasinghe, D. Vitanage, and G. Iori, "Robust sensing suite for measuring temporal dynamics of surface temperature in sewers," *Scientific Reports*, vol. 8, no. 1, p. 16020, 2018. [Online]. Available: http://www.nature.com/articles/s41598-018-34121-3

[15] T. Wells and R. E. Melchers, "Modelling concrete deterioration in sewers using theory and field observations," *Cement and Concrete Research*, vol. 77, pp. 82–96, 2015.
[16] B. Li, X. Fan, J. Zhang, Y. Wang, F. Chen, S. Kodagoda, T. Wells, L. Vorreiter, D. Vitanage, G. Iori, D. Cunningham, and T. Chen, "Predictive Analytics Toolkit for H2S Estimation and Sewer Corrosion," in *OZWater*. Sydney: Australian Water Association, 2017.
[17] Y. Liu, K. R. Sharma, M. Fluggen, K. O'halloran, S. Murthy, and Z. Yuan, "Online dissolved methane and total dissolved sulfide measurement in sewers," *Water research*, vol. 68, pp. 109–118, 2015.
[18] I. Choi, H. Lee, J. Shin, and H. Kim, "Evaluation of the effectiveness of five odor reducing agents for sewer system odors using an on-line total reduced sulfur analyzer," *Sensors (Switzerland)*, 2012.
[19] J. Hur, B.-M. Lee, T.-H. Lee, and D.-H. Park, "Estimation of biological oxygen demand and chemical oxygen demand for combined sewer systems using synchronous fluorescence spectra," *Sensors*, 2010.
[20] K. Bremer, M. Meinhardt-Wollweber, T. Thiel, G. Werner, T. Sun, K. T. V. Grattan, and B. Roth, "Sewerage tunnel leakage detection using a fibre optic moisture-detecting sensor system," *Sensors and Actuators A: Physical*, vol. 220, pp. 62–68, 2014.
[21] K. Thiyagarajan, S. Kodagoda, and J. K. Alvarez, "An instrumentation system for smart monitoring of surface temperature," in *2016 14th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, 2016, pp. 1–6.
[22] Z. You, J. Mills-Beale, B. D. Pereles, and K. G. Ong, "A Wireless, Passive Embedded Sensor for Real-Time Monitoring of Water Content in Civil Engineering Materials," *IEEE Sensors Journal*, 2008.
[23] A. Cataldo, E. De Benedetto, G. Cannazza, E. Piuzzi, and E. Pittella, "TDR-Based Measurements of Water Content in Construction Materials for In-the-Field Use and Calibration," *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 5, pp. 1230–1237, 2018.
[24] P. Pursula, I. Marttila, K. Nummila, and H. Seppa, "High frequency and ultrahigh frequency radio frequency identification passive sensor transponders for humidity and temperature measurement within building structures," *IEEE Transactions on Instrumentation and Measurement*, 2013.
[25] A. Cataldo, E. De Benedetto, and G. Cannazza, "Hydration monitoring and moisture control of cement-based samples through embedded wire-like sensing elements," *IEEE Sensors Journal*, 2015.
[26] T. L. Yeo, M. A. C. Cox, L. F. Boswell, T. Sun, and K. T. V. Grattan, "Optical fiber sensors for monitoring ingress of moisture in structural concrete," *Review of Scientific Instruments*, 2006.
[27] T. Sokoll and A. F. Jacob, "Self-Oscillating Measurement System for In Situ-Monitoring Moisture in Buildings," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 12, pp. 2911 – 2918, 2014.
[28] M. N. Alam, R. H. Bhuiyan, R. Dougal, and M. Ali, "Concrete moisture content measurement using interdigitated near-field sensors," *IEEE Sensors Journal*, vol. 10, no. 7, pp. 1243–1248, 2010.
[29] K. J. Bois, A. D. Benally, P. S. Nowak, and R. Zoughi, "Cure-state monitoring and water-to-cement ratio determination of fresh portland cement-based materials using near-field microwave techniques," *IEEE Transactions on Instrumentation and Measurement*, 1998.
[30] S. Laurens, J. P. Balayssac, J. Rhazi, G. Klysz, and G. Arliguie, "Non-destructive evaluation of concrete moisture by GPR: Experimental study and direct modeling," in *Materials and Structures/Materiaux et Constructions*, 2005.
[31] S. Peer, K. E. Kurtis, and R. Zoughi, "An Electromagnetic Model for Evaluating Temporal Water Content Distribution and Movement in Cyclically Soaked Mortar," *IEEE Transactions on Instrumentation and Measurement*, 2004.
[32] S. F. Senin and R. Hamid, "Ground penetrating radar wave attenuation models for estimation of moisture and chloride content in concrete slab," *Construction and Building Materials*, 2016.
[33] S. Peer, K. E. Kurtis, and R. Zoughi, "Evaluation of microwave reflection properties of cyclically soaked mortar based on a semiempirical electromagnetic model," *IEEE Transactions on Instrumentation and Measurement*, 2005.
[34] K. L. Chung and S. Kharkovsky, "Monitoring of microwave properties of early-age concrete and mortar specimens," *IEEE Transactions on Instrumentation and Measurement*, 2015.
[35] M. Ams, P. Giri, P. Dekker, S. Taheri, J. Gonzalez, S. Clark, T. Kuen, L. Vorreiter, H. Bustamante, and M. J. Withford, "Optical Fibre Sensors for Monitoring Sewer Concrete Corrosion," in *The European Conference on Lasers and Electro-Optics 2019*. Munich: Optical Society of America, 2019.
[36] P. Giri, S. Kharkovsky, X. Zhu, S. M. Clark, and B. Samali, "Debonding detection in a carbon fibre reinforced concrete structure using guided waves," *Smart Materials and Structures*, vol. 28, no. 4, 2019.
[37] L. Piyathilaka, B. Sooriyaarachchi, S. Kodagoda, and K. Thiyagarajan, "Capacitive Sensor Based 2D Subsurface Imaging Technology for Non Destructive Evaluation of Building Surfaces," in *2019 IEEE 9th international conference on cybernetics and intelligent systems (CIS) and IEEE conference on robotics, automation and mechatronics (RAM)*. IEEE, 2019.
[38] P. Giri and S. Kharkovsky, "Dual-Laser Integrated Microwave Imaging System for Nondestructive Testing of Construction Materials and Structures," *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 6, pp. 1329–1337, 2018.
[39] N. Giovanangeli, L. Piyathilaka, S. Kodagoda, K. Thiyagarajan, S. Barclay, and D. Vitanage, "Design and development of drill-resistance sensor technology for accurately measuring microbiologically corroded concrete depths," in *Proceedings of the 36th International Symposium on Automation and Robotics in Construction*. IAARC, 2019, pp. 735–742.
[40] K. Thiyagarajan and S. Kodagoda, "SMART monitoring of surface temperature and moisture content using multisensory data fusion," in *2015 IEEE 7th International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM)*, 2015, pp. 222–227.
[41] K. Thiyagarajan, S. Kodagoda, and N. Ulapane, "Data-driven machine learning approach for predicting volumetric moisture content of concrete using resistance sensor measurements," in *2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA)*, 2016, pp. 1288–1293.
[42] K. Thiyagarajan and S. Kodagoda, "Analytical Model and Data-driven Approach for Concrete Moisture Prediction," in *33rd International Symposium on Automation and Robotics in Construction (ISARC 2016)*. Auburn: IAARC, 2016, pp. 298–306.
[43] S. Wickramanayake, K. Thiyagarajan, S. Kodagoda, and L. Piyathilaka, "Frequency Sweep Based Sensing Technology for Non-destructive Electrical Resistivity Measurement of Concrete," in *2019 Proceedings of the 36th ISARC*. IAARC, 2019, pp. 1290–1297.
[44] V. Chatzigiannakis and S. Papavassiliou, "Diagnosing anomalies and identifying faulty nodes in sensor networks," *IEEE Sensors Journal*, 2007.
[45] T. Cheng, F. Harrou, Y. Sun, and T. Leiknes, "Monitoring Influent Measurements at Water Resource Recovery Facility Using Data-Driven Soft Sensor Approach," *IEEE Sensors Journal*, 2019.
[46] S. Cheng, K. Tom, L. Thomas, and M. Pecht, "A wireless sensor system for prognostics and health management," *IEEE Sensors Journal*, 2010.
[47] W. He, P. L. Qiao, Z. J. Zhou, G. Y. Hu, Z. C. Feng, and H. Wei, "A New Belief-Rule-Based Method for Fault Diagnosis of Wireless Sensor Network," *IEEE Access*, vol. 6, pp. 9404–9419, 2018.
[48] K. Thiyagarajan, S. Kodagoda, L. V. Nguyen, and R. Ranasinghe, "Sensor Failure Detection and Faulty Data Accommodation Approach for Instrumented Wastewater Infrastructures," *IEEE Access*, vol. 6, pp. 56 562–56 574, 2018.
[49] K. Thiyagarajan, S. Kodagoda, and L. Nguyen, "Predictive Analytics for Detecting Sensor Failure Using Autoregressive Integrated Moving Average Model," in *12th IEEE Conference on Industrial Electronics and Applications*. Siem Reap: IEEE, 2017, pp. 1923–1928.
[50] "Resipod-Resistivity Meter," p. 3. [Online]. Available: http://www.pcte.com.au/images/pdf/Resipod-ResistivityMeter/Resipod.pdf
[51] S. T. Method, "Field Measurement of Soil Resistivity Using the Wenner Four-Electrode Method 1," *Current*, 2001.
[52] "Operating Instructions Concrete Durability Testing," Proceq, Switzerland, Tech. Rep., 2017. [Online]. Available: https://www.proceq.com/uploads/tx_proceqproductcms/import_data/files/Resipod%20Family_Operating%20Instructions_English_high.pdf
[53] A. Mudroch, J. M. Azcue, and P. Mudroch, *Manual of physico-chemical analysis of aquatic sediments*. CRC Press, 1996.
[54] L. J. Parrott, *A review of methods to determine the moisture conditions in concrete*, 1990.
[55] P. Azarsa and R. Gupta, "Electrical Resistivity of Concrete for Durability Evaluation: A Review," *Advances in Materials Science and Engineering*, vol. 2017, p. 30, 2017.
[56] R. J. Hyndman and Y. Khandakar, "Automatic time series forecasting: The forecast package for R," *Journal Of Statistical Software*, 2008.
[57] S. Hussain, M. Mokhtar, and J. M. Howe, "Sensor failure detection, identification, and accommodation using fully connected cascade neural network," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 3, pp. 1683–1692, 2015.

[58] C. S. Luo, L. Y. Zhou, and Q. F. Wei, "Application of SARIMA Model in Cucumber Price Forecast," *Applied Mechanics and Materials*, 2013.
[59] R. J. Hyndman, A. B. Koehler, R. D. Snyder, and S. Grose, "A state space framework for automatic forecasting using exponential smoothing methods," *International Journal of Forecasting*, 2002.
[60] C. Bergmeir, R. J. Hyndman, and J. M. Benítez, "Bagging exponential smoothing methods using STL decomposition and Box-Cox transformation," *International Journal of Forecasting*, 2016.
[61] P. Y. Chen, S. Yang, and J. A. McCann, "Distributed real-time anomaly detection in networked industrial sensing systems," *IEEE Transactions on Industrial Electronics*, 2015.
[62] K. Thiyagarajan, S. Kodagoda, L. V. Nguyen, and S. Wickramanayake, "Gaussian Markov Random Fields for Localizing Reinforcing Bars in Concrete Infrastructure," in *2018 Proceedings of the 35th International Symposium on Automation and Robotics in Construction*. Berlin: IAARC, 2018, pp. 1052–1058.
[63] T. Wells, "Identification of controlling factors for the corrosion rate of concrete," Centre for Infrastructure Performance and Reliability, The University of Newcastle, Tech. Rep., 2016. [Online]. Available: https://score.org.au/++theme++/score-kms/Reports/SP1/Final%20report%20SP1B.pdf

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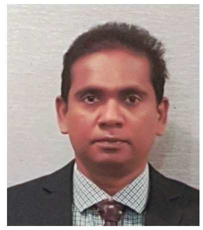

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