Robust Sensor Technologies Combined with Smart Predictive Analytics for Hostile Sewer Infrastructures

by

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University of Technology Sydney

25th July 2018

Declaration of Authorship

I certify that the work in this dissertation has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the dissertation has been written by me. Any help that I have received in my research work and the preparation of the dissertation itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the dissertation.

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UNIVERSITY OF TECHNOLOGY SYDNEY

Abstract

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Underground sewer systems are an important national infrastructure requirement of any country. In most cities, they are old and have been exposed to significant levels of microbial induced concrete corrosion, which is widely regarded as a serious global problem as they pose threats to public health and cause economic repercussions to water utilities. In order to maintain those underground assets efficaciously, it is pivotal for water utilities to estimate the amount of intact concrete left to rebar by predicting the rate of corrosion throughout the sewer network. Existing predictive models incorporate concrete surface temperature and surface moisture conditions as observations. However, researchers and water utilities often use indirect measures like ambient temperature and humidity data as inputs to their models. This is primarily due to unavailability of proven technologies in the state-of-the-art systems and sensing limitations predominantly attributed to the corrosive nature of the sewer environment. Hence, the focus of this dissertation is to provide reliable measures of surface temperature and moisture conditions by developing robust sensor technologies that can facilitate measurements under the hostile sewer conditions.

This dissertation encompasses three main parts:

In the first part, a robust sensor technology using an infrared radiometer sensor for quantifying surface temperature dynamics inside concrete sewer pipes is proposed. In this regard, the sensor was comprehensively evaluated in the laboratory conditions to

study the effects of optical window fogging, incident angle, limit of detection, distance, lighting conditions, reproducibility, humidity and increased surface temperature conditions. Thereafter, the sensor was deployed in sewer pipe for real-time continuous measurements. The field study revealed the suitability of the proposed sensor technology for non-contact surface temperature measurements under the hostile sewer environment. Further, the accuracy of the sensor measurements was improved by calibrating the sensor with emissivity coefficient of the sewer concrete.

In the second part of the dissertation, a non-invasive sensing technique to determine the concrete surface moisture conditions is proposed. In this context, laboratory experiments were conducted to study the behaviour of concrete moisture to electrical resistance variations and different pH concentrations. This study led to utilize the Wenner array method to determine the surface moisture conditions based on concrete surface electrical resistivity measurements. Then, the sensor suite was deployed in concrete sewer pipe to measure the surface resistivity for about three months. Upon on-site calibration, surface moisture conditions were determined and thereof, the field campaign exhibited the feasibility of the proposed sensing method. Further investigations were conducted to locate the reinforcing bar embedded in concrete for optimal sensor installation in order to minimize the effects of reinforcing bar during measurements.

In the third part, sensor technologies were combined with smart predictive analytics to develop a diagnostic toolkit that can digitally monitor the health conditions of the sensors is proposed. This toolkit embraces a seasonal autoregressive integrated moving average model with statistical hypothesis testing technique to enable temporal forecasting of sensor data; identify and isolate anomalies in a continuous stream of sensor data; detect early sensor failure and finally to provide reliable estimates of sensor data in the event of sensor failure or during the scheduled maintenance period of sewer monitoring systems.

Overall, this dissertation significantly contributes to ameliorating the way sewer assets are monitored and maintained in Australia and globally by providing information-rich new data to the predictive models for better corrosion prediction.

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Acronyms & Abbreviations

1D	One-dimensional
2D	Two-dimensional
3D	Three-dimensional
AC	Alternating Current
AIC	Akaike Information Criterion
AR	Autoregressive
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
CAS	Centre for Autonomous Systems
CCTV	Closed-circuit television
CW	Critical Wavelength
DC	Direct Current
DTS	Distributed Temperature Sensing
ETS	Exponential Smoothing
FBG	Fiber Bragg Gratings
FDR	Frequency Domain Reflectometry
FG	Fiber Grating

GMRF	Gaussian Markov Random Fields
GP	Gaussian Process
GPR	Gaussian Process Regression
H_2S	Hydrogen Sulphide
H_2SO_4	Sulphuric acid
IRR	Infrared Radiometer
IRT	Infrared Thermography
MA	Moving Average
MAE	Mean Absolute Error
MAPD	Mean Absolute Percentage Deviation
MAPE	Mean Absolute Percentage Error
MPE	Mean Percentage Error
NTC	Negative Temperature Coefficient
RF	Radio Frequency
RFs	Radio Frequencies
RH	Relative Humidity
RMSE	Root Mean Square Error
RTD	Resistance Temperature Detector
RW	Random Walk
SARIMA	Seasonal Autoregressive Integrated Moving Average
SDR	Successful Detection Rate
SES	Simple Exponential Smoothing

SFA Sensor Failure Accommodation

SFDA Sensor Failure Detection and Accommodation

SPDE Stochastic Partial Differential Equations

TDR Time Domain Reflectometry

UTS University of Technology Sydney

Nomenclature

	General Notations
cm	Centimetre (unit).
Dt	Time interval between the two sensor measurements.
df	Degrees of freedom.
mm	Millimetre (unit).
g	Gram (unit).
m_d	Mass of the concrete sample in a dry condition.
m_w	Mass of the concrete sample in a wet condition.
n	Number of Samples.
ppm	Parts per Million (unit).
t	Time (continuous).
V	Voltage (unit).
$^{\circ}C$	Degree Celsius.
μ	Mean.
σ	Standard deviation.
σ^2	Variance.
ρ_d	Density of concrete sample in a dry condition.
ρ_w	Density of pH solution.
θ_G	Wet basis moisture content of a material.
θ_V	Volumetric moisture content of a material.

	Sensors
T_{IRR}	Surface temperature measurements from the infrared radiometer sensor.
T_{RIT}	Surface temperature measurements from the reference instrument thermistor sensor.
	On-site Calibration of Sensors
E	Measurement error.
E_{ir}	Radiant energy detected by the infrared surface temperature sensor.
E_{tr}	Radiant energy detected by the contact-type surface temperature sensor.
SM	Surface moisture conditions.
SR_S	Surface resistivity value measured from the resistivity meter.
SR_W	Surface resistivity value measured at wet area of the concrete sewer pipe.
SR_D	Surface resistivity value measured at dry area of the concrete sewer pipe.
T_{is}	Temperature measured by the infrared surface temperature sensor.
T_{tr}	Temperature measured by the contact-type surface temperature sensor.
ϵ_{is}	Set emissivity of the infrared sensor.
ϵ_t	True emissivity of the measured surface.
ϵ_{IR}	Set emissivity of the infrared radiometer sensor.
ϵ_T	Estimated emissivity of the surface.
μ	Mean value of ϵ_T.
	SFDA Algorithm
$AR(p)$	Autoreggressive model of order p.
$AR(p)_t$	Actual value of $AR(p)$ at time t.
$ARMA(p,q)$	Autoreggressive Moving Average model of order p and q.
$ARMA(p,q)_t$	Actual value of $ARMA(p,q)$ at time t.

$ARIMA(p, d, q)$	Autoreggressive Integrated Moving Average model of order p, d and q.
$ARIMA(p, d, q)_t$	Actual value of $ARIMA(p, d, q)$ at time t.
B	Backshift operator.
d	Parameter governs the level of differencing.
D	Degree of seasonal differencing parameter.
k	Backward observation of the time series.
K_n	Number of parameters estimated to compute one-step ahead forecasts.
L	Maximized likelihood of the $SARIMA(p, d, q)(P, D, Q)_{S_p}$ model.
$MA(q)$	Moving Average model of order q.
$MA(q)_t$	Actual value of $MA(q)$ at time t.
p	Autoregressive model order.
P	Seasonal Autoregressive model order.
q	Moving Average model order.
Q	Seasonal Moving Average model order.
R_t	Observe red sensor data coming from the sewer.
$SARIMA$	$SARIMA(p, d, q)(P, D, Q)_{Sp}$ model with parameters p, d, q, P, D and Q.
S_p	Seasonal period of the stochastic model.
S_{t+f}	Future observable variable.
$\widetilde{S}_{t-n}$	Previous deviations from the mean value of the time series data.
$\hat{S}_{t+f}(+)$	Forecast value resulting from the SARIMA model.
$\hat{S}_{t+f}(+)$	Upper limit of the forecast.
$\hat{S}_{t+f}(-)$	Lower limit of the forecast.
W_L	Size of sliding window
ϕ_n	Finite set of weight parameters of the $AR(p)$.
θ_n	Finite set of weight parameters of the $MA(q)$.
ε_t	Random shock.
$\mu_{\lambda/2}$	Percentiles of the standard normal distribution.
σ_g	Standard deviation of the Gaussian distribution.

χ^2	Pearson's chi-squared test.
χ^2_{df}	Chi-squared distribution.
α	Critical value.

Glossary of Terms

Ambient	Pertains to the immediate surroundings.
Anomalies	Data that deviates from the standard, normal, or expected.
Autonomous	Without human intervention.
Data Accommodation	Utilizing the data coming from the reliable measure, prediction or estimation.
Field Deployment	The transportation of equipment to a place or position for desired operations.
Forecasting	Predict or estimate the future trends or unknown events.
Infrared Radiometer	An instrument for detecting or measuring the intensity of radiation using infrared signals.
Measurements	The action of measuring the physical quantities.
Modelling	A description of a system using mathematical concepts and language. The process of developing a mathematical model is termed mathematical modelling.
Predictive Analytics	A variety of statistical techniques from predictive modelling, machine learning and data mining to predict future trends or unknown events by using historical and transactional data.
Real-time	Relating to a system in which input data is processed within milliseconds so that it is available virtually immediately as feedback to the process from which it is coming.
Relative Humidity	The amount of water vapour present in air expressed as a percentage of the amount needed for saturation at the same temperature.

Resistance	The measure of the degree to which a conductor opposes an electric current through that conductor.
Resistivity	It is a fundamental property that quantifies how strongly a material under test is opposing the flow of electric current.
Robust	Able to withstand or overcome adverse conditions.
Sensing Suite	A set of sensors enclosed in a housing to perform measurements of interest.
Sensor	A device that detects or measures a physical property, indicates or otherwise responds to it.
Sensor Characterization	A description of the distinctive nature or features of the sensor under different condition.
Sensor Failure	The state of improper functioning of a sensor.
Sewers	An underground conduit for carrying off drainage water and waste matter.
Smart	Device programmed so as to be capable of some independent action.
Study	A detailed investigation and analysis of a subject or situation.
Technology	Device or equipment developed from the application of scientific knowledge.
Temporal Dynamics	The properties that changes within a system or process relating to or denoting time.
Quantification	The measurement of the variable of interest.