PIEZO BASED STRUCTURAL HEALTH MONITORING OF CONCRETE SYSTEMS USING MACHINE LEARNING

Thesis submitted in fulfilment of the requirements for the Degree of

DOCTOR OF PHILOSOPHY

By

TUSHAR BANSAL (E17SOE834)



DEPARTMENT OF CIVIL ENGINEERING BENNETT UNIVERSITY

(Established under UP Act No 24, 2016)

Plot Nos 8-11, Tech Zone II,

Greater Noida-201310, Uttar Pradesh, India.

May, 2022

@ Copyright Bennett University, Greater Noida May, 2022 ALL RIGHTS RESERVED

DECLARATION BY THE SCHOLAR

I hereby declare that the work reported in the Ph.D. thesis entitled "Piezo based structural

health monitoring of concrete systems using machine learning" submitted at

Bennett University, Greater Noida, India, is an authentic record of my work carried

out under the supervision of Prof. Visalakshi Talakokula and Prof. Prabhakar

Sathujoda. I have not submitted this work elsewhere for any other degree or diploma. I am

fully responsible for the contents of my Ph.D. Thesis.

fushar

Signature of the Scholar

Tushar Bansal

Department of Civil Engineering

Bennett University, Greater Noida, India

Date: 16th May 2022

i

SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in the Ph.D. thesis entitled "Piezo Based Structural Health Monitoring of Concrete Systems Using Machine Learning" submitted by Mr. Tushar Bansal at Bennett University, Greater Noida, India, is a bonafide record of his original work carried out under our supervision. This work has not been submitted elsewhere for any other degree or diploma.



(Signature of Supervisor)

Prof. Visalakshi Talakokula

Department of Civil Engineering

Ecole Centrale School of Engineering

Mahindra University, India

Date: 16th May 2022

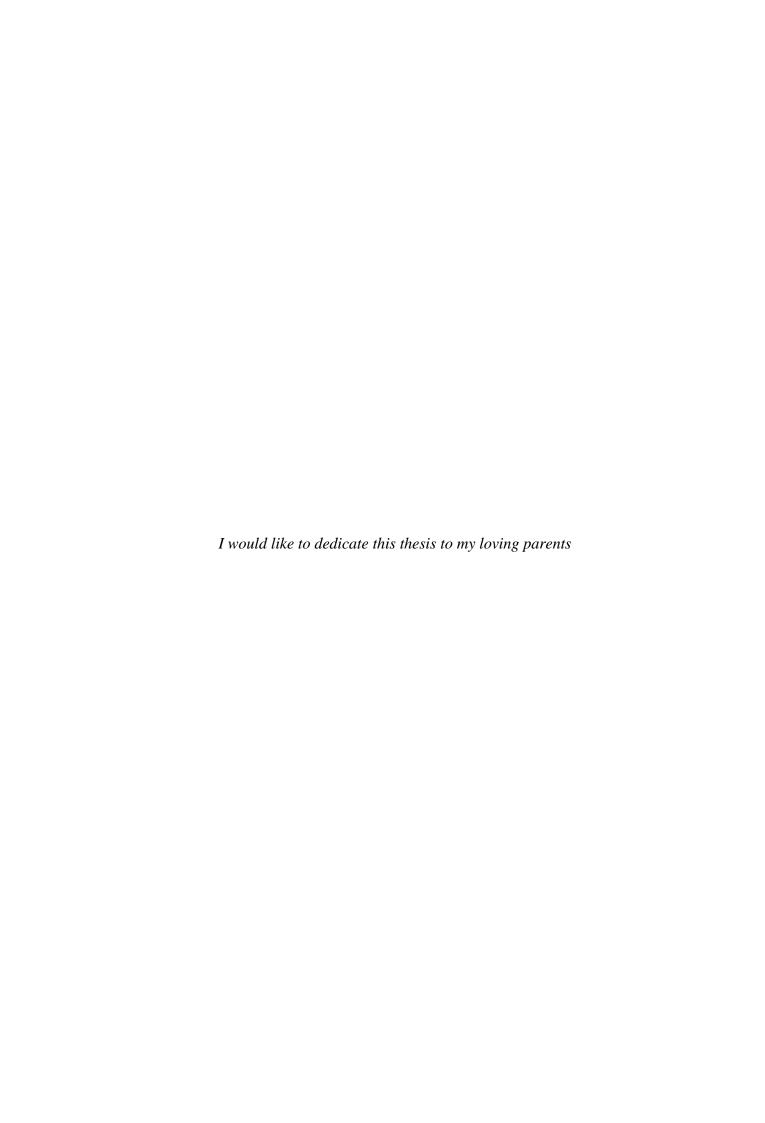
(Signature of Supervisor)

S. Brashele

Prof. Prabhakar Sathujoda Department of Mechanical Engineering

Bennett University, India

School of Engineering and Applied Sciences



ACKNOWLEDGEMENTS

First and foremost, I would like to extend my sincere thanks and gratitude to my supervisors,

Prof. Visalakshi Talakokula and Prof. Prabhakar Sathujoda for their consistent guidance,

continuous encouragement, and strong support in every stage of my Ph.D. research. I am forever

grateful for their kindness and contributions, not only towards my research, but towards my

professional growth as well.

I am grateful to my committee members and other members, namely Prof. Deepak Garg, Dr.

Priyadharshini B, Dr. Tanveer Ahmed and Dr. Gaurav Singal for giving useful suggestions and

valuable advice regarding my research. I am also thankful to my colleague, Mr. Sumit Sharma,

Mr. Manish Chauhan, Ms. Shikha Singh and Ms. Srijna Singh for providing valuable

suggestions and support whenever required.

My thanks are also due to all the faculty and other staff members for their support and keenness

in my work. I am extremely grateful to the staff of Civil Engineering Laboratory, departmental

and central library for providing books, journals etc., which made this research work possible.

I express my special thanks to Mr. Prakash Singh and other technicians, who provided their

technical support generously during the lab work.

My special thanks to Prof. Suresh Bhalla for instrumental support through the Concrete

Structural Laboratory (CSTL) and Smart Structures and Dynamics Laboratory (SSDL),

Department of Civil Engineering, Indian Institute of Technology (IIT) Delhi.

A special thanks goes to almighty God and my parents for their encouragement and sacrifices,

Last but not least, I wish to express my gratitude to my family, and in particular to my father

Late Radhey Lal Bansal and my mother Rama Devi.

TUSHAR BANSAL

fushar

iii

ABSTRACT

Monitoring the health of infrastructure has become imperative now a days due to vast infrastructure development in the last few decades which has now aged. Proper monitoring of the structures during the construction as well as design life stage can avoid catastrophic failures. Strength and durability are the two main aspects of reinforced concrete structures and providing a real time monitoring of these are the big challenges which almost all the concrete researchers are working around the world. The field of structural health monitoring (SHM) using piezo sensors via electro-mechanical impedance (EMI) has grown tremendously in recent years can provide a solution to these issues. The application of machine learning (ML) techniques is experiencing exponential growth in SHM domain using sensors because of the immense capability of handling voluminous datasets and making past and future predictions based on input data used for training.

The aim of the present research is to utilize smart sensors, namely PZT sensors, in different configurations and analyse its sensitivity for strength monitoring, durability studies and suitably propose its application in real-life. ML models were developed using the sensor data to predict the strength of different cementitious systems and concrete systems. The research was further extended to develop ML models to predict the baseline/healthy and future EMI data of different blended RC structures (conventional, fly ash blended and fly ash based geopolymer) subjected to a chloride-laden environment. Also, different corrosion phases have been identified based on the famous Tuutti's model for the RC and prestresses structures subjected to corrosion. Further pioneering work has been carried out on different concrete systems subjected to combined environmental and mechanical loading wherein physical models for structural parameter deterioration were developed and also empirical relations between equivalent stiffness and surface concentration were established.

The developed strength prediction models can be used to predict the strength of the newly developed concrete non-destructively which will aid for proper project management. The ARIMA model can be used for prediction of baseline/healthy data for existing structures to study durability. It is expected that this research work will serve as new important guidelines to the industry as well as to the research community working in the field of structural health monitoring.

CONTENTS

DECLARATION BY THE SCHOLAR	i
SUPERVISOR'S CERTIFICATE	ii
ACKNOWLEDGEMENTS	iii
ABSTRACT	iv
CONTENTS	v
LIST OF FIGURES	ix
LIST OF TABLES	xiv
LIST OF ABBREVIATIONS	xvi
LIST OF SYMBOLS	xix
CHAPTER-1 INTRODUCTION	
1.1 Background.	1
1.2 Research Hypothesis	2
1.3 Research Objectives	3
1.4 Research Significance.	3
1.2 Outline of the Thesis	4
CHAPTER-2 LITERATURE REVIEW	6
2.1 Introduction.	6
2.2 Concrete Systems.	6
2.3 Structural Health Monitoring using Piezo Sensor via EMI Technique	9
2.3.1 Physical Principles	10
2.3.2 Frequency Range Selection and Excitation Voltage	
2.3.3 Effect of Harsh Environment, Noise and Other Miscellaneous Factors	12
2.3.4 Influence Bond Conditions	13
2.3.5 Signature Processing Techniques and Damage Quantification	13
2.3.6 Extraction of Equivalent Structural Parameters	14

2.4 Installation/Development of Different Piezo Configurations	17
2.4.1 Surface Bonded Piezo Configuration	17
2.4.2 Embedded Piezo Configuration	18
2.4.3 Non-Bonded Piezo Configuration.	19
2.5 Major Research in Hydration Process and Strength Monitoring Using Piezo Sensor V	ia
EMI Technique	19
2.6 Major Research in Corrosion Monitoring Using Piezo Sensor Via EMI	
Technique	21
2.7 Structural Health Monitoring Based on Artificial Intelligence Techniques	22
2.8 Summary: Critical Points of Review	24
CHAPTER-3 MACHINE LEARNING BASED COMPRESSIVE STRENGTH	
PREDICTION OF CEMENTITIOUS SYSTEM	27
3.1 Introduction.	27
3.2 Experimental Program	27
3.3 Analysis Based on Vicat's Needle Penetration Depth	30
3.4 Analysis Based on FTIR, XRD, and SEM	31
3.5 Analysis Based on EMI Signature	39
3.6 Analysis Based on Strength Development	45
3.7 Analysis Based on Equivalent Structural Parameters	53
3.8 Calibration of PZT Identified Equivalent Stiffness with Maturity and Compressive	
Strength	55
3.9 Validation of Piezo Based Analysis with Maturity Method.	58
3.10 Development of Machine Learning Models	60
3.11 Prediction of Compressive Strength Using Machine Learning Models	61
3.12 Concluding Remarks	65
CHAPTER-4 MACHINE LEARNING BASED COMPRESSIVE STRENGTH	
PREDICTION OF CONCRETE SYSTEMS	66
4.1 Introduction	66
4.2 Experimental Program	66
4.3 Analysis Based on Equivalent Structural Parameters	75

4.4 Prediction of Compressive Strength Using Machine Learning Models	83
4.5 Concluding Remarks	88
CHAPTER-5 MACHINE LEARNING BASED PREDICTION OF EMI DATA	
DIFFERENT RC STRUCTURES SUBJECTED TO CORROSION	89
5.1 Introduction.	89
5.2 Preparation of Concrete Specimens and Data Acquisition	89
5.3 Development of ARIMA Model	98
5.4. Analysis Based on ARIMA Model	101
5.5 Qualitative and Quantitative Validation of Predicted and Experimental Data	107
5.6 Concluding Remarks	110
CHAPTER-6 DETERIORATION OF EQUIVALENT STRUCTURAL PARAM	METERS
IN PRESTRESSED CONCRETE SYSTEMS SUBJECTED TO CHLORIDE L	ADEN
ENVIRONMENT	111
6.1 Introduction.	111
6.2 Preparation of Concrete Specimens and Data Acquisition	
6.3 Results and Discussion.	
6.4 Concluding Remarks	
CHAPTER-7 MONITORING THE DURABILITY OF DIFFERENT CONCRE	TTF.
SYSTEMS SUBJECTED TO COMBINED ENVIRONMENTAL AND MECHA	
LOADING	
7.1 Introduction.	123
7.2 Sample Preparation and Methodology	123
7.3 Determination of Chloride Profile	126
7.4 Results and Discussion.	127
7.5 Concluding Remarks	137

CHAPTER-8 CONCLUSIONS AND RECOMMENDATIONS	138
8.1 Introduction	138
8.2 Research Conclusions.	138
8.3 Limitations	140
8.4 Significant Contributions	140
8.5 Recommendations for the Future Work	141
LIST OF PUBLICATIONS	143
REFERENCES	146
ANNEXURE-I	164
ANNEXURE-II	166
BIOGRAPHY OF TUSHAR BANSAL	169

LIST OF FIGURES

2.1	Bonded PZT patch and its interaction (a) Modelling of a PZT-structure	11		
	interaction (Bhalla and Soh, 2003), (b) A 2D representation of PZT patch			
	bonded to the host structure (Visalakshi, 2014)			
2.2	Embedded Piezo Sensor	18		
2.3	Non-Bonded Piezo Sensor	19		
3.1	Experimental setup of the signature measurement	28		
3.2	Temperature variations in the early-age hydration process of different	29		
	cementitious systems			
3.3	Vicat penetration depth at early-age hydration process of different cementitious	30		
	systems			
3.4	Difference spectra in the range of 500-4000 cm-1 where the cement has been	33		
	allowed to hydrate up to initial setting, final setting and 24 hour: (a) OPC; (b)			
	FA; and (c) LC ³			
3.5	XRD spectra of different cementitious systems obtained at different intervals:	35		
	(a) OPC; (b) FA; and (c) LC ³			
3.6	SEM images of OPC cementitious system (a) Initial setting, (b) Final Setting,	37		
	and (c) 24 hr			
3.7	SEM images of FA cementitious system (a) Initial setting, (b) Final Setting, and	38		
	(c) 24 hr			
3.8	SEM images of LC ³ cementitious system (a) Initial setting, (b) Final Setting,	39		
	and (c) 24 hr			
3.9	Conductance signature during early-age hydration process at different intervals	40		
	of a typical OPC specimen (a) 1-5 hr, (b) 6-9 hr, and (c) 10-24 hr			
3.10	Conductance signature during hydration process at different intervals of a	41		
	typical FA specimen (a) 1-5 hr, (b) 6-9 hr, and (c) 10-24 hr			
3.11	Conductance signature during hydration process at different intervals of a	42		
	typical LC ³ specimen (a) 1-3 hr, (b) 4-5 hr, and (c) 6-24 hr			
3.12	2 Resonance peak shift of conductance signature of different cementitious 43			
systems: (a) OPC; (b) FA; and (c) LC ³				

3.13	different cementitious systems: (a) OPC; (b) FA; and (c) LC ³	44
3.14	Destructive analysis result of compressive strength of different cementitious	45
	systems during strength development	
3.15	Relationship between (a) Actual compressive strength vs duration, (b)	46
	Maturity vs duration, (c) Actual compressive strength vs maturity for typical	
	OPC specimen	
3.16	Relationship between (a) Actual compressive strength vs duration, (b) Maturity	47
	vs duration and (c) Actual compressive strength vs maturity for typical LC ³	
	specimen	
3.17	Relationship between (a) Actual compressive strength vs duration, (b) Maturity	48
	vs duration and (c) Actual compressive strength vs maturity for typical FA	
	specimen	
3.18	Conductance signature during strength development at different intervals of a	49
	typical OPC cementitious system	
3.19	Conductance signature during strength development at different intervals of a	50
	typical FA cementitious system	
3.20	Conductance signature during strength development at different intervals of a	50
	typical LC ³ cementitious system	
3.21	Resonance peak shift of conductance signature of different cementitious	51
	systems during strength development: (a) OPC; (b) FA; and (c) LC ³	
3.22	RMSD variation during strength development at different intervals of different	53
	cementitious systems: (a) OPC; (b) FA; and (c) LC ³	
3.23	Piezo identified stiffness during strength development of different cementitious	54
	systems: (a) OPC; (b) FA; and (c) LC ³	
3.24	Relationship between PZT identified equivalent stiffness vs maturity identified	56
	compressive strength for a typical specimen (a) OPC, (b) LC ³ and (c) FA	
3.25	Relationship between PZT identified equivalent stiffness vs maturity identified	58
	compressive strength vs maturity for a typical specimen (a) OPC, (b) LC ³ and	
	(c) FA	
3.26	Comparison between maturity identified equivalent stiffness vs PZT identified	59
	equivalent stiffness (a) OPC, (b) LC ³ and (c) FA	

3.27	Workflow of training regression model	61
3.28	Prediction performance for cubic SVM model for a typical OPC binder system	62
3.29	Prediction performance for cubic SVM model for a typical FA binder system	64
3.30	Prediction performance for medium gaussian SVM model for a typical LC ³	65
4.1	Specimens installed with different Piezo Configurations	67
4.2	EMI Data acquisition setup of concrete cube sample	67
4.3	Baseline conductance signatures of LC ³ specimen with different piezo configuration	68
4.4	Baseline susceptance signatures of LC ³ specimen with different piezo	69
4.5	configuration Baseline conductance signatures of OPC specimen with different piezo configuration	69
4.6	Baseline susceptance signatures of OPC specimen with different piezo configuration	70
4.7	Destructive result of compressive strength vs curing time	70
4.8	EMI signature of LC ³ using SBPS configuration (a) Variation in conductance signature with frequency (b) RMSD (c) MAPD	72
4.9	EMI signatures of LC ³ using EPS configuration (a) Variation in conductance signature with frequency (b) RMSD (c) MAPD	73
4.10	EMI signatures of LC ³ using NBPS configuration (a) Variation in conductance signature with frequency (b) RMSD (c) MAPD	75
4.11	Identified system (a) Series combination of spring, mass and damper (b) variation of x vs f and (c) variation of y vs f	76
4.12	Equivalent structural parameter of LC ³ concrete using piezo sensor data of EPS (a) Stiffness (b) Damping	77
4.13	Equivalent structural parameter of LC ³ concrete using piezo sensor data of SBPS (a) Stiffness (b) Damping	78
4.14	Equivalent structural parameter of LC ³ concrete using piezo sensor data of NBPS (a) Stiffness (b) Damping	79
4.15	Equivalent structural parameter of OPC concrete using piezo sensor data of SBPS (a) Stiffness (b) Damping	80
4.16	Equivalent structural parameter of OPC concrete using piezo sensor data of EPS (a) Stiffness (b) Damping	80

4.17	Equivalent structural parameter of OPC concrete using piezo sensor data of NBPS (a) Stiffness (b) Damping	81
4.18	Comparison of destructive and non-destructive analysis (a) day-to-day percentage increase in compressive strength values (destructive) with respect to 3 day, and (b) day-to-day percentage increase in equivalent stiffness value (non-destructive) with respect to 3 day using EPS configuration	82
4.19	9 Performance of fine gaussian SVM model, (a and b) CSM-1-EPS, (c and d) CSM-1-SBPS, and (e and f) CSM-1-NBPS	
4.20	Performance of fine gaussian SVM model; (a and b) CSM-2-EPS, (c and d) CSM-2-SBPS, and (e and f) CSM-2-NBPS	87
5.1	Experimental setup	91
5.2	Accelerated corrosion setup	92
5.3	Variation of actual conductance signature during accelerated corrosion exposure (a) Mix A, (b) Mix B (c) Mix C	93
5.4	Variation of RMSD index during accelerated corrosion progression: (a) Mix A, (b) Mix B, (c) Mix C	97
5.5	ARIMA model analysis process	99
5.6	Variation of conductance signature during accelerated corrosion at 60 kHz frequency	101
5.7	Experimental and predicted baseline signature comparison for (a) Mix A, (b) Mix B, and (b) Mix C	102
5.8	Comparison of predicted EMI with experimental EMI data using 0 to 25 days training data for (a) Mix A, (b) Mix B and (c) Mix C	105
5.9	Comparison of predicted EMI with experimental EMI data using 0 to 75 days training data for (a) Mix A, (b) Mix B and (c) Mix C	106
5.10	Comparison between experimental and predicted signature for (a) Mix A-experimental, (b) Mix A- predicted, (c) Mix B- experimental, (d) Mix B-Predicted, (e) Mix C- experimental, and (f) Mix C- predicted	107
5.11	Comparison between experimental and predicted RMSD value for (a) Mix A-experimental, (b) Mix A- predicted, (c) Mix B- experimental, (d) Mix B-Predicted, (e) Mix C- experimental, and (f) Mix C- predicted	109
6.1	Installation of sensor	112
6.2	Experimental setup of prestressed concrete structures	113
6.3	Identified system (a) Series combination of spring, mass and damper (b) variation of x vs f and (c) variation of y vs f	114

6.4	Variation of conductance vs frequency for a typical specimen (a) 7 th Day vs baseline, (b) signature at various days during corrosion exposure	116
6.5	Variation of RMSD index with corrosion exposure	117
6.6	Initiation, propagation, and cracking phase (a) Tutti's Model, (b) Identification of corrosion phases based on RMSD, (c) Specimen condition in cracking phase	119
6.7	Identified equivalent structural parameter during corrosion exposure (a) Identified mass, (b) Identified stiffness, (c) Identified damping	120
6.8	Corrosion rate vs equivalent stiffness	121
7.1	Schematic representation of: (a) Concrete sample, (b) tumbler with filled solution, and (c) setup for chloride diffusion into concrete under compression	125
7.2	Average compressive strength	125
7.3	Experimental Setup	126
7.4	(a) Chloride profiles comparison between OPC and LC ³ during ideal chloride and mechanochemical effect and (b) schematic representation of chloride concentration decreases with increasing depth	128
7.5	(a) Apparent chloride diffusion coefficient of different concrete system at 6 and 10 weeks of ideal chloride and mechanochemical effect and (b) schematic representation of chloride diffusion coefficient decreases with increasing time	129
7.6	Surface concentrations value of different concrete system at 6 and 10 weeks of ideal chloride and mechanochemical effect	130
7.7	Baseline conductance signature of OPC and LC ³	130
7.8	Comparison of variation in conductance signature due to ideal chloride and mechanochemical effect for a typical concrete specimen (a) OPC and (b) LC ³	132
7.9	RMSD value of different concrete system at 6 and 10 weeks of ideal chloride and mechanochemical effect	132
7.10	Comparison between experimental and identified equivalent structural system: (a) x vs frequency and (b) y vs frequency	133
7.11	Equivalent stiffness variation for different concrete system (a) ideal chloride effect and (b) mechanochemical effect	134
7.12	Equivalent stiffness loss for different concrete system at 6 and 10 weeks of ideal chloride and mechanochemical effect for a typical specimen	135
7.13	Correlation between equivalent stiffness and surface concentration with exposure duration for both concrete system (a) LC ³ -C, (b) OPC-C, (c) LC ³ -I, and (d) OPC-I	136

LIST OF TABLES

2.1	A literature review on various conventional strength measurement techniques	7
2.2	A literature review on various conventional corrosion detection techniques	8
	(Daniyal and Akhtar, 2019)	
2.3	Mechanical impedance of combinations of spring, mass, and damper	16
3.1	A comparison of chemical properties of OPC and mineral admixtures	28
3.2	Maturity identified compressive strength of different cementitious system	55
3.3	Comparison between different models for OPC cementitious system	62
3.4	Comparison between different models for FA cementitious system	63
3.5	Comparison between different models for LC ³ cementitious	64
4.1	Comparison between different models	84
4.2	Performance of the machine learning model for ternary blended concrete	85
	system	
4.3	Performance of the machine learning model for conventional concrete system	85
5.1	Mix Proportion of Mix A, Mix B and Mix C	90
5.2	Sieve analysis of Fine Aggregate	90
5.3	Physical properties of Fine Aggregate	91
5.4	Sieve analysis of Coarse Aggregate	91
5.5	Interpretation of RMSD, visual inspection and raw signature for Mix A	94
5.6	Interpretation of RMSD, visual inspection and raw signature for Mix B	94
5.7	Interpretation of RMSD, visual inspection and raw signature for Mix C	94
5.8	ARIMA Model details	100
5.9	Analysis of baseline predictions using 10 to 100 days training data	103
5.10	Analysis of tenth-step prediction using 0 to 25 days training data for all mixes	106
5.11	Analysis of tenth-step prediction using 0 to 75 days training data for all mixes	106

- 5.12 Comparison between experimental and predicted conductance values for all 108 mixes
- 5.13 Comparison between experimental and predicted RMSD values for all mixes 110
- 7.1 Equivalent stiffness loss of different concrete system at 6 and 10 weeks of ideal 135 chloride and mechanochemical effect

LIST OF ABBREVATIONS

CO₂ Carbon Dioxide

MT Million Tonnes

SCMs Supplementary Cementitious Materials

IIT Indian Institute of Technology

OPC Ordinary Portland Cement

LC³ Limestone Calcined Clay Cement

EMI Electro-Mechanical Impedance

ML Machine Learning

SHM Structural Health Monitoring

SPPS Smart Probe-Based Piezo Sensor

PC Prestressed Concrete

Fa Fine Aggregate

CA Coarse Aggregate

FA Fly Ash

GGBS Ground Granulated Blast Furnace Slag

GDP Gross Domestic Product

EIS Electrochemical Impedance Spectroscopy

OCP Open-Circuit Potential

NaCl Sodium Chloride

GPC Geopolymer Concrete

NDE Non-Destructive Evaluation

PZT Piezoelectric-Ceramic

MITs Mechatronic Impedance Transducers

LCR Inductance Capacitance and Resistance

RMSD Root Mean Square Deviation

SAC Signature Assurance Criteria

MAPD Mean Absolute Percentage Deviation

WCC Waveform Chain Code

ESPs Equivalent Structural Parameters

SBPS Surface Bonded Piezo Sensor

EPS Embedded Piezo Sensor

NBPS Non-Bonded Piezo Sensor

SCC Smart Corrosion Coupon

RC Reinforced Concrete

MNS Modified Non-Bonded Sensor

FEM Finite Element Method

AI Artificial Intelligence

ML Machine Learning

DL Deep Learning

SVM Support Vector Machine

RVM Relevance Vector Machine

PCA Principal Component Analysis

CS Compressive Sensing

CV Computer Vision

SVR Support Vector Regression

BPNN Back-Propagation Neural Network

PSO Particle Swarn Optimization

GA Genetic Algorithms

ANN Artificial Neural Networks

MAPE Mean Absolute Percentage

ARIMA Autoregressive Integrated Moving Average

FTIR Fourier Transform Infrared Ray

XRD X-Ray Diffraction

SEM Scanning Electron Microscope

C-S-H Calcium Silicate Hydrate

 C_3S Alite

C₂S Belite

AFt Ettringite

CH Portlandite

C₃A Tricalcium Aluminate

C₄AF Tetra-Calcium Alumina Ferrite

Mc Monocarboaluminate

Hc Hemicarboaluminate

C-A-H Calcium Aluminate Hydrates

ESP Equivalent Stiffness Parameter

RMSE Root Mean Square Error

MSE Mean Square Error

MAE Mean Absolute Error

*R*² Coefficients Of Multiple Determination

HYSD High Yield Strength Deformed

RCPT Rapid Chloride Penetration Test

RMSRE Root Mean Square Relative Error

LIST OF SYMBOLS

 E_3 Electric field applied in the direction '3'

l Patch half-length

h Thickness of patch S_I Strain along axis'1'

 D_3 Electric displacement over the surface of PZT patch

 d_{31} Piezoelectric strain coefficient

 T_1 Axial stress in the patch along the axis '1'

Y^E Complex Young's modulus of elasticity of the patch at constant electric

field

 $\overline{\varepsilon_{33}^T}$ Complex electric permittivity at constant stress

 η Mechanical loss factors of the patch

 δ Dielectric loss factors of the patch

u Displacement at any point on the patch in direction '1'

k Wave number

 ρ Density

Y Electro-mechanical admittance

 $Z_{a,eff}$ Short-circuited mechanical impedance of the structure

 $Z_{s,eff}$ Effective impedance of the PZT sensor

 \overline{T} Complex tangent ratio

G ConductanceB Suseptance

f Frequency

 ϕ Angle

 ω Angular frequency

ν Poisson's ratio

m Mass

k Spring constant

c Damping constant

 G_i Conductance of the PZT patch at any stage during the test

*G*_{bl} Baseline conductance value

i Frequency index

N Number of data points in conductance signature

x Real components of structural impedance

y Imaginary components of structural impedance

 ω Angular frequency

 G_A Real components of the active admittance

 B_A Imaginary components of the active admittance

M(t) Maturity age at time t

 T_a Average Temperature

 T_d Datum Temperature

S Compressive Strength

M Maturity

ES PZT identified equivalent stiffness

ESM Equivalent stiffness identified by maturity method

y_i Observed Values

 $\hat{y_i}$ Predicted Values

 $\overline{y_i}$ Mean Values

n Number of observations

X(t) Measured deviation for the moment 't'

a(t) Residual error at the moment 't'

D Difference operator

p Autoregressive order

d Difference order

q Moving average order

 ϵ White noise

C_i Initial chloride content in percentage

 $C_{\rm s}$ Surface concentration in percentage

X Depth at which chloride content measured

D Apparent chloride diffusion coefficient

C_i Chloride content measure at distance 'x'

CHAPTER-1

INTRODUCTION

1.1 BACKGROUND

Concrete is the most widely used construction material in the civil engineering structures because of its versatility, cost effectiveness and ease in handling. Civil engineering structures are expensive assets and play an essential role in a country's socio-economic activity. However, many structures such as buildings and bridges constructed around the globe is nearing to the end of its intended design life (An et al., 2015) or premature end of its life due to problems related to ageing, changes in boundary conditions, corrosion, etc. Also, the repairs if initiated, around 30% fail due to inappropriate specification/choice of the material used and incorrect diagnosis of the cause of the initial damage/deterioration of the structure (Matthews and Morlidge, 2008). Many of these structures will remain in use for some time due to economic and logistical restrictions, despite the fact that they are ageing and accumulating damage, affecting the user's safety and the preservation of public and private assets. Hence, the ability to monitor and maintain the integrity of civil engineering structures is becoming increasingly important to prevent unexpected losses, catastrophic failure, ensure user's safety and facilitate precautionary measures.

Generally, in civil engineering infrastructures, strength development and durability issues such as corrosion are the two main worldwide problem in which concrete technologists, scientists and engineers are focussed on it. The conventional methods to check the integrity and strength of the concrete consists of rebound hammer test (ASTM C805), ultrasonic pulse velocity test (ASTM C597), penetration resistance test (ASTM C803), pull out test (ASTM C900) and drilled core techniques (ASTM C42) and for detecting the behaviour of corrosion consists of potential measurements, alternating current impedance spectroscopy, gravimetric (mass loss) and linear polarization techniques (Daniyal and Akhtar, 2020). However, these techniques even though provide fair results but fail in provide details in real-time. Hence, there is need for the development of smart sensing technique to non-destructively monitor and predict the strength and corrosion of structure in real-time. In the demand for real-time monitoring of civil structures, electro-mechanical impedance (EMI) technique using piezo sensors has been proven as a low cost, wide bandwidth, dual capacity (actuator and sensor), quick response and high

damage sensitivity technique. In this technique, the diagnosis/prognosis of the structural health is based on the acquired voluminous EMI data. However, the major limitation is the availability of baseline signature as the technique is based on the relative deviation/change in signatures taken at different periods with respect to baseline signature, which can be easily acquired for new construction but not for the existing structures. To deal with this voluminous EMI data and alleviate this limitation, machine learning (ML) algorithm plays an important role due to its immense capability of handling voluminous datasets and making past and future predictions based on input data used for training. The prediction of strength helps in taking an on-spot decision on the removal of formwork, contractors will be able to schedule their planning of finishing works and remedial measures can be taken to prevent catastrophic failures. The prediction of baseline/healthy and futuristic EMI data of different reinforced concrete structures subjected to corrosion non-destructively will aid the researchers to predict the baseline data for the existing structures and utilize the EMI technique for structural health monitoring (SHM) purposes, which is the main goal of this research work.

1.2 RESEARCH HYPOTHESIS

The ability to monitor and maintain the integrity of the civil structures has become increasingly important in recent years in order to avoid catastrophic failure during both the construction and service life stages. Monitoring the strength development of concrete during the construction process and detecting damages/deterioration of the structure due to mechanical and environmental factors during its service life are the two most significant challenges facing RC structures around the world. Most failures could be avoided if the structure was properly monitored from the start of construction to the end of its service life. Therefore, SHM using sensors combined with ML techniques can provide a novel way not only to predict strength of the fresh concrete but also diagnose the distress during its service life non-destructively without any a-prior information regarding the structure. The strength prediction model developed using the acquired sensor data from different piezo configurations would be useful for the researchers to predict the compressive strength of the newly developed concrete non-destructively during the construction process for timely decision making on the application of load on the structures, removal of formwork, etc. Corrosion prediction model would be useful to predict the baseline data for the existing structures and utilize the EMI technique for SHM purposes and the deterioration model would be helpful to identify the deterioration in the concrete when structure is subjected to combined chloride-induced corrosion and compression loading.

1.3 RESEARCH OBJECTIVES

This research encompasses the following specific objectives:

- 1. To analyse the sensitivity of different piezo configurations for strength monitoring of different concrete systems and suggesting its suitability for real-life applications.
- 2. To develop ML models for strength prediction of different concrete systems based on EMI data acquired from embedded piezo sensor.
- 3. To develop ML model to predict baseline and futuristic EMI data of corrosion for different reinforced concrete systems under chloride laden environment.
- 4. To identify different phases of corrosion and assess the deterioration of structural parameter in prestressed concrete (PC) structure subjected to chloride laden environment using piezo sensor.
- 5. To develop physical models for assessing the deterioration of structural parameters in different concrete systems subjected to combined environmental and mechanical loading using piezo sensor.

1.4 RESEARCH SIGNIFICANCE

It is expected that the developed ML models using EMI data from different piezo configurations will facilitate more realistic performance prediction of concrete strength and durability. It is believed that this thesis will make significant contribution to the state-of the-art related to strength and corrosion prediction in different concrete systems as the developed ML models are more realistic and totally non-destructive compared to the conventional strength and corrosion monitoring techniques. The strength prediction based on these ML models can help make on-the-spot decisions about removing formwork and applying load to the structure during the hydration/curing process. The corrosion prediction based on ML model can provide baseline and futuristic response of the structures by predicting EMI signatures of corrosion. As these ML models is data based, it can be implemented in various SHM applications such as material deterioration/damage assessment, deformation monitoring, strength monitoring, corrosion monitoring, and objectionable movements and geometry changes.

1.5 OUTLINE OF THE THESIS

This thesis has been organized into eight chapters. First chapter covers the background, research hypothesis, objectives, scope of the research and its significance.

Chapter 2 outlines the literature review of different concrete systems, application of EMI technique using piezo sensor for health monitoring, development of different piezo configurations, application of ML techniques for health monitoring and state-of-art of SHM in concrete structures using piezo sensor via EMI technique. The chapter begins with a brief introduction of concrete systems, factors affecting the strength and durability of concrete systems, various conventional techniques for strength and durability monitoring, their advantages and limitations, followed by the application of EMI technique using piezo sensor. The application of ML techniques for health monitoring is also summarized. The chapter closes with a discussion of the research gaps in the current state-of-the art.

Chapter 3 covers specific experiments conducted on various cement pastes followed by the development of ML models based on the measured EMI data. The quantification of compressive strength based on equivalent structural parameters and performance of the developed ML models based on different statistical methods is also presented.

Chapter 4 presents the detailed development of ML models to predict the compressive strength of different concrete systems using the EMI data acquired from the different piezo configurations. The sensitivity of different piezo configurations with respect to strength monitoring of concrete systems is also presented and the suitability of different configurations for real-life field applications is suggested.

Chapter 5 covers extensive experiments conducted on different blended RC structures (conventional, fly ash blended, and fly ash based geopolymer) subjected to a chloride-laden environment followed by the development of ARIMA model to predict baseline and future EMI data.

Chapter 6 presents monitoring and assessing the deterioration of structural parameters namely equivalent stiffness, mass and damping due to corrosion in PC structures using a smart probebased piezo sensor (SPPS) via EMI technique.

Chapter 7 presents the pioneering work related to durability of concrete structures under combined environmental and mechanical loading. Chloride penetration, chloride profiles, diffusion coefficient and surface concentrations were the various parameters considered for evaluation of durability performance. Further, a physical model has been proposed to identify the deterioration in the concrete and established an empirical relation between equivalent stiffness and surface concentration.

Chapter 8 highlights the summary and conclusions of this research. Suggestions for future research is also included in this chapter, followed by a list of publications and a comprehensive list of references along with author's curriculum vitae.

CHAPTER-2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents the state-of-art literature review related to different concrete systems their strength development and durability issues, introduction to SHM with emphasis on application of EMI technique using piezo sensor in SHM, introduction to ML techniques along with its applications in Civil Engineering problems are also covered.

2.2 CONCRETE SYSTEMS

Concrete is the most widely utilized man-made material in the construction industry. It is composed of fine aggregate (Fa) and coarse aggregate (CA) together with a fluid cement (cement + water) system. The concrete made up of binder content such as ordinary Portland cement (OPC) having 95% clinker and 5% gypsum; and remaining materials (Fa, CA, and water) as constant is termed as *conventional concrete system*. The concrete made up of cement having 65% clinker and 5% gypsum, 30% fly ash (FA) and the remaining materials as constant is called as *blended concrete system* or FA-concrete system. The concrete system made up of 50% clinker, 30% calcined clay, 15% limestone, 5% gypsum and the remaining materials as constant is called as *ternary blended concrete system* or LC³ concrete system. The concrete system made up of 95% FA + ground granulated blast furnace slag (GGBS), 5% gypsum and the remaining materials as constant is called as *geopolymer concrete system* (GPC).

In the production of different concrete systems, generally, concrete technologists are focussed on strength development and durability issues such as corrosion. Table 2.1 shows the literature review on various conventional strength measurement techniques. From this table, it can be concluded that these techniques are relatively easy to use and can be done directly onsite. However, these techniques are evidently undesirable, destroy the structural integrity and hardly provide details in real-time monitoring.

Table 2.1: A literature review on various conventional strength measurement techniques (ASTM C805, C803, C597, C900, C42, C873)

Techniques	Principle	Advantages	Disadvantages
Rebound hammer	A spring release mechanism is used to activate a hammer which impacts a plunger to drive into the surface of the concrete. The rebound distance from the hammer to the surface of the concrete is given a value from 10 to 100. This measurement is then correlated to the concrete's strength.	Relatively easy to use and can be done directly onsite.	Pre-calibration is required for accurate measurements. The results can be skewed by surface conditions and the presence of large aggregates or rebar below the testing location.
Penetration resistance	A device drives a small pin or probe into the surface of the concrete. The force used to penetrate the surface, and the depth of the hole is correlated to the strength of the in-place concrete.	Simple, directly used on onsite	Data is significantly affected by surface conditions as well as the type of form and aggregates used.
Ultrasonic pulse velocity	This technique determines the velocity of a pulse of vibrational energy through a concrete surface. The data is then correlated to the strength.	This is a non-destructive technique which can be used to detect flaws within the concrete such as cracks and honeycombing.	This technique is highly influenced by the presence of reinforcements, aggregates, and moisture in the concrete element.
Pullout test	The main principle behind this test is to pull concrete using a metal rod that is cast-in-place or post-installed in the concrete. The pulled conical shape, in combination with the force required to pull the concrete which is then correlated to compressive strength.	Easy to use and can be performed on both new and old constructions	This test involves crushing or damaging the concrete.
Drilled Core	A core drill is used to extract hardened concrete from the slab, The samples are then compressed in a machine to monitor the strength of the in-situ concrete.	Is considered more accurate than field-cured specimens because the	This is destructive technique that requires damaging the structural integrity of the slab.

Cast-in-	Cylinder mods are places in the	concrete is	
place	location of the pour and fresh	subjected to the	
cylinders	concrete is poured into these	same curing	
	molds. Once hardened, these	conditions	
	specimens are removed and		
	compressed for strength		

On the other hand, corrosion which is one of the primary causes of deterioration affecting the service life when the aggressive environmental agent reaches the reinforcement by depassivating the protective layer effecting the safety and serviceability of the reinforced concrete structures. According to the World Corrosion Organization report, it is estimated that the cost of corrosion including all infrastructures is about US \$2.5 trillion, which is equivalent to 3 % to 4 % of the gross domestic product (GDP) of industrialized countries (NACE International report, 2016). Table 2.2 shows the literature review on various conventional corrosion measurement techniques.

Table 2.2: A literature review on various conventional corrosion detection techniques (Daniyal and Akhtar, 2020)

Techniques	Principle	Advantages	Disadvantages
Open circuit	Measurement of corrosion	Provide	Cannot specify
potential	potential of steel	information for	corrosion rate
measurement	reinforcement with respect to	degree of	
	standard reference electrode	corrosion risk only	
Surface	Measurement of corrosion	Identifying the	The measured
potential	potential between the fixed	possibility of	potential
measurement	electrode and movable	corrosion of steel	difference depends
	reference electrode by means	in concrete	on the corrosion
	of high impedance voltmeter.		condition of the
			steel and the type
			of reference
			electrode.
Linear	Small polarization	It is simple and	Compensation of
polarization	perturbation is applied about	easy to use	IR drops, presence
resistance	open circuit electrical potential		of localised
	of metal using a potentio-stat		corrosion,
	and the resulting induced		interference with
	current is recorded.		other electrical
			signals and the
			determination of
			the rebar area
			being testing

Electrochemical impedance spectroscopy	Application of small alternating current (AC) potential with variable frequencies to the specimen and measuring the induced AC response	Provide information regarding the corrosion kinetics, accurate and reproducible technique	Time consuming and difficult to perform
Galvanostatic pulse	The steel is polarised anodically and the resulting potential response is recorded using a reference electrode a function of polarisation time.	It is simple and easy to use	The area of steel surface being measured is difficult to quantify
Electrical resistivity measurement	In this method, four equally spaced electrodes (probes) are used to measure the concrete resistivity. A small AC current is applied between the outermost probes whereas potential difference between the inner probes is recoded.	Resistivity of concrete can be easily determined	Concrete resistivity depends upon the water/cement ratio, microstructural properties of concrete, existence of steel reinforcement etc

From this table 2.2, it can be concluded that these techniques are relatively easy to use providing the information related to degree of corrosion risk, and resistivity of concrete. However, these techniques are time consuming, depends on various properties of concrete, cannot provide real-time monitoring and it fails in automaton. To overcome these issues related to strength and corrosion monitoring techniques in concrete structures, next section deals with the SHM using piezo sensors via EMI technique.

2.3 STRUCTURAL HEALTH MONITORING USING PIEZO SENSOR VIA EMI TECHNIQUE

SHM is defined as the acquisition, validation, and analysis of technical data to facilitate life cycle management decisions. SHM denotes a reliable system with the ability to detect and interpret adverse 'changes' in a structure due to damage or normal operations (Kessler et al., 2002). The advancements in smart materials have provided new applications and avenues for SHM. Smart materials, such as the PZT, shape memory alloys, and fibre-optic materials, can aid in the development of non-obtrusive miniaturized systems with higher resolution, faster response, and far greater reliability than the traditional non-destructive evaluation (NDE) techniques. Among the numerous smart materials, the PZT materials have emerged as high

frequency mechatronic impedance transducers (MITs) for SHM (Sun et al., 1995; Soh et al., 2000; Bhalla et al., 2001; Park et al., 2003). In this application, a PZT patch is usually affixed to the structure which is to be examined and measure the electrical admittance signature across the pre-defined frequency range. Any change in the mechanical properties of the examined structure causes change in the mechanical impedance which in turn changes the signature of the admittance indicating damage. The technique is popularly called as the EMI technique. The following sections describe the various aspects of this technique in detail.

2.3.1 Physical Principles

In the EMI technique, a PZT patch is affixed to the structure which is to be examined using high strength epoxy adhesive, and electrically excited using an inductance capacitance and resistance (LCR) meter. In this configuration, the PZT patch essentially behaves as a thin plate undergoing axial vibrations and interacting with the host structure (as shown in Figure 2.1) and these interactions are reflected back in the form of electrical admittance signature consisting of conductance and susceptance. The PZT patch-host structure system can be modelled as a mechanical impedance (due to host structure) connected to an axially vibrating thin bar (the patch), as shown in Figure 2.1(a) The patch in this figure 2.1(a) expands and contacts dynamically in direction '1' when an alternating electric field E_3 (which is spatially uniform i.e. $\left(\frac{\partial E_3}{\partial x} = \frac{\partial E_3}{\partial y} = 0\right)$ is applied in the direction '3'. The patch has half-length 'l' and thickness

'h'. The direct and converse effects, can be mathematically expressed as (Ikeda 1990)

$$D_3 = \overline{\varepsilon_{33}^T} + d_{31}T_1 \tag{2.1}$$

$$S_1 = \frac{T_1}{V^E} + D_{31}E_3 \tag{2.2}$$

where axis '3' points along the thickness of the patch and axes '1' and '2' lie in the plane of patch as shown in Figure 2.1. Further, S_1 is the strain along axis '1', D_3 is the electric displacement over the surface of PZT, d_{31} is the piezoelectric strain coefficient and T_1 the axial stress in the patch along the axis '1'. $Y^E = Y^E(1 + \eta j)$ is the complex Young's modulus of elasticity of the PZT patch at constant electric field and $(\overline{\varepsilon_{33}^T}) = \varepsilon_{33}^T(1 - \delta j)$ is the complex electric permittivity (in direction '3') of the PZT material at constant stress, where $j = \sqrt{-1}$. Here, η and δ denote the mechanical loss factor and dielectric loss factor of the PZT material, respectively.

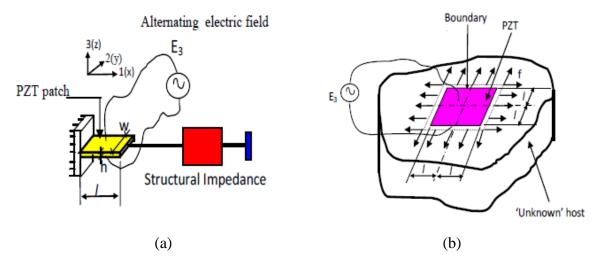


Figure 2.1: Bonded PZT patch and its interaction (a) Modelling of a PZT-structure interaction (Bhalla and Soh, 2003), (b) A 2D representation of PZT patch bonded to the host structure (Visalakshi, 2014)

The pioneering work of modelling the 1D structure-PZT interacting system was done by Liang et al. (1994). They developed a one-degree freedom impedance analytical model and assumed that the PZT patch is fixed on one end and connected to the host structure on the other end. Zhou et al. (1996), then extended the Liang's model to a two-dimensional case by assuming the two edges of the PZT patch to be fixed and the other two edges attached to the host structure. However, neither Liang's model nor Zhou's model has been used to predict the EMI of a PZT-structure interacting system for direct comparison with the recording of impedance analyzer. To alleviate the shortcomings inherent in the existing models, Bhalla and Soh (2004a) introduced a new concept called 'effect impedance'. The actual interaction between the patch and the structure is not restricted at the end points but extended all over the finite size of PZT patch as shown in Figure 2.1(b). They introduced the concept of effective velocity rather than drive point velocity, thus ensuring that the force transmission between PZT patch and structure occurs along the entire boundary of the patch as shown in Figure 2.1(b). They derived the coupled EMI equation of effective impedance model as

$$\overline{Y} = G + Bj = 4\omega j \frac{l^2}{h} \left[\overline{\varepsilon_{33}^T} - \frac{2d_{31}^2 \overline{Y^E}}{(1-v)} + \frac{2d_{31}^2 \overline{Y^E}}{(1+v)} \left(\frac{Z_{a,eff}}{Z_{s,eff} + Z_{a,eff}} \right) \overline{T} \right]$$
(2.3)

where, conductance (G), susceptance (B) with its imaginary unit (j); width (w), length (l), height (h), angular frequency (ω) , short-circuited effective impedance of the structure $(Z_{a,eff})$,

effective impedance of the PZT sensor $(Z_{s,eff})$, mechanical loss factor (η) , dielectric loss factor (δ) , piezoelectric strain coefficient (d_{31}) , complex tangent ratio (\overline{T}) and Poisson's ratio (ν) . Any change in the mechanical properties of the monitored structure will cause the structural parameters to change and will this alter the structural impedance which in turn changes the signature of the admittance \overline{Y} in the above equation, thus indicating the state of the health of the structure.

2.3.2 Frequency Range Selection and Excitation Voltage

The correct selection of frequency range is very important to analyse the behaviour of the structure. Various researchers (Adhikari and Bhalla, 2019; Kaur et al., 2016; Kim et al., 2017; Lu et al., 2017; Panigrahi et al., 2010; Quinn et al., 2012; Shin and Oh, 2009; Talakokula et al., 2018; Tawie and Lee, 2010a; Wang and Zhu, 2011) utilized different excitation frequency ranges, but Park et al. (2003) recommended a frequency range of 40-300 kHz for piezo-based SHM as there is a greater dynamic interaction between the structure and the PZT patch in these ranges which is signified by large number of peaks. Further, the frequency ranges higher than 500 kHz were found unfavourable, because the sensing region of the PZT patch becomes too small and the acquired signature shows adverse sensitivity to its own bonding condition rather than any damage to the monitored structure (Park et al., 2003; Sun et al., 1995). The PZT patch is normally excited by the LCR meter with an alternating voltage signal of one-volt over the user specified frequency range. Sun et al. (1995) reported that the conductance signature remains practically constant when the excitation voltage was increased from 0.5 V to 15 V.

2.3.3 Effect of Harsh Environment, Noise and Other Miscellaneous Factors

The electrical admittance signatures are bound to be influenced by harsh environments such as temperature fluctuations, in practical situations, the effects of damage and temperature are bound to be mixed. This necessitates a method to decouple the two, in 2001, Bhalla studied temperature effects using finite element simulation and found that the major effects of temperature on the signatures are the horizontal and vertical shifts due to change in the host materials Young's modulus and variations in ϵ_{33} and d_{31} of the PZT patch. So, to compensate this effect, a simple temperature compensation methodology can be used which required acquisition of the baseline signatures at two different temperatures as suggested by (Bhalla, 2001). The noise such as mechanical noise, electrical noise, and electromagnetic noise also

effect admittance signatures. However, the greatest advantage of using high frequency ranges is that the signatures are not likely affected by the mechanical noise which is predominantly dominant in the low frequency range only. Regarding electrical noise which is also not too crucial in the EMI technique because the power required by each PZT patch is in the low milliwatt range. The only possible noise could be electromagnetic noise, which can be minimized by using coaxial cables. Also, another source of error could be the parasitic electrical admittance of the connection wire, but it can be accounted by performing zero-connection in the LCR meter.

2.3.4 Influence of Bond Conditions

In the EMI technique, bond layer can significantly influence the signal transmission from the PZT material to the host structure if not carefully accounted. The PZT sensor when bonded to the structure using an adhesive mix (such as epoxy) forms a permanent finite thickness interfacial layer between the structure and the patch, the force transmission from the PZT patch to the host structure takes place through this interfacial bond layer via shear mechanism (Sirohi and Chopra, 2000; Bhalla, 2004; Qing et al., 2006; Dugnani, 2009; Bhalla et al., 2009, Bhalla and Moharana, 2013). Bhalla 2004 observed that as bond layer thickness increases, the peaks subside down and shift rightwards. Besides, the average slope of the susceptance curve falls down. Exceptionally thick bond layer (thickness ratio > 1.0) may lead to highly erroneous structural identification; hence, it is recommended that the bond layer thickness be maintained as minimum as possible, preferably less than 1/3rd of the patch thickness (Bhalla, 2004). The sensor debonding and sensor breakage can also influence the characteristics of EMI signature. The sensor debonding caused a decrease in the magnitudes of resonances and an increase in the slope of the imaginary admittance. The sensor breakage caused upward shifts in the patterns of the real part of the EMI signature and a decrease in the slope of the imaginary admittance. By contrast, the structural damage did not cause any variations in the slope of the imaginary admittance.

2.3.5 Signature Processing Techniques and Damage Quantification

The prominent effects of structural damages on the conductance signature are the appearance of new peaks along with lateral and vertical shifting of the peaks (Sun et al., 1995), which are the main damage indicators. To quantify this damage, several statistical techniques such as root mean square deviation (RMSD), signature assurance criteria (SAC), waveform chain code

(WCC), adaptive template matching, mean absolute percentage deviation (MAPD) can be used. In the present research, two statistical parameters named RMSD and MAPD were used to quantify changes in the signatures, which can be computed by (Bhalla et al., 2012; Girugiutiu et al., 1999; Bharathi Priya et al., 2018)

$$RMSD(\%) = \sqrt{\frac{\sum_{i=1}^{N} (G_i - G_{bl})^2}{\sum_{i=1}^{N} (G_{bl})^2}}$$
 (2.4)

$$MAPD(\%) = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(G_i - G_{bl})}{(G_{bl})} \right|$$
 (2.5)

where G_i is the conductance signature data at any day during monitoring, G_{bl} is baseline/ healthy conductance signature data, and number of data points in the conductance signature is denoted by N.

2.3.6 Extraction of Equivalent Structural Parameters

Many researchers working in the field of EMI technique have utilized the deviation in the raw conductance signature alone for damage assessment, using statistical indices such as RMSD, MAPD etc. However, these statistical methods, are easy to implement but the main drawback is that at times, they do not provide any clear information of the associated damage mechanism and also doesn't provide insights about the change in mechanical/structural parameters of the host structure under question. This fact has motivated to extract the drive point structural impedance from measured raw signatures for damage quantification. The extraction of equivalent structural parameters (ESPs) can be done conveniently by means of decomposing the EMI equation (2.3) into active and passive parts by rearranging the various terms as

$$\overline{Y} = 4\omega j \frac{l^2}{h} \left[\overline{\varepsilon_{33}^T} - \frac{2d_{31}^2 \overline{Y^E}}{(1-\nu)} \right] + \frac{8\omega d_{31}^2 \overline{Y^E} l^2}{(1-\nu)} \left(\frac{Z_{a,eff}}{Z_{s,eff} + Z_{a,eff}} \right) \overline{T} j$$
(2.6)

Passive Part

Active Part

or

$$\overline{Y} = \overline{Y_P} + \overline{Y_A} \tag{2.7}$$

where, $\overline{Y_P}$ can be termed as 'passive part' and $\overline{Y_A}$ can be termed as 'active part'. The passive part is solely depends on the parameters of the PZT patch and the active part is partly depends

on the structural parameters and partly on the parameters of the PZT patch since both the $Z_{s,eff}$ and $Z_{a,eff}$ are appear in the active part only. By using the computational procedure as recommended by (Bhalla et al., 2012; Moharana and Bhalla, 2019; Soh and Bhalla, 2005; Talakokula et al., 2018, 2016), mechanical impedance of the host structure can be extracted at a particular frequency ' ω ', from the conductance and susceptance signature consists of x the real and y imaginary component of the mechanical impedance as

$$(Z_{s,eff} = x + yj) (2.8)$$

where

$$x = \frac{M(x_a R - y_a S) + N(x_a S + y_a R)}{M^2 + N^2} - x_a$$
 (2.9)

$$y = \frac{M(x_a R + y_a S) - N(x_a S - y_a R)}{M^2 + N^2} - y_a$$
 (2.10)

$$M = \frac{B_A h}{4\omega K L^2} \text{ and } N = -\frac{G_A h}{4\omega K L^2}$$
 (2.11)

$$R = r - \eta t, S = t + \eta r, K = \frac{2d_{31}^2 \overline{Y^E}}{(1 - \nu)}$$
 (2.12)

where, G_A and B_A are the real and the imaginary components of the active admittance, computed from

$$\overline{Y_A} = \overline{Y} - \overline{Y_P} \tag{2.13}$$

This procedure of extracting the structural impedance of the structure which carries information about the dynamic characteristics of the host structure enables to 'identify' any unknown structure (consists of stiffness, mass, and damping) without demanding any a-priori information governing the phenomenological nature of the structure. Any real-life structure is a combination of the basic structural elements, the mass, the spring and the damping combined in different ways such as parallel, series or a mixture. Hixon, 1998 presented the impedance plots (x, y) and the frequency for some possible combinations of the basic elements. The unknown structure can be idealized as an equivalent structure based on the graphs between x vs f and y vs f. are shown in Table 2.3. In the present research, model number 1, 4, and 7 have been utilized and the equivalent system paramters such as stiffness 'k', mass 'm' and damping 'c' for these models can be determined as (detailed analysis is given in Annexure I)

Model 1: Parallel combination of spring and damper

$$c = x \tag{2.14}$$

$$k = -\omega y \tag{2.15}$$

Model 4: Parallel combination of spring, mass and damper

$$c = x \tag{2.16}$$

$$m = \frac{y\omega}{(\omega^2 - \omega_o^2)} \tag{2.17}$$

$$k = \frac{y\omega \,\omega_o^2}{(\omega^2 - \omega_o^2)} \tag{2.18}$$

Model 7: Series combination of spring, mass and damper

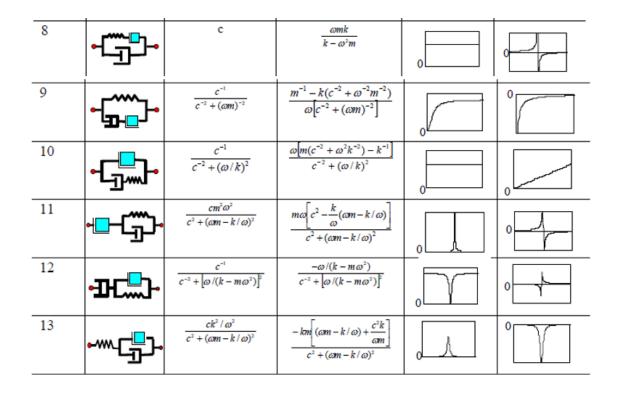
$$m = \frac{(\omega_o^2 - \omega^2)(x^2 + y^2)}{\omega \omega_o^2 y}$$
 (2.19)

$$k = \frac{(\omega_o^2 - \omega^2)(x^2 + y^2)}{\omega y}$$
 (2.20)

$$c = \frac{(x^2 + y^2)}{x} \tag{2.21}$$

Table 2.3: Mechanical impedance of combinations of spring, mass, and damper

No.	COMBIN— ATION	x	у	x vs Freq.	Y vs Freq.
1	*	c	$-\frac{k}{\omega}$	0	0
2	ţ.	С	mω	0	0
3	-	0	$m\omega - \frac{k}{\omega}$	0	0
4		С	$m\omega - \frac{k}{\omega}$	0	0
5	• 1 }-□•	$\frac{c^{-1}}{c^{-2} + (\omega n)^{-2}}$	$\frac{(\omega m)^{-1}}{c^{-2} + (\omega m)^{-2}}$		
6		0	$\frac{-1}{(\omega/k)-(\omega m)^{-1}}$	0	0
7	•]••••	$\frac{c^{-1}}{c^{-2} + (\omega/k - 1/\omega m)^2}$	$\frac{-(\omega/k-1/\omega m)}{c^{-2}+(\omega/k-1/\omega m)^2}$		0



2.4 INSTALLATION/DEVELOPMENT OF DIFFERENT PIEZO CONFIGURATIONS

2.4.1 Surface Bonded Piezo Configuration

The installation of surface bonded piezo sensor (SBPS) is most straightforward method involving cleaning of surface of the specimen with sandpaper, then bonding the PZT patch with a simple two-part Loctite adhesive consisting of an epoxy resin and a hardener followed by 10 minutes of curing at laboratory room temperature before soldering the electrodes. Wires are soldered into PZT patch either after or before the bonding process. Finally, layer of epoxy resin is applied to PZT patch to cover and protect against environmental effects and enhance its durability. The advantage of SBPS configuration include ease of installation, reduced risk of damage as the patch is bonded after the concrete is demoulded, higher precision and sensitivity (as PZT patch is directly affixed to the monitored structure reflecting structural response directly), and easy maintenance and replacement of the PZT patch (as accessibility of PZT patch is towards the surface only so that it can be easily removed). The major limitation in using this configuration for concrete strength monitoring is that the crucial information during the early hours of the hydration process cannot be acquired (as installation of PZT patch on the wet surface of newly casted concrete is not possible, until unless concrete attains its final setting). The bonding of this configuration can only be surface bonded on a flat and hard surface once the concrete is demoulded after 24 hrs of casting.

2.4.2 Embedded Piezo Configuration

Embedded piezo sensor (EPS) configuration is especially useful for concrete application, and the main challenge in developing this configuration include withstanding the curing temperature and vibration process of concrete. Many researchers have used different materials such as mortar layer, silicone rubber coating, combination of asphaltic lacquer, gelatinous silica and common asphalt coating, non-conductive unsaturated polyester resign coating, self-made mould to coat a PZT patch with epoxy Styrofoam case and multi-layer scheme to sandwich/coat the PZT patch for providing protection to these challenges (Annamdas and Rizzo, 2010; Bhalla, 2004; Kim et al., 2017, 2014; Lee et al., 2012; Narayanan et al., 2017; Quinn et al., 2012; Saravanan et al., 2015; Wang et al., 2009). In the present study, the EPS configuration is developed by sandwiching the PZT sensor with mortar and epoxy layers (as seen in Figure 2.2) which is then embedded inside the host structure. The advantages of EPS configuration are relatively easy installation as compared to SBPS, high durability because PZT patch is protected within the mortar layers, and early age monitoring of curing process is possible (as monitoring the hydration process can be carried out immediately after pouring the concrete in the mould). The limitations of EPS include: it reflects structural responses with low to average sensitivity (because addition of different mortar coatings results in a significant decrease in resonance frequency with a slight decrease in magnitude of PZT), inspection, replacement and maintenance cannot be done (as it is embedded inside the concrete) and there is no reusability of setup.



Figure 2.2 Embedded Piezo Sensor

2.4.3 Non-Bonded Piezo Configuration

To overcome the limitations of non-reusability of sensors, non-bonded piezo sensor (NBPS) configurations have been developed. (Sabet Divsholi and Yang, 2009) used PZT patch surface bonded to aluminium and plastic enclosure with two bolts. (Tawie and Lee, 2011) used a non-bonded EMI setup with PZT patch attached to a metallic rod through a bolt in which metallic rod was partially embedded in the cementitious material. In our study, "Smart-Probe" -based installation was proposed, which consists of PZT patch surface bonded on thin aluminium foil of size 100mm x 10mm x 1mm as shown in Figure 2.3. This smart probe based piezo sensor (SPPS) was then non-directly affixed as NBPS in reusable form to the specimens on its top surface. The advantages of this configuration are ease of installation, maintenance, and replacement of PZT patch. The major limitations of NBPS include it reflects the structural signal indirectly because PZT patch initially actuates the cage (which may be metal, aluminium foil and bolts), which then transfers the vibration waves to the monitored structure through the cage (Naskar and Bhalla, 2016) and PZT is potentially exposed to a harsh environment due to which extra protection is required to enhance the durability.

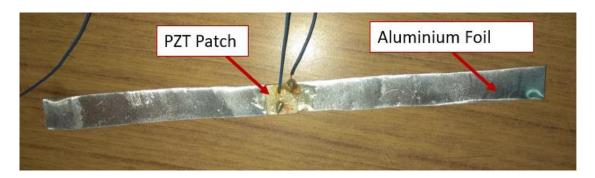


Figure 2.3 Non-Bonded Piezo Sensor

2.5 MAJOR RESEARCH IN HYDRATION PROCESS AND STRENGTH MONITORING USING PIEZO SENSOR VIA EMI TECHNIQUE

The capabilities of the EMI technique and its advantages have been proven over extensive investigations. Major developments and contributions made by various researchers in the field strength monitoring during the last two decades are presented here. (Soh and Bhalla, 2005) were the pioneers to determine in situ concrete strength non-destructively using admittance signatures of SBPS impedance transducers followed by the 'identification' of appropriate impedance parameters for concrete. They concluded that the identified parameters were found

to be sensitive to structural damages as well as to concrete strength gain during curing. Qin and Li (2008) utilized an EPS via EMI technique to monitor the hydration at the age of 5 and 24 hours by capturing the impedance signature in the frequency range of 50-200 kHz. They revealed that EPS has a good bond with the cement paste and can be used as an in-situ technique to monitor the hydration process at an early stage. Later many researchers also utilized the EMI technique for strength monitoring of concrete using different piezo configurations e.g. SBPS configurations (Shin et al., 2008; Shin and Oh, 2009; Soh and Bhalla, 2005; Su et al., 2019; Tawie and Lee, 2010a), EPS configuration (Annamdas and Rizzo, 2010; Jothi Saravanan et al., 2017; Kong et al., 2013; Saravanan et al., 2015; Wang et al., 2014; Wang and Zhu, 2011), and, NBPS configuration (Bharathi Priya et al., 2018; Lu et al., 2019, 2017; Moharana and Bhalla, 2019; Tawie and Lee, 2010b; (Providakis et al., 2013; Yang et al., 2010). Narayanan and Subramaniam (2017) used the EMI technique for assessing the hydration progression of cement mortar. Furthermore, the effect of various water-to-cement ratios (w/c) which have a significant impact on the mechanical properties of the measured conductance signature was also investigated. They revealed that changes in the mechanical impedance of the cement mortar as it transforms from liquid stage to hardened stage are well associated with the conductance signature. Ghafari et al. (2018) investigated the feasibility of a PZT sensor to evaluate the strength gain process of cement paste by substituting SCMs and found that the evolution of strength gain at the age of 1-28 days were effectively determined by establishing the correlation between the statistical indices and the compressive strength. The first state-of-art review on monitoring of curing of concrete using EMI technique was given by Lim et al. (2019). Recently, Pan and Huang (2020) utilized an EPS based on the EMI technique to monitor cement mortar's strength and found that the EPS is more evident in terms of monitoring capability due to its broader frequency width of recognizing higher ability. Zhang et al. (2020) evaluated the strength and stiffness gain of cement by monitoring the hydration process (within 72 hours) of cement paste using PZT sensor excited at two different frequency range such as 100-1000 kHz and 100-3000 kHz. They revealed that conductance signatures are well associated with each stage of the setting process at higher frequency ranges, and statistical indices effectively monitored the phases of cement paste from liquid to hardened. Zhang et al. (2020) further extended the EMI technique's effectiveness and applicability for real-time monitoring of the stiffness degradation of cement paste under compression loadings.

2.6 MAJOR RESEARCH IN CORROSION MONITORING USING PIEZO SENSOR VIA EMI TECHNIQUE

The monitoring of corrosion using piezo sensor via EMI technique has been started in metallic structures followed by the RC structures. Lalande et al. (1996) detect the abrasive wear (a type of corrosion) in complex precision parts like those found in gear sets by using PZT sensors. Simmars (2005) detected corrosion induced damage in plates and beams using PZT sensors via EMI technique and found that the technique correlated well with the change in the corrosion pit depth and could reasonably detect and quantify the pre-crack surface corrosion, which often leads to shortened fatigue life in structures. Thomas and Welter (2004) used piezoelectric wafer sensors in pitch-patch configurations to detect material loss through corrosion in thin plate's representative of aircraft skins using Lamb waves. They found that as the "Lamb" waves travelled through the simulated corrosion damage, the signal changed and correlated well with the magnitude of the damage. Park et al. (2007) detect and quantify corrosion in aluminium structures using PZT sensors in the form of miniaturized impedance measuring chip (AD5933) and a self-sensing macro fiber composite (MFC) patch. Park and Park (2010) conducted an experimental study involving wireless monitoring of corrosion damage in metallic structures and found that the amount of resonant frequency shift increased with the increase in the extent of corrosion. Bedekar et al. (2008) noted a systematic variation in the conductance of the PZT patch as corrosion progressed in their aluminium test specimen. Their results also indicated an optimal distance between the piezoelectric sensor and the location of corrosion. Yang et al. (2013) conducted experimental study to monitor the local corrosion of a steel beam using the EMI technique and found that a quantitative relationship exists between the damage index and corrosion time, which can be used as a baseline reference for subsequent local corrosion monitoring. Pioneering studies were performed by Talakokula et al. (2014) in extending the applications of EMI technique to corrosion in RC structures by developing physical models based on the equivalent structural parameters, for both chloride and carbonation induced corrosion in rebars, thereby circumventing the determination of actual structural parameters, which are either very difficult or impossible. Talakokula et al. (2016) used PZT sensors-based EMI technique to detect and quantify the carbonation induced corrosion initiation and progression in RC structures and found that the equivalent stiffness parameter extracted from the EMI signatures increased with penetration of carbon dioxide inside the surface. Huo et al. (2018) presented a corrosion detection method of steel bars based on piezoceramic transducer enabled time reversal method and found that the signal recorded by the piezoceramic transducers changed linearly with the mass loss ratio of the reinforcement bar. Sriramadasu et al. (2018) identified incipient pitting corrosion in RC structures using guided waves and piezoelectric wafer transducers. They found that the mechanism of corrosion process, which involves the corrosion initiation, progression, and diameter reduction-and-cracking phases, can be established from the signal characteristics of the longitudinal and flexural-guided wave mode. Li et al. (2019) presented a novel corrosion monitoring method based on piezo-based smart corrosion coupon (SCC) via EMI technique and found that the peaks in the conductance signatures present a leftward shift and the peak frequencies decrease linearly with increase of the corrosion amount. Li et al. (2019) presented EMI-instrumented corrosion-measuring probe for corrosion monitoring and found that the proposed corrosion-measuring probe is effective in monitoring corrosion and shows promising application potentials. The peak magnitude of the conductance signatures was reduced with the increase in corrosion amount. Shi et al. (2019) investigated the piezo sensor's resistance spectra to assess the corrosion process of RC. Their result showed that rebar's corrosion process has a significant influence on the resistance spectra. Raju et al. (2020) computed corrosion damage in pipeline segment using modified non-bonded sensor (MNS) and surface bonded piezo sensor (SBPS) and found that piezo based on nondimensional mass parameter from the MNS measurements are very effective in damage detection and quantification. Li et al. (2020) carried out theoretical analysis of the EMI responses of the EMI instrumented circular piezoelectric-metal transducer for corrosion monitoring purpose and was validated by Finite element method (FEM) and impedance measurement. They concluded that peak frequency in the conductance signatures is linearly reduced with increase of thickness loss and FEM calculations show good agreement with the measurement results with discrepancies within 4.29 %. The next section deals with the SHM based in artificial intelligence techniques.

2.7 STRUCTURAL HEALTH MONITORING BASED ON ARTIFICIAL INTELLIGENCE TECHNIQUES

SHM is a multidiscipline field that involves automatic sensing of structural loads and responses by means of a large number of sensors and instrumentation, followed by diagnosis of the structural health based on the collected data. Data have recently become crucial in society, as their availability and effectiveness create value. Data is the core part in the field of SHM; the field dealing with data is termed data science and engineering. The SHM system provides a variety of data, including vehicle load, wind speed, temperature, humidity, strain, cable tension,

deflection, deformation, corrosion current, and scour geography. In addition, the latest technologies enable advanced inspection technologies and provide images and videos by cameras, point clouds by laser scanners, temperature by infrared ray thermometers, various signals by portable non-destructive testing devices, and various kinds of low-quality big data by crowdsensing technology, among others. The combination of SHM and advanced inspection techniques generates multisource heterogeneous big data. Nowadays, the field of machine learning (ML) and deep learning (DL), originated from the domain of artificial intelligence (AI) is experiencing exponential growth because of the immense capability of handling voluminous datasets and making past and future predictions based on input data used for training. The truth is that partial ML algorithms such as support vector machine (SVM) and relevance vector machine (RVM), principal component analysis (PCA), compressive sensing (CS), Bayesian sparse learning, and particular DL, reinforcement learning, and computer vision (CV) have produced surprising good results in many cases in SHM. ML has attracted a great deal of scientific attention and has been successfully used in civil engineering to predict compressive strength, identify building energy consumption patterns, scour, and corrosion rate prediction (Chou et al., 2017; Chou and Ngo, 2016; Chou and Pham, 2013; Goel and Pal, 2009; Wen et al., 2009). Support Vector Regression (SVR) is one of the ML techniques that has been widely used as a valuable tool for formulating the relationship between dependent and independent variables (Akande et al., 2017; Keshtegar et al., 2021). The SVR has been applied in various fields, including time-series predictions, regression estimation problems, and pattern recognition (El-Sebakhy, 2009; Jung et al., 2018). Wen et al. (2009) predicted the corrosion rate of 3C steel in different seawater environments using the SVR model, and their results show a precise prediction than the back-propagation neural network (BPNN). El Amine Ben Seghier et al. (2020) developed a model for predicting the maximum pitting corrosion in pipelines using hybrid meta-heuristic optimization algorithms such as Genetic Algorithms (GA), Particle Swarn Optimization (PSO) and Firefly Algorithms (FFA) which are integrated with SVR to select hyper-parameters. Their study reveals that all the hybrid models have high efficiency and accuracy when predicting the maximum depth of pitting corrosion in pipelines. However, the training time of the model increases after the hybrid of ML, especially when dealing with complex problems, which has great disadvantages (Qian et al., 2020). Artificial neural networks (ANN) is one the artificial intelligence (AI) technique that has been widely used for modelling non-linear problems and to predict the output values for given input parameters from their training. Shi et al. (2011) applied ANN for predicting pitting corrosion in steel-reinforced concrete, and their results show a coefficient of determination (R²) of 0.8741. ANN approach has been applied to predict the tensile strength of corroded steel plates and revealed that ANN approach predicted the tensile strength more accurately with a mean absolute percentage error (MAPE) below 5 % (Karina et al., 2017). The advantages of ANN including storing information on the entire network, learn events and make decisions by commenting on similar events, and perform more than one job at the same time. Despite the advantages, ANN has many disadvantages such as hardware dependence, unexplained behaviour of the network, and the duration of the networks are unknown (Mijwil, 2018). The autoregressive integrated moving average (ARIMA) approach which is especially for time-series forecasting has been widely applied in solving prediction problems, and it avoids the problem (such as more than one variable to forecast outcomes) which sometimes occurs in the multivariate models. Liu and Mu (2011) predict the corrosion depth of aircraft LY12CZ (Luoyang Bearning Factory) aluminium alloy under airport environment conditions. Their results show that the ARIMA model predicted the value of propagation trend of corrosion depth realistically and effectively. Yidong (2016) applied ARIMA model to predict the variation tendency of pitting depth in corroded reinforced bars quantitatively. Many researchers (Amini et al., 2016; Erdal et al., 2018; Feng et al., 2020; Na et al., 2009; Oh et al., 2017) used ML algorithms such as functions, generalizable model, tree-based learning algorithms, lazy-learning algorithms, ANN and adaptive boosting approach for predicting the concrete compressive strength using non-destructive test results data and EMI data. Using various learning algorithms, their study found different accuracy (R²) value for different algorithms ranging between 0.90 - 0.982. Among the various learning algorithms as mentioned above, it is concluded that every algorithm has different accuracy.

2.8 SUMMARY: CRITICAL POINTS OF REVIEW

In this chapter, initially a general idea about the concrete systems and its factors affecting the strength and durability of these systems is presented. Various conventional techniques for strength measurement and to detect and quantify the rebar corrosion are presented with their advantages and disadvantages.

As this research is focussed on strength and corrosion monitoring and prediction using ML models via EMI technique, the basic principles and the governing equations of the technique are elaborately discussed, major research in strength and corrosion monitoring using EMI technique are described and finally SHM using artificial intelligence (AI) techniques is

presented. From the critical literature review discussed regarding strength and corrosion monitoring techniques and from SHM using EMI and AI techniques, following points can be noted

The research gaps based on strength monitoring techniques are

- 1. The conventional strength monitoring techniques are providing fair results and are mostly destructive since they tend to destroy structural integrity and its fail in providing details in real-time.
- 2. From the literature review of strength monitoring using EMI technique, researchers mainly focussed on monitoring, evolution, and strength development of OPC, mortar, and concrete made with OPC and hardly extended the applications of EMI technique for different concrete systems.
- 3. A very few studies on monitoring the cement paste's initial and final setting process were reported in the literature. More importantly, only few researchers have analyzed the mechanical changes in the structure during the hydration process by identifying the equivalent structural parameters (ESPs) using the EMI technique and that too only for the conventional concrete not the blended systems.
- 4. Based on the different piezo configurations literature review, none of the study utilized the different piezo configurations in same concrete system to analyze the effectiveness and sensitivity in terms of concrete strength development.

The research gaps based on corrosion monitoring techniques are

- Researchers mainly focussed on corrosion monitoring and identification of structural
 parameters of conventional RC structures. However, extensive research is required for
 corrosion monitoring to understand the phases of corrosion and identification of
 structural parameters in different blended RC structures.
- 2. The quantification of corrosion phases in prestressing wire embedded in PC is very challenging and none of the study has been carried out to identify the deterioration and the phases of corrosion in PC structures.
- 3. The piezo sensor-based EMI technique has provided a new path for real-time non-destructive evaluation, assessment, and structural health monitoring (SHM) of RC structures under corrosion. However, none of the researcher has reported real-time non-

destructive monitoring of corrosion in concrete structures under combined action of mechanical and environmental loading.

The research gaps based on SHM using AI techniques are

- Researchers mainly used ML algorithms for predicting compressive strength, identify building energy consumption patterns, scour, and corrosion rate. However, none of the researcher has reported EMI based strength prediction via ML algorithms using structural parameters as a feature.
- 2. Avery few studies for prediction of corrosion using EMI technique were reported in the literature. However, none of the researcher reported the prediction of futuristic and baseline EMI signature during corrosion process using ML model.\

Based on the critical review points relating to the strength and corrosion detection techniques and SHM using EMI and AI technique, the scope of the research work is develop ML models for strength prediction of different fresh concrete systems, prediction of corrosion and deterioration of structural parameters during its service life under the combined action of loads and environmental effects using EMI data acquired from piezo sensor. This is the pioneering work on developing physical models for assessing the deterioration of concrete structures subjected combined action of mechanical and environmental loading.

The following chapters present details of how the research objectives are met, starting from experimental study on strength monitoring of cementitious system to concrete systems followed by the development of ML model to predict the strength and corrosion EMI data.

CHAPTER-3

MACHINE LEARNING BASED COMPRESSIVE STRENGTH PREDICTION OF CEMENTITIOUS SYSTEM

3.1 INTRODUCTION

Supplementary cementitious materials (SCMs) contribute significantly in improving concrete sustainability by reducing the carbon footprint and are extensively used, typical examples are LC³, FA, silica fume (SF), and GGBS. To have practical applicability it is imperative to monitor its physical and chemical process between these cements and water during hydration. The hydration process, especially during a very early age has a significant influence on the mechanical properties of cement. Therefore, a real-time monitoring and prediction technique is essential for determining early age hydration processes and strength development.

This chapter presents a ML based compressive strength prediction for various cementitious systems using the PZT-based EMI technique. The spectral features, mineral constituents, and surface morphology of the cementitious systems are assessed using FTIR, XRD, and SEM tests during the early-age hydration process. The quantification of compressive strength is based on equivalent structural parameters identified by the EPS configuration. Furthermore, the equivalent structural parameters were calibrated with the maturity based on empirical relations. The chapter covers the specific experiments conducted on various cementitious systems followed by the development of ML models based on the measured EMI data.

3.2 EXPERIMENTAL PROGRAM

In this investigative study, three different cementitious systems such as OPC (contain 95 % clinker and 5 % gypsum), FA-based cement (contains 30 % FA, 65 % clinker, and 5 % gypsum), and limestone calcined clay-based cement (contains 50% calcined clay and limestone in the ratio of 2:1, 45 % clinker and 5 % gypsum) were used with 0.45 w/c ratio to prepare the paste. The chemical properties of OPC and mineral admixtures are shown in Table 3.1. All the specimens were cast using a metal mould of size 70.1 mm x 70.1 mm and 70.1 mm. An EPS was placed in the specimen's centre position during casting along with a K-type temperature sensor to record the EMI measurements and temperature variations over time during the early-

age hydration process respectively. For the EMI measurement, an E4980A LCR meter with a scanning frequency of 30 kHz to 300 kHz was used, as shown in Figure 3.1.

Table 3.1: A comparison of chemical properties of OPC and mineral admixtures

Constituents (%)	LC^2	Raw clay	Limestone	OPC	FA
LOI	9.21	10.28	36.96	1.69	1.72
CaO	28.29	0.06	44.24	63	44
SiO ₂	34.28	54.67	11.25	22	32
Al ₂ O ₃	19.45	27.69	2.53	5	10
Fe ₂ O ₃	3.43	4.93	1.55	3.299	6
MgO	1.38	0.13	1.96	2.12	2
SO ₃	1.58	0.01	-	1.42	2.5
Na ₂ O	0.31	0.12	0.5	0.3	0.48
K ₂ O	0.27	0.25	0.28	0.71	0.4
TiO ₂	1.63	1.68	-	0.46	-

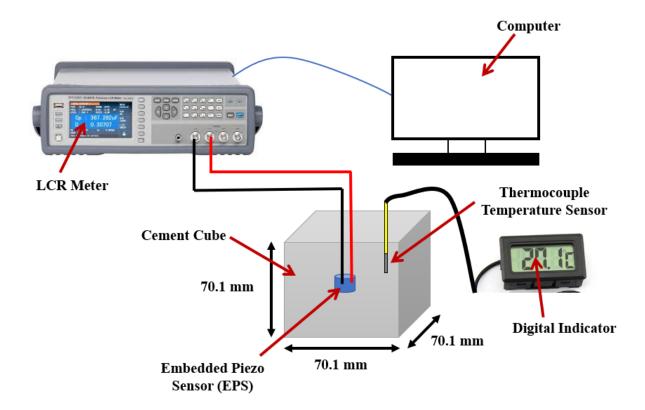


Figure 3.1: Experimental setup of the signature measurement

Additionally, Vicat needle apparatus was used to measure the initial and final setting time of the cement paste. Further, to evaluate the process of early-age hydration reaction, FTIR, XRD, and SEM tests were performed on the specimens at various ages (initial setting, final setting, and 24 hours) using an infrared spectrometer, an X-ray diffractometer, and a scanning electron microscope, respectively. After the cement paste reached the final setting time, the specimens are cured at standard conditions (temperature: 20 ± 2 °C, relative humidity: ≥ 95 %) for strength development and the signature were acquired frequently at every 24 hours. An additional ninety-nine specimens (three specimens for each age and three cement paste) were cast with same composition and destructive tests were performed at the age of 1, 3, 7, 10, 14, 18, 28, 30, 45, 60, 90 days of curing of specimens to correlate the strength development results with the EMI measurement along with nine specimens for EMI measurements. Figure 3.2 depicts the temperature variation obtained during the early-age hydration process of various cementitious systems. It can be observed that the temperature variation is ± 4 °C for the duration of the early-age hydration process; thus, its effect on the captured EMI signature is negligible. The similar observation was recorded by Zhang et al. (2020).

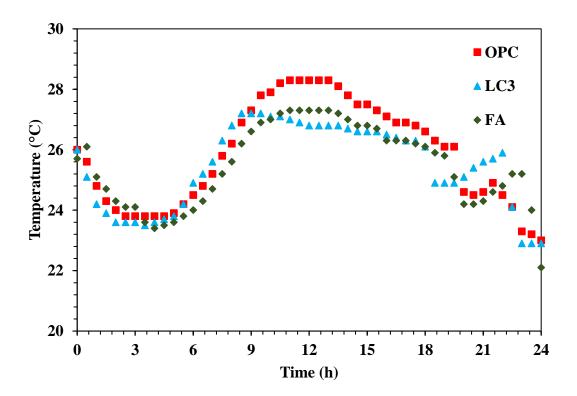


Figure 3.2: Temperature variations in the early-age hydration process of different cementitious systems

3.3 ANALYSIS BASED ON VICAT'S NEEDLE PENETRATION DEPTH

The Vicat needle penetration depth of different cementitious systems obtained at various stages of hydration process with a constant w/c ratio of 0.45 is shown in Figure 3.3. It is found that all the three curves of different cementitious systems are divided into three stages: liquid stage, semi-solid stage, and hardened stage. In the liquid stage, the penetration depth basically remains unchanged and shows a slightly decreasing tendency as the slurry approaches towards the initial setting of the cement with the penetration depth of $(35 \pm 1 \text{ mm})$ in all the cementitious systems. However, the recorded initial setting time are 2 hours 30 minutes, 5 hours, and 5 hours for LC³, OPC, and FA cement paste, respectively. As the cement paste initially set, all the curve shows sharp reduction in the penetration depth which indicates that the cement paste turns into the semi-solid stage. At this stage, the recorded final setting time are 5 hours, 8 hours 30 minutes, and 9 hours, for LC³, OPC, and FA cement paste, respectively. Subsequently, upon applying the final setting needle, the needle fails to make an impression on the surface which indicates that the cement paste has completely lost its plasticity and has attained sufficient firmness to withstand definite pressure, the paste at this stage is considered as the hardened stage. On comparison, it is observed that the initial and final setting time of LC³ cementitious system is comparatively lower than OPC and FA, it is due to the presence of calcined clays which increases the water demand due to high fineness (caused by the sheet like structure) and narrow particle size distribution which helps in faster setting. FA cementitious system indicates higher final setting time than OPC, however, the differences are not significant. It is due to the presence of spherical shape of FA particles which acts as miniature ball bearings within the concrete matrix, thus delay the setting time.

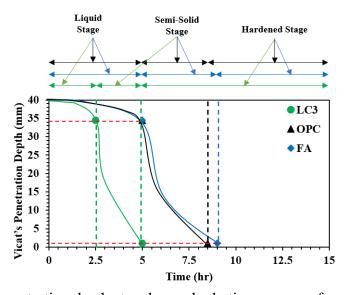


Figure 3.3: Vicat penetration depth at early-age hydration process of cementitious systems

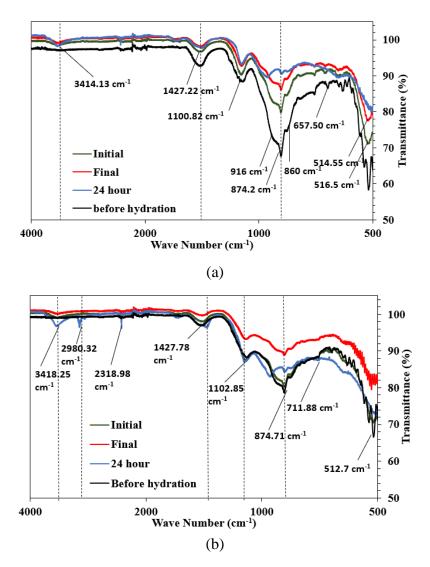
3.4 ANALYSIS BASED ON FTIR, XRD AND SEM

In the previous sections, analysis based on Vicat needle penetration depth have been discussed. This section attempts to correlate the setting time with the evolution of spectral features in FTIR spectra, formation of different hydration products and morphology of the microstructures during the very early-age hydration and setting process. Figure 3.4 shows the FTIR spectra of different cementitious systems obtained before hydration (dry cement), initial setting time, final setting time, and 24 hours in the range of 500-4000cm⁻¹. As it can be seen in Figure 3.4(a), there is a loss of spectral intensity (i.e. absorption) at an initial and final setting time and 24 hours compared to before hydration. This is due to a reduction in surface area caused by large cement modules that are difficult to grind after hydration as described by Choudhary et al. (2015). The spectral features are clearly visible in the wavenumber of 657.50 cm⁻¹, 860 cm⁻¹, 874.2 cm⁻¹, 916 cm⁻¹, 1100.82 cm⁻¹, 1427.22 cm⁻¹, and 3414.13 cm⁻¹. The spectral peak at 657.50 cm⁻¹ and 916 cm⁻¹ are generally found in silica-associated bands due to v_4 vibration of SiO₄ and Si-O asymmetric stretching vibration of C₃S and C₂S phase, respectively (Omotoso et al., 1998; Palomo et al., 1999; Stepkowska et al., 2005; Yousuf et al., 1993). As the hydration progressed, the peak at 916 cm⁻¹ were shifted to the higher spectral intensity, and the formation of these peaks indicates dissolution of alite and polymerization of silica to form calcium silicate hydrate (C-S-H) gel. The spectral peak at 874.2 cm⁻¹ and 1472.22 cm⁻¹ are appeared in carbonates bands and correspond to v₃ out of plane vibration of CO₃²⁻ and asymmetric stretching of CO₃²⁻ (Vagenas et al., 2003). The intensity of these peaks is very high as the hydration progressed. At 3413.13 cm⁻¹, a broader peak corresponds to v₁ vibrations of H₂O were observed by Preaud (1980). This could be due to the evaporation of excess water from the specimens. Sulphate bands are generally found in the range of 1100-1200 cm⁻¹ due to the v_3 vibration of SO_4^{2-} group in sulphates which are present in OPC cement in the form of gypsum (CaSO₄.2H₂0), hemihydrate (CaSO₄.2H₂0), and anhydrite (CaSO₄). Also, some sharp sulphates bands are developed in the range of 1100 cm⁻¹ and 3400 cm⁻¹ due to dissolution of sulphates followed by crystallization (Kloprogge et al., 2002; Ylmén et al., 2009).

In Figure 3.4(b), the intensity of transmittance is higher at an initial and final setting time while lower at 24h in comparison to before hydration in all the spectral bands. The spectral feature observed at wavenumber 512.7 cm⁻¹, 711.88 cm⁻¹, 874.71 cm⁻¹, 1102.85 cm⁻¹, 1427.78 cm⁻¹, 2318.98 cm⁻¹, 2980.32 cm⁻¹, and 3414.13 cm⁻¹. In comparison to Figure 11(a), some sharp peaks were developed at wavenumber 512.7 cm⁻¹, 711.88 cm⁻¹, 2318.98 cm⁻¹ and 2980.32 cm⁻¹. The

peak at 512.7 cm⁻¹, 711.88 cm⁻¹ corresponds to symmetric stretching of Si-O-Si and Al-O-Si bonds which describes the formation of amorphous to semi-crystalline alumino-silicate materials such as C-S-H gel and calcium aluminate hydrates (C-A-H) and structural bonds (Si-O-Si and Al-O-Si). The peak at 2318.98 cm⁻¹ and 2980.32 cm⁻¹ indicates stretching of (-OH) and bending (H-O-H) bonds of bound water molecules as observed by Fauzi et al. (2016).

In Figure 3.4(c), the intensity of these peaks increases as the hydration progressed. At 3238.94 cm⁻¹, and 3412.89 cm⁻¹ wavenumbers, some broader peaks were observed during hydration (initial and final set, and 24h), corresponding to the υ_1 vibrations of H₂O. Some sharp peaks were observed at 712.80 cm⁻¹ and 873.46 cm⁻¹ wavenumbers, corresponding to the symmetric stretching of Si-O-Si and Al-O-Si bonds. This indicates the formation of aluminum and silicon phase which after changes into the C-S-H and form more C-S-H gels. The spectral peak at 873.46 cm⁻¹, 1418 cm⁻¹, and 1432.11 cm⁻¹ correspond to υ_3 out of plane vibration of CO₃²- and asymmetric stretching of CO₃².



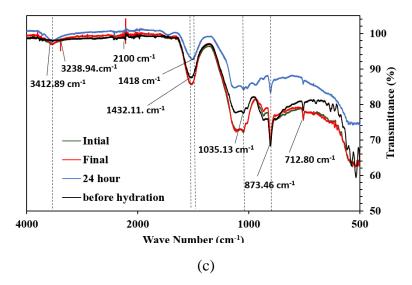
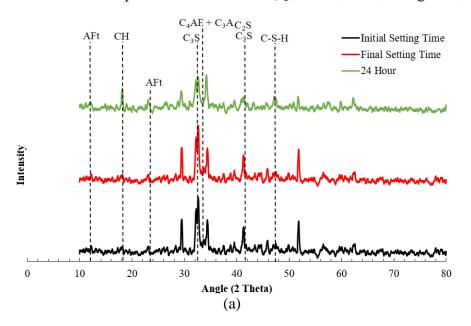


Figure 3.4: Difference spectra in the range of 500-4000 cm-1 where the cement has been allowed to hydrate up to initial setting, final setting and 24 hour: (a) OPC; (b) FA; and (c) LC³

In all the cementitious systems, it can be observed that the transmission bands from ~500 cm⁻¹ to 1650 cm⁻¹ progressively decreased during the hydration process, which suggests the formation of an amorphous phase. Hence, this promising finding verified that the C-S-H hydration product is formed during the very early-age hydration of cement with good agreement. The further verify the FTIR results, XRD and SEM analysis were carried out, which are discussed in the following paragraphs.

To identify the formation of different hydration products and morphology of the microstructures during the very early-age hydration process, XRD and SEM tests were conducted on typical OPC, FA, and LC³ cement specimens. Before conducting the XRD and SEM test, the hydration stoppage at initial setting, final setting, and 24 hours is a crucial step in preparing samples in the study of hydration of cement. The samples' hydration stoppage was carried by using the RILEM TC-238 SCM recommendation on hydration stoppage by solvent exchange method (Snellings et al., 2018). Figure 3.5 (a) shows the XRD spectra of OPC cementitious system obtained at the very early-age hydration process. It can be observed that the cement hydration products at the initial setting time contain a specific amount of alite (C₃S), belite (C₂S), ettringite (AFt), portlandite (CH), tricalcium aluminate (C₃A), tetra-calcium alumina ferrite (C₄AF) and calcium silicate hydrate (C-S-H). As the water is added into the cement, C₃A reacts with the gypsum which is originally present in the cement and forms Aft rapidly. The C₃S and C₂S peaks at the initial setting time tend towards weaker as the hydration

of cement increases significantly due to the formation of additional CH and C-S-H hydration products, as seen in Figure 3.5(a). In this stage, the upward trends of CH and C-S-H peaks were seen between the initial and final settings. After that, as the duration of hydration increases, the cement hydration product gradually accumulates in the process, which is also seen in the XRD spectra at the curing age of 24 hours. Figure 3.5 (b) shows the XRD spectra of FA cementitious system obtained at the very early-age hydration process. It can be observed that the extra amorphous to semi-crystalline alumino-silicate materials such as C-S-H gel and calcium aluminate hydrates (C-A-H) were formed due to addition of fly ash in the cement. In case of LC³ cementitious system as shown in Figure 3.5(c), it can be observed that the extra aluminates in the form of hemicarboaluminate (Hc) and monocarboaluminate (Mc) phases were formed at the angle of around 12° and 21° respectively. It is due to the synergy effect between calcined clay and limestone together in the system which can react with the C₃A from the clinker to form these phases (Parashar and Bishnoi, 2021). This finding is consistent with the FTIR results that the amorphous C-S-H hydration product is formed as the hydration progressed. Similar observations have also been reported in the literature (Qin et al., 2018; Zhang et al., 2020).



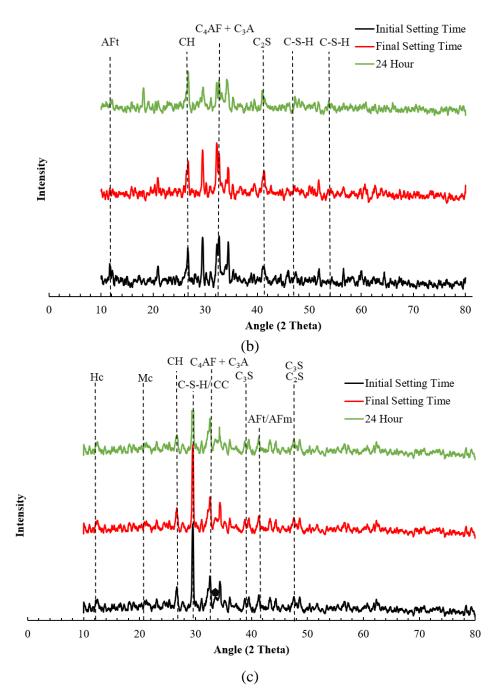
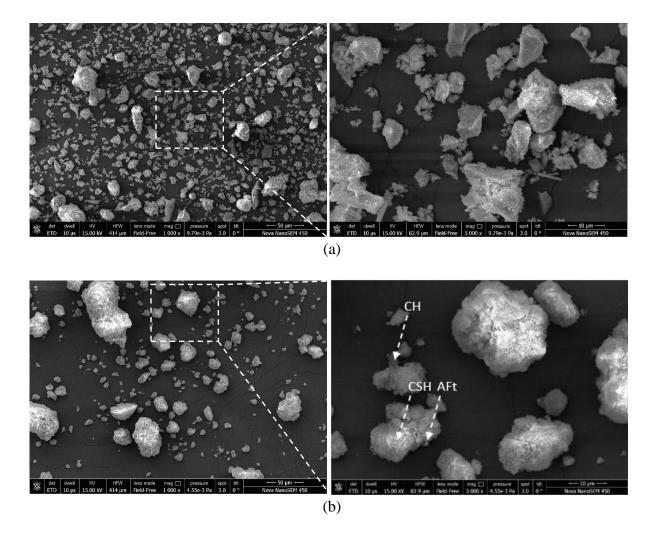
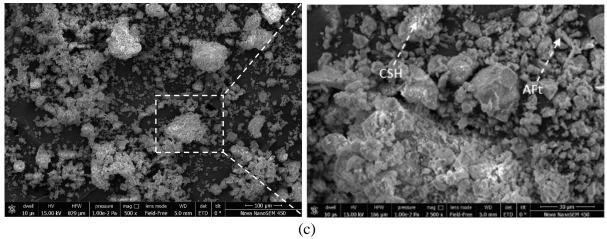


Figure 3.5: XRD spectra of different cementitious systems obtained at different intervals: (a) OPC; (b) FA; and (c) LC³

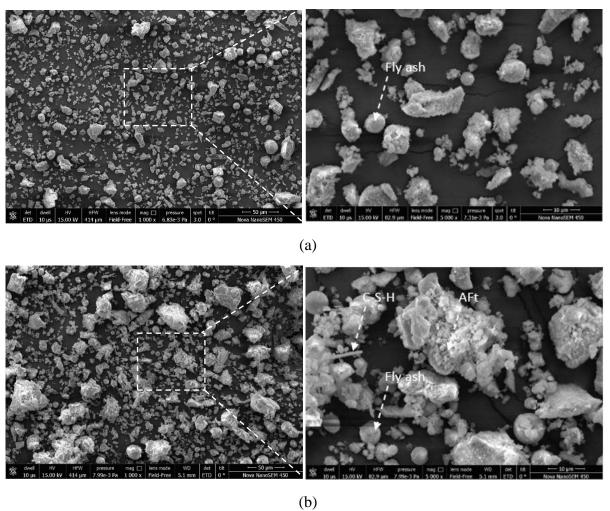
This study can also be further verified with the SEM analysis observations during the very early-age hydration process, as shown in Figure 3.6-3.8. At the initial setting time, the cement hydration products form a very loose and porous structure with many micro-gaps, as shown in Figure 3.6-3.8(a). Although the FTIR and XRD spectra show that the spectral intensity is lower at the initial setting time and only the specific amount of hydration product were formed. As the hydration reaches the final setting time, the microgaps present in the initial setting start

filling by connecting all the cement particles to form a network-like structure and deals with the formation of C-S-H gel, as shown in Figure 3.6-3.8(b). At this stage, the initial peaks shifted to the higher spectral intensity, and the formation of these peaks indicates alite dissolution and polymerization of silica to form C-S-H gel which is remarkably indicated in the FTIR and XRD results. After that, as the hydration progresses, a strong and denser structure were observed in the SEM images as shown in Figure 3.6-3.8(c) due to the increase of hydration products, and ettringite forms a needle-like structure which serves as an essential role in the growth of strength development. On comparing the SEM images for different cementitious systems, it is observed that LC³ blend exhibit denser structure than that of OPC and FA blends. Hence, the results of XRD and SEM provide a good agreement with the hydration of cement.





(c)
Figure 3.6: SEM images of OPC cementitious system (a) Initial setting, (b) Final Setting, and (c) 24 hr



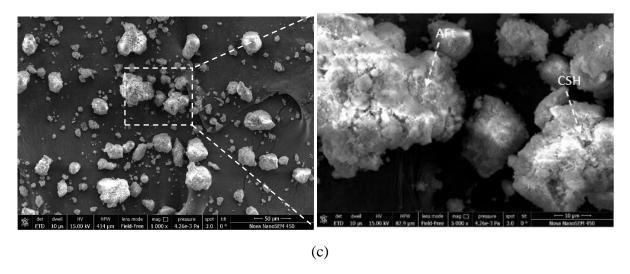
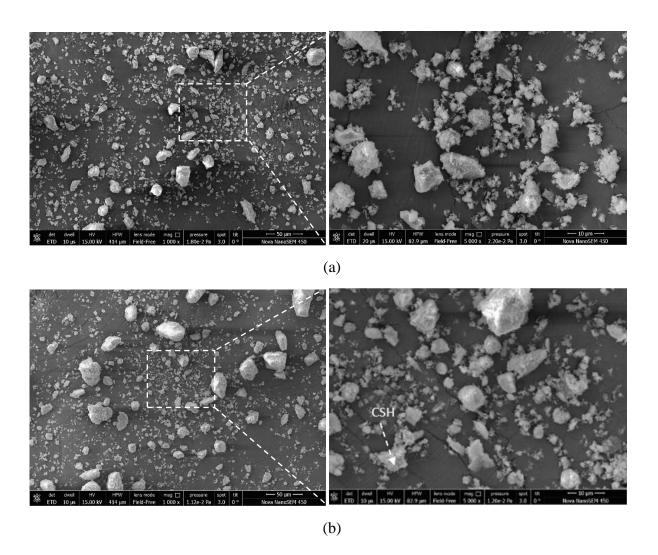


Figure 3.7: SEM images of FA cementitious system (a) Initial setting, (b) Final Setting, and (c) 24 hr



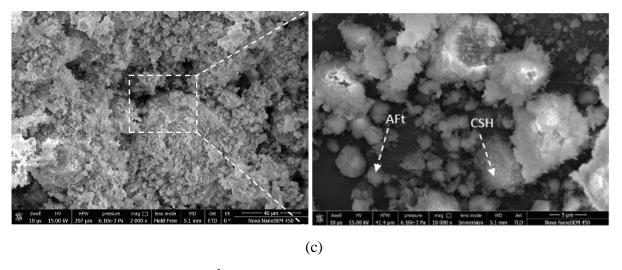


Figure 3.8: SEM images of LC³ cementitious system (a) Initial setting, (b) Final Setting, and (c) 24 hr

3.5 ANALYSIS BASED ON EMI SIGNATURE

This section attempts to correlate the EMI signature with the formation of different hydration products and morphology of the microstructures during the very early-age hydration and setting process. The variation in conductance signature versus frequency during the very early-age hydration process at different time intervals of a typical OPC specimen in a frequency range of 220 kHz-300 kHz is shown in Figure 3.9. It can be observed from the figure that the trend of conductance signatures has distinct characteristics at different stages (liquid stage, semi-solid stage, and hardened stage), which correlates to the development of cement's paste early-age hydration. In the first 5 hours of hydration, the amplitudes of the resonance peak depict a significant decline as shown in Figure 3.9(a). It is due to the fact that as the hydration progressed, the mix transform from liquid to semi-solid stage. This process resulted in a higher damping to the PZT patch, thus causing a reduction in the amplitude of the resonance peak (Zhang et al., 2020). In terms of frequency, a slightly right shift in the resonance peak has been observed in the first 5 hours. This indicates that the mix was starting to gain stiffness, thus caused an increase in resonance frequency of the PZT resonance peak. From physical observation, the mix transformed from liquid stage to semi-solid stage and the Vicat's penetration depth reduced from 40 mm to 35 mm. From 6 to 9 hours, the amplitudes at resonance peak still decrease, and the frequencies of the resonance peak gradually shift towards the right direction with the development of the cement hydration, as shown in Figure 3.9(b). It is due to the formation of CH and C-S-H hydration products and reduction in the C₃S and C₂S peaks at the initial setting time. Also, at this stage, the micro gaps present in the initial setting start filling by connecting all the cement particles to form a network-like structure. The same has been confirmed with the XRD and SEM results in the previous section. From 10 to 24 hours, the amplitudes of the resonance peak decrease gradually while the frequencies significantly shift towards the same direction, as shown in Figure 3.9(c). The rate of increase of resonance frequency shift is considered fairly high as compared to the first 5 hours, indicating a high rate of hydration and thus rapid gain in strength and stiffness. Also, the ettringite presents in the cement paste forms a strong and denser needle-like structure which is confirmed by the SEM results as mentioned in the section 3.4.

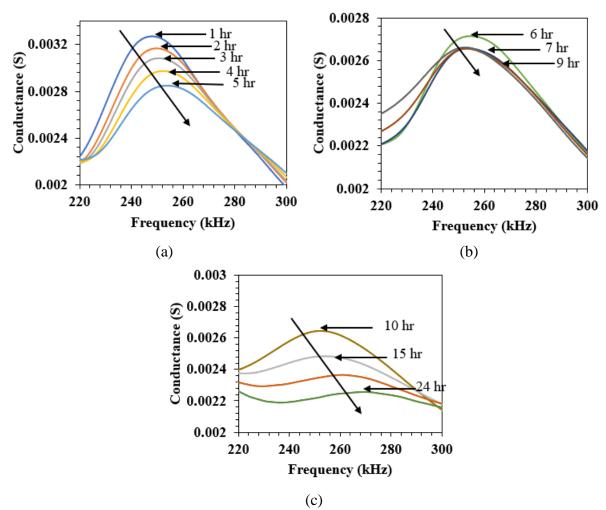


Figure 3.9: Conductance signature during early-age hydration process at different intervals of a typical OPC specimen (a) 1-5 hr, (b) 6-9 hr, and (c) 10-24 hr

Figure 3.10 shows the variation in conductance signature versus frequency during the very early-age hydration process at different time intervals of typical FA specimen in a frequency range of 220 kHz-300 kHz. It can be observed that during the first 5 hours, the amplitudes of the resonance peak show a significant decline while the frequencies of the resonance peak

slightly shift towards the right direction, as shown in Figure 3.10(a). From 6 to 24 hours, the amplitudes of the resonance peak decrease gradually while the frequencies significantly shift towards the same direction, as shown in Figure 3.10(b and c).

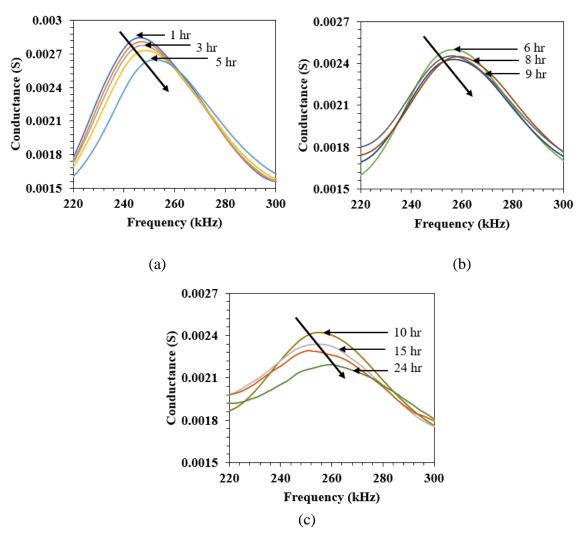


Figure 3.10: Conductance signature during hydration process at different intervals of a typical FA specimen (a) 1-5 hr, (b) 6-9 hr, and (c) 10-24 hr

In case of typical LC³ cementitious system, the frequencies and the amplitudes of the resonance peak show a significant shift in the first 3 hours only, as shown in Figure 3.11(a). From 4 to 24 hours, the amplitudes of the resonance peak decrease gradually while the frequencies significantly shift towards the same direction, as shown in Figure 3.11(b and c). On comparing the variation in conductance signatures versus frequency of all the different systems, it can be seen that the conductance signature of OPC and FA cementitious systems are very similar in terms of amplitude (0.00327 s to 0.0026 for OPC and 0.00284 s to 0.00219 for FA) and frequency (247.4 kHz to 271.5 kHz for OPC and 246.7 kHz to 259.9 kHz for FA) variation during the hydration process. It is due to the fact that the initial and final setting time of both

(OPC and FA) the cementitious system are same. However, in case of LC³ cementitious system, the amplitude of conductance signature (0.0028 s to 0.00268 s) is completely different due to its different initial and final setting time. Hence, this finding illustrate that the signatures obtained at different time intervals from EPS, meticulously senses the changes during the stages of setting process in all the different cementitious systems.

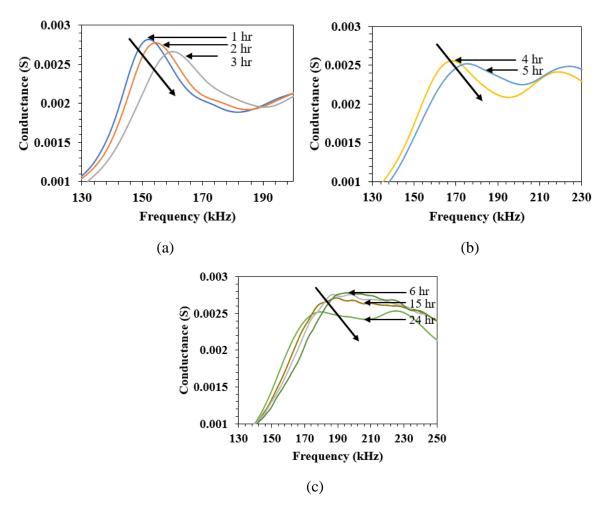


Figure 3.11: Conductance signature during hydration process at different intervals of a typical LC³ specimen (a) 1-3 hr, (b) 4-5 hr, and (c) 6-24 hr

To further analyze the dynamic characteristics of the conductance signature, the trends of the resonance peak amplitudes and frequencies at different time intervals of different cementitious systems have been obtained, as shown in Figure 3.12. From Figure 3.12, it can be seen that the amplitudes at resonance peak follows a linearly decreasing trend with reduction in amplitude as 12.84 % in OPC, 7.04 % in FA, and 10.35 % in LC³, while the frequencies follow a linearly increasing trend with increment in frequency as 1.89 % in OPC, 2.55 % in FA, and 14.79 % in LC³ during the first 5 hours with respect to 1 hour. As the hydration time reached upto 24 hours,

the reduction in amplitude was 30.88 % in OPC, 22.88 % in FA and 4.28 % in LC³ and the increase in frequency was 9.74 % in OPC, 5.35 % in FA and 46.08 % in LC³. The higher percentage increase in frequency indicating a high rate of hydration and thus rapid gain in strength and stiffness in LC³ as compared to OPC and FA. A comparative study about the gain in strength during the early-age hydration process of all the different cementitious systems are discussed in the next section. From the above results, it can be concluded that the resonance frequency peak in the ranges from 245 kHz to 275 kHz for OPC, 245 kHz to 267 kHz for FA, and 150 kHz to 230 kHz for LC³ can serve as an effective indicator for identifying the various stage of hydration process non-destructively.

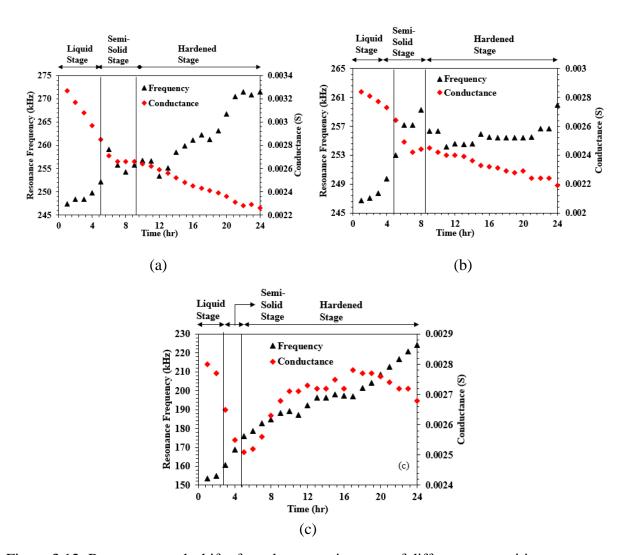


Figure 3.12: Resonance peak shift of conductance signature of different cementitious systems: (a) OPC; (b) FA; and (c) LC³

Figure 3.13 shows the RMSD trend during the early-age hydration process of different cementitious systems. In the liquid stage, the RMSD trend follows a significant increase of 9.65 %, 9.35 % and 12.44 % in OPC, FA, and LC³ cementitious systems respectively, with respect to 1st hour. As the hydration commenced and proceeded, the RMSD values follows a gradual increasing with 12.41 %, 13.33 % and 24.84 %, in OPC, FA, and LC³ cementitious systems, respectively, up to the semi-solid stage. As the cement paste completely set, this RMSD value reaches to 21.75 %, 17.74 % and 34.85 % in OPC, FA, and LC³ cementitious systems, respectively, followed by gradual increment. On comparing the three different stages of three different cementitious systems with respect to RMSD value, it can be observed that the trend of OPC and FA are similar during the liquid and semi-solid stage while the growth rate is gradually higher in OPC cementitious system as the cement paste completely set and gains strength and stiffness. LC³ cementitious systems. Hence, it is concluded that the statistical indices RMSD serve as an effective indicator during the early age hydration and setting process.

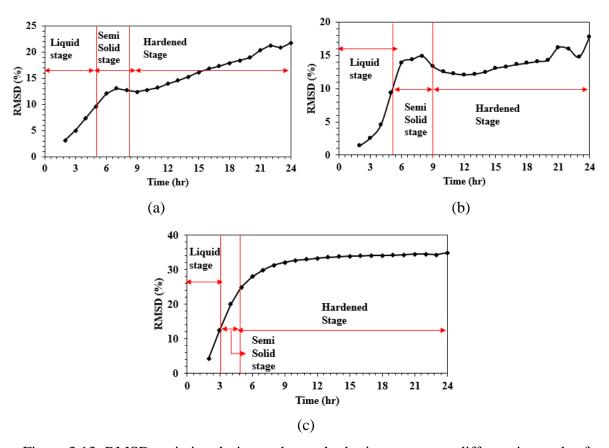


Figure 3.13: RMSD variation during early-age hydration process at different intervals of different cementitious systems: (a) OPC; (b) FA; and (c) LC³

3.6 ANALYSIS BASED ON STRENGTH DEVELOPMENT

The destructive analysis result of compressive strength of different cementitious systems during strength development is shown in Figure 3.14. The results show that the LC³ cementitious system achieved higher early strength at the age of 5 days and 7 days in comparison to the FA and OPC cementitious systems. Such behaviour is reported due to the higher rate of hydration at early ages in LC³ due to the synergy effect between calcined clay and limestone together in the system which can react with the C₃A from the clinker to form extra aluminates in the form of Hc and Mc phases. Similar observations were also observed in the literature (Dhandapani et al., 2018). Moreover, the fineness of clay was higher than FA resulted in the early age strength development in LC³. The compressive strength of LC³ was comparable to OPC up to 28 days, whereas FA cementitious system strength was less than OPC and LC³. In the case of FA cementitious system, the strength development was slow at the early ages due to slow pozzolanic reaction at early ages and continuous gain in strength was observed up to 90 days.

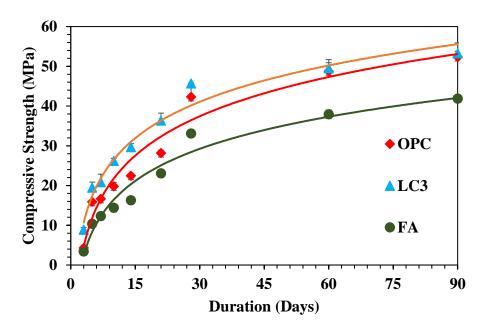


Figure 3.14: Destructive analysis result of compressive strength of different cementitious systems during strength development

To calibrate the destructive results of compressive strength, a new approach has been used to estimate the real-time strength development based on the hydration temperature history (ASTM C1074). In this approach, the area under the temperature curve is taken as the difference between the average recorded temperature and the datum temperature (T_d). The datum temperature is defined as the temperature at which the hydration of the cement stops, in other

words, the temperature at which concrete stops developing strength. The maturity and temperature equation is mathematically represented as follow

$$M(t) = \sum (T_a - T_d) \Delta t \tag{3.1}$$

where, M(t) is the maturity age at t in °C-hrs, T_a is the average temperature (°C), T_d is the datum temperature (°C) and Δt is the time interval (hrs). For a better accuracy, T_d can be calculated through laboratory testing as specified in ASTM C1074, but, in most cases, it can be defined as 0 °C (32 °F), -5 °C (23 °F) or -10 °C (14 °F). In this study, the value of T_d is taken as 0°C according to ASTM C1074. Figure 3.15 to 3.17 shows the relationship between actual compressive strength and maturity for a typical OPC, FA and LC³ specimen. It can be observed that as the maturity increases, the compressive strength increases, and the curve follows a logarithmic trend in all the cementitious systems. Based on the values of compressive strength and maturity for all the cementitious systems, an empirical relation was developed to calibrate the strength-maturity relationship.

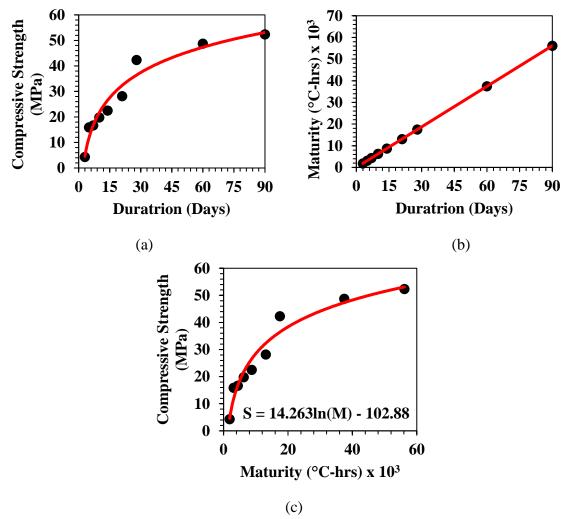


Figure 3.15: Relationship between (a) Actual compressive strength vs duration, (b) Maturity vs duration, (c) Actual compressive strength vs maturity for typical OPC specimen

The equation 3.2 to 3.4 shows the strength-maturity relationship for OPC, FA and LC³ cementitious systems, respectively.

$$S = 14.263\ln(M) - 102.88$$
 (3.2)

$$S = 13.199\ln(M) - 88.517$$
 (3.3)

$$S = 11.654\ln(M) - 85.182 \tag{3.4}$$

where M is the maturity and S is the compressive strength.

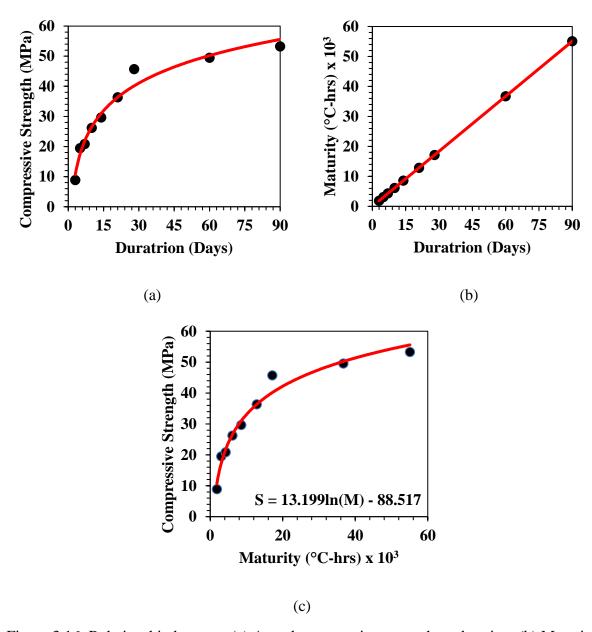


Figure 3.16: Relationship between (a) Actual compressive strength vs duration, (b) Maturity vs duration and (c) Actual compressive strength vs maturity for typical LC³ specimen

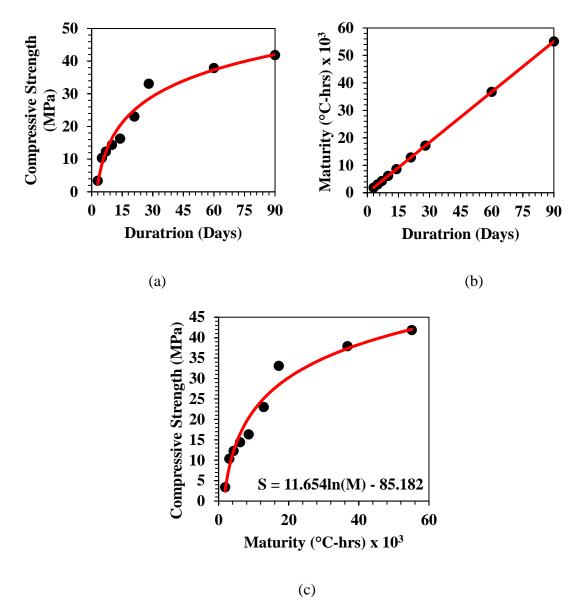


Figure 3.17: Relationship between (a) Actual compressive strength vs duration, (b) Maturity vs duration and (c) Actual compressive strength vs maturity for typical FA specimen

Figure 3.18 shows the variation in conductance signature during strength development at different time intervals of a typical OPC specimen in a frequency range of 100 kHz-300 kHz. It can be observed that the trend of conductance signatures shifts in the right-upwards direction from the 1st day signature and amplitudes of the resonance peak increases significantly up to 28 days, whereas the variation in the amplitudes of the resonance peak is minimal after 28 days. These peaks are called structural peaks which correspond to the structural vibration modes of EPS in the experiment. The movement of structural peaks shifts upwards indicates stiffening of cementitious material during the curing process. In terms of the resonance frequency, which shows a good correlation with the strength development. The resonance frequency presents a

significant increase up to 28 days, afterwards, it flattens up to 90 days. It is due to the fact that in 28 days, the cement structure attains its maximum strength during the curing process. Similar trends were also seen in the typical specimen of FA and LC³ during the strength development, as shown in Figures 3.18 and 3.20. However, the variation in the amplitude and frequency at resonance peak is different in comparison to the OPC specimen. To better understand the shift and deviation in the conductance signature, resonance peak amplitude (conductance) and frequency trends during strength development of different cementitious systems have been obtained and plotted, as shown in Figure 3.21. It can be observed that up to 28 days, the amplitude and frequency at resonance peak show a significant increasing trend; however, as the curing period increases up to 90 days, resonance peak frequency and amplitude followed gradual increase in values in all the cementitious systems. The variation in amplitude and frequency value at the early ages in LC³ and OPC cementitious systems is higher in comparison to the FA cementitious system. It is due to higher fineness and higher rate of hydration in LC³ and OPC and slow pozzolanic reaction in FA.

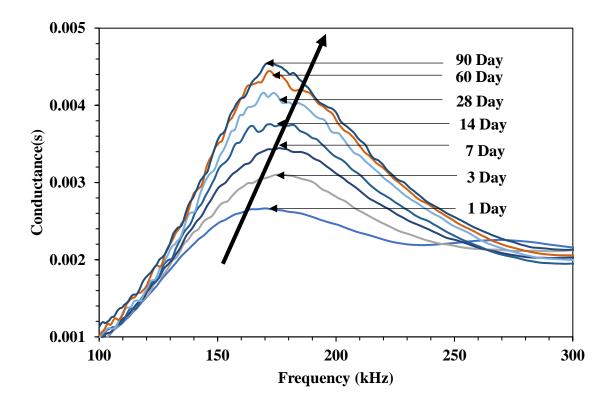


Figure 3.18: Conductance signature during strength development at different intervals of a typical OPC cementitious system

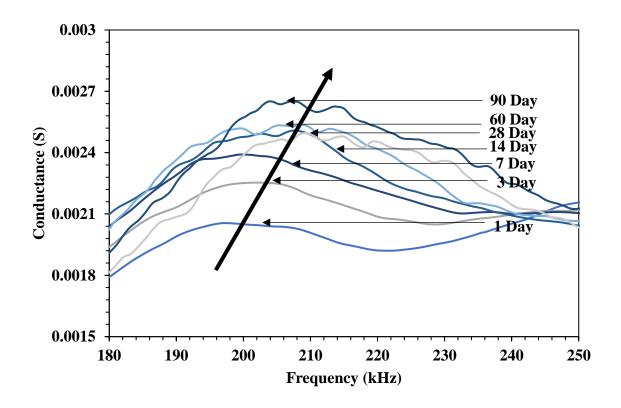


Figure 3.19: Conductance signature during strength development at different intervals of a typical FA cementitious system

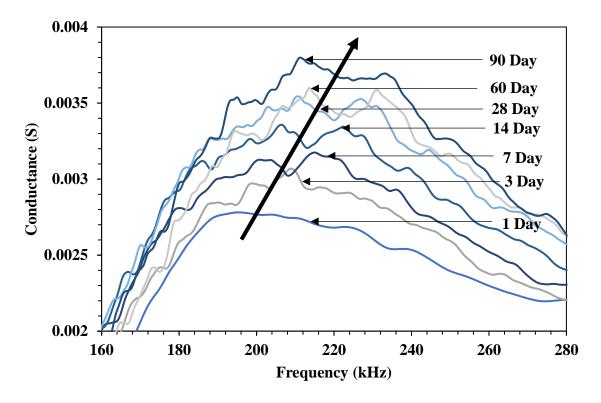


Figure 3.20: Conductance signature during strength development at different intervals of a typical LC³ cementitious system

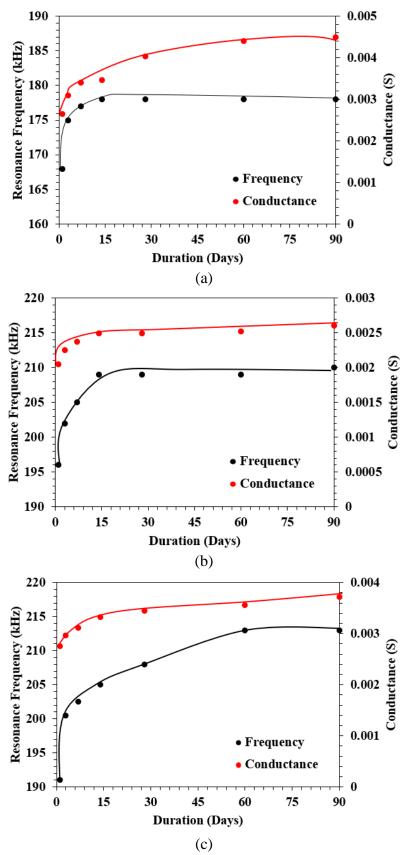
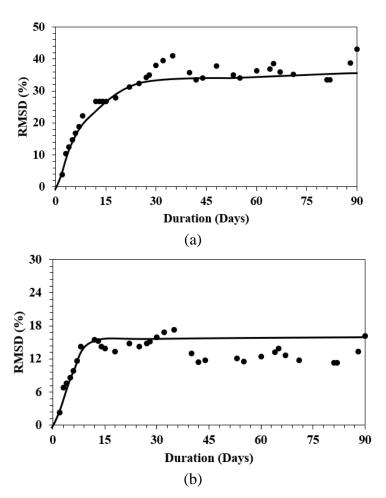


Figure 3.21: Resonance peak shift of conductance signature of different cementitious systems during strength development: (a) OPC; (b) FA; and (c) LC³

On quantitative analysis, a significant increment is also found in RMSD value which is about 35 % with respect to baseline value during the 28 days of curing of cement specimen, after that, it reaches 43 % in the period of 90 days which indicates a gradual increment as shown in Figure 3.22(a). The RMSD value of FA and LC³ specimens is 15 % and 24 %, respectively, during the 28 days of curing. As the curing period increases, a similar pattern was observed as OPC specimen in 90 days as shown in Figure 3.22(b and c) and at this stage, the RMSD value of FA and LC³ specimen reaches 16 % and 29 %, respectively. On comparing the trends of resonance peak amplitude, frequency and RMSD indices as shown in Figure 3.18-3.21 with the compressive strength and maturity trends as shown in Figure 3.14 to 3.17, it is found that the trend are similar which indicates that the sensor which is embedded inside the concrete capture the signatures well in all the cementitious systems as strength develops. Hence, it is concluded that the raw signatures from the EPS can provide a general idea about increase in compressive strength of cementitious systems. Further, equivalent structural parameters (ESPs) are extracted which would be beneficial than these raw signatures and statistical models covered in the next section.



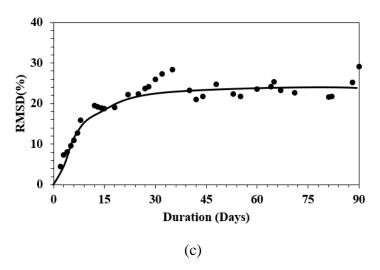


Figure 3.22: RMSD variation during strength development at different intervals of different cementitious systems: (a) OPC; (b) FA; and (c) LC³

3.7 ANALYSIS BASED ON EQUIVALENT STRUCTURAL PARAMETERS

To understand deeper insight about the strength development, an equivalent stiffness has been calculated by developing a physical model based on spring, and damper element. The extracted impedance plots of 'x' and 'y' in a healthy state with frequency range 120 kHz-140 kHz for OPC, 260 kHz-300 kHz for FA and 160 kHz-180 kHz for LC³, it found that the experimental and an equivalent system consisting of the spring element (k) and damper (c) is behaving similarly in parallel combination as discussed in Ch.2. Figure 3.23 shows the variation of piezo identified equivalent stiffness parameter (ESP) during strength development for different cementitious systems at different intervals. It can be seen in Figure 3.23(a), equivalent stiffness (k) increases with curing time throughout the monitoring period. At the age of 7 days, the increase in k values from 1st day was ranges from 15.60 kNs/m - 22.88 kNs/m, at 28 days was 15.60 kNs/m - 24.30 kNs/m and at 90 days was 15.60 kNs/m - 25.57 kNs/m. This finding indicates that the equivalent stiffness increases significantly at the early age (1 to 7 days), wheras as the curing period increases, the gain in stiffness values are minimal. The ESP determined during the strength development for FA cementitious system is shown in Figure 3.23(b), it is observed that in the early age the variation in k values was minimal with respect to 1st day, however, as the curing period increases the k values increases from 6.95 - 8.7 kNs/m at 28 days and 6.96-12.48 kNs/m at 90 days. In case of LC³ as shown in Figure 3.23(c), the increase in k values at 28 days from 1st day was ranges from 22.14 kNs/m - 26.73 kNs/m and at 90 days was ranges from 22.14 kNs/m -32.83 kNs/m. When comparing the k value increase in different cementitious systems, it is observed that the k value of LC³ cementitious system is higher than the other two cementitious systems (OPC and FA).

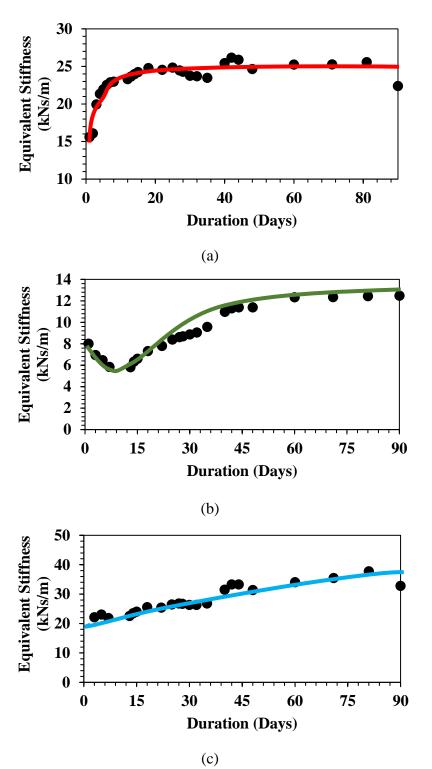


Figure 3.23: Piezo identified equivalent stiffness during strength development of different cementitious systems: (a) OPC; (b) FA; and (c) LC³

3.8 CALIBRATION OF PZT IDENTIFIED EQUIVALENT STIFFNESS WITH MATURITY AND COMPRESSIVE STRENGTH

This section attempts to calibrate the PZT identified equivalent stiffness (ES) with the compressive strength of different cementitious system. For the calibration, the compressive strength of different cementitious systems was identified using the equation 3.2 to 3.4, as mentioned in the section 3.6. Table 3.2 shows the value of maturity identified compressive strength of different cementitious system.

Table 3.2: Maturity identified compressive strength of different cementitious system

Age	OPC	LC ³	FA
3	4.58832	10.67803	2.371764
5	11.87423	17.42042	8.322883
7	16.67333	21.86152	12.24278
10	21.76058	26.56927	16.39805
14	26.55969	31.01037	20.31795
21	32.34284	36.3621	25.04162
28	36.44605	40.15922	28.39311
60	47.31645	50.2187	37.27205
90	53.0996	55.57044	41.99571

Based on the values of maturity identified compressive strength and PZT identified ES for all the cementitious systems, an empirical relation was developed. The equation 3.5 to 3.7 shows the equivalent stiffness-strength relationship for OPC, FA and LC³ cementitious systems, respectively.

$$ES = 102.83S + 20665 \tag{3.5}$$

$$ES = 273.02S + 16919 \tag{3.6}$$

$$ES = 174.29S + 4352.8 \tag{3.7}$$

where ES is the PZT identified ES and S is the maturity identified compressive strength. Figure 3.24 shows the relationship between PZT identified ES vs maturity identified compressive strength for different cementitious systems. It can be observed that the PZT identified ES follows a smooth linearly increasing trend with the maturity identified compressive strength in OPC, however, LC³ shows the linearly increasing trend with less scatter and FA with large scatter.

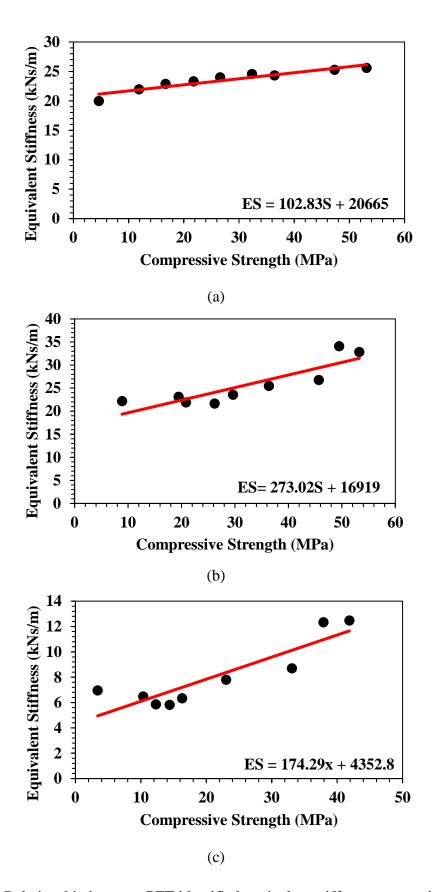
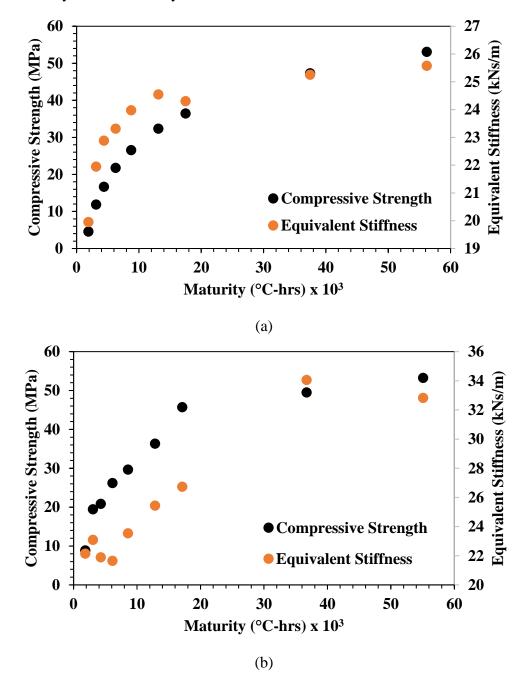


Figure 3.24: Relationship between PZT identified equivalent stiffness vs maturity identified compressive strength for a typical specimen (a) OPC, (b) LC³ and (c) FA

Figure 3.25 shows the three-dimensional relationship between the PZT identified ES and maturity identified compressive strength with maturity for different cementitious systems. It can be observed that compressive strength and ES increases with the maturity. Also, the trend of PZT identified ES are similar with good agreement to the maturity identified compressive strength in all the systems. It is due to the fact that as the curing period increases, the cement particles start combining with each other and gaining its strength, thus causing increment in the ES which is very well detected by the EPS.



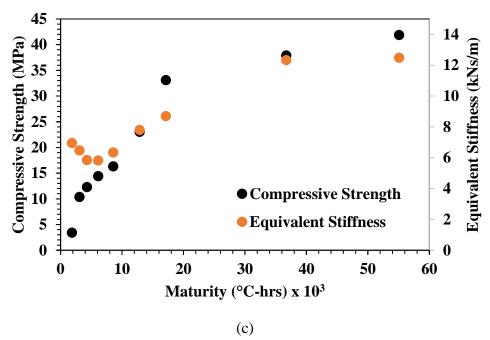


Figure 3.25: Relationship between PZT identified equivalent stiffness vs maturity identified compressive strength vs maturity for a typical specimen (a) OPC, (b) LC³ and (c) FA

3.9 VALIDATION OF PIEZO BASED ANALYSIS WITH MATURITY METHOD

This section attempts to validate the PZT identified ES with the maturity identified ES. For the validation, the ES based on maturity method of different cementitious systems was identified using the equation 3.2 to 3.7. Equation 3.2 to 3.4 represents the strength-maturity relationship for OPC, FA and LC³ cementitious systems, respectively and equation 3.5 to 3.7 represents the equivalent stiffness-strength relationship for OPC, FA and LC³ cementitious systems, respectively. By putting the equation 3.3 to 3.4 in equation 3.5 to 3.7 in respective cementitious systems, the following equations were generated as shown below

$$ESM = 1503.68 \ln(M) + 10085.84 \tag{3.8}$$

$$ESM = 3603.59 \ln(M) - 7247.91 \tag{3.9}$$

$$ESM = 2030.47 \ln(M) - 10493.8 \tag{3.10}$$

where ESM represents the equivalent stiffness identified by the maturity method.

Figure 3.26 shows the comparison between ESM and PZT identified ES. It can be observed that both the ESM and PZT identified ES follow the same upward increasing trend in all the different cementitious systems; hence from the above empirical relations, it can be concluded

that the piezo based via EMI technique is validated with the established conventional technique which is based on maturity method. Moreover, by using the above empirical relations, piezo based analysis non-destructively can provide the maturity index and compressive strength non-destructively.

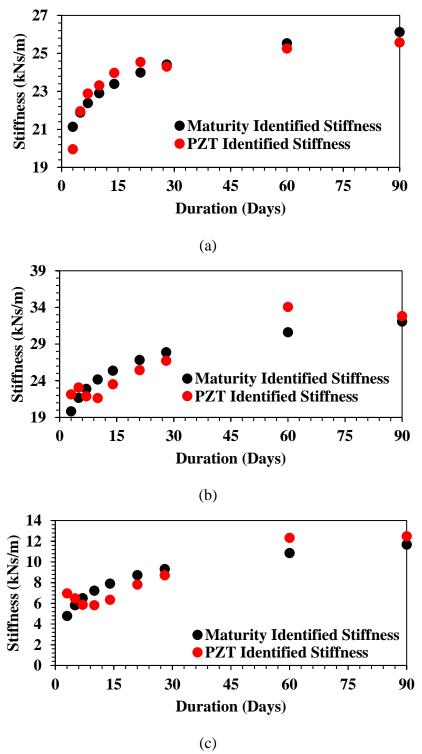


Figure 3.26: Comparison between maturity identified equivalent stiffness vs PZT identified equivalent stiffness (a) OPC, (b) LC³ and (c) FA

3.10 DEVELOPMENT OF MACHINE LEARNING MODELS

In this study, EMI dataset of OPC, FA and LC³ consisting of five features (independent variables) such as x, y, k, f, a and one response which is compressive strength (dependent variable), where x is the real component of mechanical impedance, y is the imaginary part of mechanical impedance, k is the equivalent stiffness, f is the frequency and a is the curing age of the specimen were considered. Each feature consists of 1600 data points imported into the app in the form of predictor (x, y, k, f, a) and response (compressive strength). The reason attributed for chosen equivalent stiffness 'k' as a feature because k consists of a direct relationship with compressive strength (k = AE/L), in which, $E = 5000 (f_{ck})^{1/2}$, where A is the cross-sectional area of the specimen, E is the elastic modulus, L is the length of the specimen and f_{ck} is the compressive strength, hence, as the stiffness increases, compressive strength of the concrete increases. Five-fold cross validation method is used in the entire training process. This dataset was then applied to various ML algorithms such as linear regression, interaction linear regression, robust linear regression, stepwise linear regression, linear support vector machine (SVM), quadratic SVM, cubic SVM, fine gaussian SVM, coarse SVM and medium SVM regression models using MATLAB and the best-suited model was selected based on their performance in the form of R^2 , root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE). The workflow for training the regression model is shown in Figure 3.27. The model performance is estimated with the following equations (3.11-3.14)

$$MSE = \sum_{i=1}^{n} (y_i - \hat{y_i})^2$$
 (3.11)

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (y_{i} - \hat{y_{i}})^{2}}{\sum_{i=1}^{n} (y_{i} - \bar{y_{i}})^{2}}$$
(3.12)

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}}{n}$$
(3.13)

$$MAE = \sum_{i=1}^{n} \frac{\left| \hat{y}_i - y_i \right|}{n} \tag{3.14}$$

where, n = number of observations, $\hat{y_i} =$ predicted values, $\overline{y_i} =$ mean values, $y_i =$ observed values, $i = 1, 2, 3, \ldots, n$.

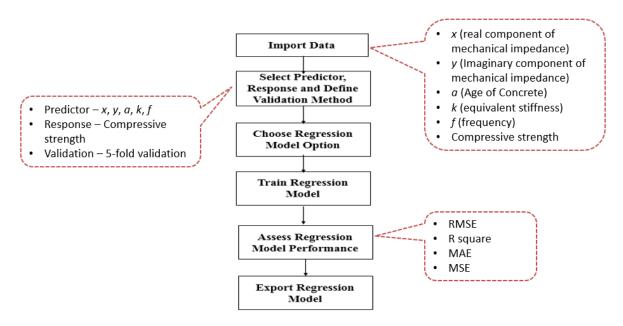


Figure 3.27: Workflow of training regression model

3.11 PREDICTION OF COMPRESSIVE STRENGTH USING MACHINE LEARNING MODELS

The performance of different regression models used for prediction of compressive strength using EPS configuration dataset for OPC binder system are shown in Table 3.3. In this table 3.3, it is observed that the coefficients of multiple determination (R^2) value for linear regression, robust linear regression and linear SVM models is 0.93, coarse gaussian SVM is 0.95, interaction linear regression and stepwise linear regression models is 0.96, quadratic SVM is 0.98 and, medium gaussian SVM, cubic SVM, fine gaussian SVM is 0.99, which indicates the prediction of compressive strength variability with 93 %, 95 %, 96 %, 98 % and 99 % accuracy in terms of R^2 . Linear regression, robust linear regression and linear SVM have shown the lower value of R^2 because these three models are linear models with linear terms. Cubic SVM, medium SVM and fine gaussian SVM model have shown the most admirable value of R^2 , but in terms of errors (RMSE and MAE), cubic SVM perform the best because cubic SVM is a medium flexible model which allows rapid variations in the response function. Therefore, the best model chosen from all machine learning regression models is cubic SVM model. The R², RMSE, MSE and MAE of this model were found to be 0.99, 1.59 %, 2.53 % and 1.38 % as shown in Table 3.3. This implies that the proposed cubic SVM model predicts the compressive strength with an error of less than 1 %. The selected features are in good agreement with the value of MSE, MAE and RMSE since a higher value of R^2 corresponds to a smaller MSE, MAE and RMSE. Figure 3.28 (a) represents the graph between response (compressive strength) and a record number of predicted value and true value. Figure 3.28 (b) represents the graph between the predicted response and true response. From these Figure 3.28, it is observed that data points are near the perfect prediction line, which indicates that the model predicts the compressive strength with good accuracy. Thus, it is concluded that the compressive strength models' prediction accuracy for the OPC binder system exhibits a good correlation.

Table 3.3: Comparison between different models for OPC cementitious system

Model		RMSE			MAE
Number	Model	(%)	\mathbb{R}^2	MSE (%)	(%)
1	Linear Regression	4.13	0.93	17.13	3.60
2	Interactions Linear				
	Regression	3.40	0.96	11.62	2.74
3	Robust Linear				
	Regression	4.14	0.93	17.18	3.56
4	Stepwise Linear				
	Regression	3.42	0.96	11.72	2.76
5	Linear SVM	4.20	0.93	17.65	3.48
6	Quadratic SVM	2.50	0.98	6.28	2.01
7	Cubic SVM	1.59	0.99	2.53	1.38
8	Fine Gaussian SVM	1.92	0.99	3.71	1.864
9	Medium Gaussian				
	SVM	1.93	0.99	3.74	1.66
10	Coarse Gaussian				
	SVM	3.53	0.95	12.48	2.88

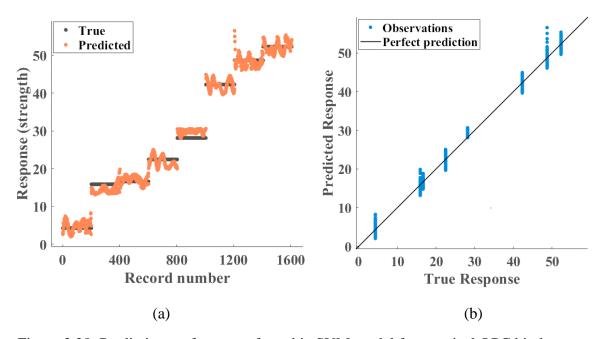


Figure 3.28: Prediction performance for cubic SVM model for a typical OPC binder system

For the FA system also the cubic SVM model performed the best with prediction error less than 1 % and the R², RMSE, MSE and MAE values of 0.99, 1.52 %, 2.33 % and 1.41 % respectively as shown in Table 3.4. Figure 3.29(a) represents the graph between response (compressive strength) and a record number of predicted value and true value. Figure 3.29(b) represents the graph between the predicted response and true response.

For LC³ system medium gaussian SVM model performed the best as compared to other regression models with prediction error less than 1 %. The R², RMSE, MSE and MAE of this model were found to be 0.99, 1.74 %, 3.03 % and 1.55 % are shown in Table 3.5. Figure 3.30(a) represents the graph between response (compressive strength) and a record number of predicted value and true value. Figure 3.30(b) represents the graph between the predicted response and true response. On comparing the model performance of all the three binder systems, it can be noticed that the proposed models provide a good correlation with the features in both the systems. By just using the EMI data in the form of x, y, f, k, and a value as input to the model, it gives the output in the form of compressive strength.

Table 3.4: Comparison between different models for FA cementitious system

Model		RMSE			
Number	Model	(%)	\mathbb{R}^2	MSE (%)	MAE (%)
1	Linear Regression	3.26	0.94	10.66	2.53
2	Interactions Linear				
	Regression	2.40	0.97	5.78	2.17
3	Robust Linear				
	Regression	3.51	0.93	12.34	2.32
4	Stepwise Linear				
	Regression	2.44	0.97	5.97	2.13
5	Linear SVM	3.34	0.94	11.21	2.42
6	Quadratic SVM	1.74	0.98	3.02	1.55
7	Cubic SVM	1.52	0.99	2.33	1.41
8	Fine Gaussian SVM	1.73	0.98	3.00	1.69
9	Medium Gaussian SVM	1.92	0.98	3.68	1.89
10	Coarse Gaussian SVM	3.18	0.94	10.11	2.23

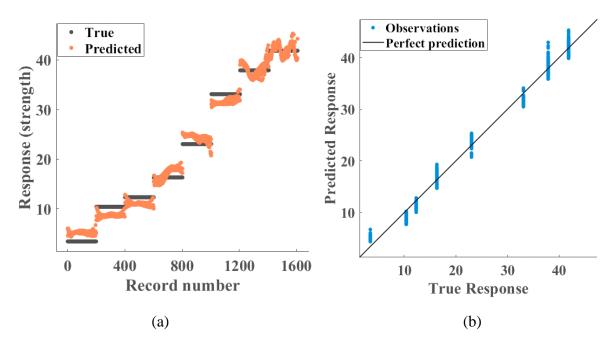


Figure 3.29: Prediction performance for cubic SVM model for a typical FA binder system

Table 3.5: Comparison between different models for LC³ Cementitious system

Model		RMSE			
Number	Model	(%)	\mathbb{R}^2	MSE (%)	MAE (%)
1	Linear Regression	4.55	0.91	20.78	3.76
2	Interactions Linear				
	Regression	2.78	0.97	7.75	2.35
3	Robust Linear				
	Regression	4.56	0.91	20.83	3.74
4	Stepwise Linear				
	Regression	2.63	0.97	6.94	2.19
5	Linear SVM	4.60	0.91	21.73	3.72
6	Quadratic SVM	2.01	0.98	4.06	1.75
7	Cubic SVM	1.99	0.98	3.96	1.65
8	Fine Gaussian SVM	1.84	0.98	3.40	1.77
9	Medium Gaussian				
	SVM	1.74	0.99	3.03	1.55
10	Coarse Gaussian SVM	2.86	0.96	8.22	2.304

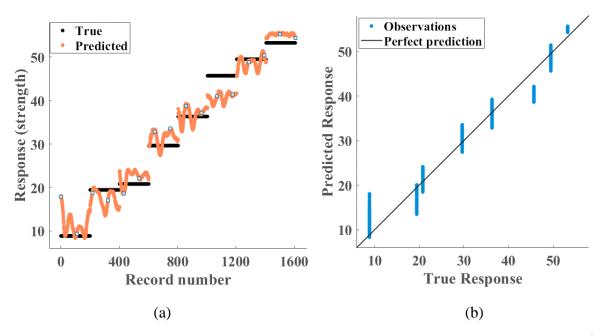


Figure 3.30: Prediction performance for medium gaussian SVM model for a typical LC³

3.12 CONCLUDING REMARKS

This chapter presents the machine learning based compressive strength prediction for various cementitious systems such as OPC, FA, and LC³ using the piezo sensor-based EMI technique. Results obtained from FTIR, XRD, and SEM tests indicates promising findings and verifies the C-S-H hydration products formed during the very early-age hydration of cement with good agreement. On comparing the raw EMI signature obtained from EPS and Vicat needle penetration depth during the hydration process at a very early stage, it is concluded that EMI results are correlated with Vicat needle penetration depth. The resonance peak shift and amplitude variation serves as a most suitable indicator for monitoring the hydration process. The equivalent stiffness parameter obtained from the EMI signature is very effective in monitoring the mechanical changes of the curing process. The developed empirical relations of the piezo based via EMI technique is validated with the established conventional technique based on maturity method. Furthermore, based on the prediction of compressive strength using ML models, it is concluded that the cubic SVM models predict the compressive strength with excellent accuracy for OPC-based and FA-based binder system while in LC³- based binder system, medium gaussian model predict the compressive strength well. The next chapter extends the study to monitor and predict the compressive strength in different concrete systems.

CHAPTER-4

MACHINE LEARNING BASED COMPRESSIVE STRENGTH PREDICTION FOR CONCRETE SYSTEMS USING PIEZO SENSOR

4.1INTRODUCTION

In the previous chapter, ML models were developed to predict the compressive strength of cementitious system using the EMI data acquired from piezo sensors. This chapter extends proposed ML models to concrete systems as discussed in Chapter 3. Also, the sensitivity of different piezo configurations with respect to strength monitoring of the conventional and ternary blended concrete systems were studied and the suitability of different configurations for real-life field applications are suggested.

4.2 EXPERIMENTAL PROGRAM

In this investigative study, concrete cube (grade M30) of size 150 mm x 150 mm x 150 mm were cast with OPC (43 grade) conforming to IS 8112:2013 and LC³ (using cement replacement level of 50 %) with calcined clay and limestone 2:1 ratio. The chemical and mineralogical compositions of the material used in the study are already mentioned in Chapter 2. While casting the concrete specimens, the different piezo configurations of PZT patch size 10 mm x 10 mm x 0.2 mm and conforming to grade PZT 5H was installed on the specimens as follows and shown in Figure 4.1.

- EPS: Installed during casting by placing it at the centre of the specimen
- SBPS: Attached to the specimens on its top surface after demoulding
- NBPS: Attached to the specimen after demoulding using epoxy

The EMI data was acquired by connecting soldered wires of the PZT patch to the crocodile cable which is then connected to the LCR meter as shown in Figure 4.2. The baseline signatures in the form of G vs f and B vs f were acquired from various piezo configurations in the range of 50-300 kHz using LCR meter after the bonding process. After acquisition of baseline data, all the specimens were immersed in water for curing until 28 days, during which compressive strength test were conducted destructively with a loading rate of 400 kg/min as per IS: 516:1959

at different intervals in between 3-28 days. Average value of three specimens were reported along with standard deviation in the results. During the hydration process, EMI data from various piezo configurations were also acquired and the quantitative analysis using the two statistical parameters named RMSD and MAPD were used to quantify changes in the signatures during curing time in different sub-frequency ranges.

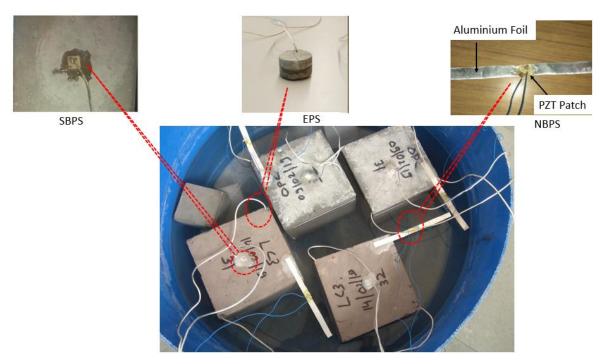


Figure 4.1: Specimens installed with different Piezo Configurations

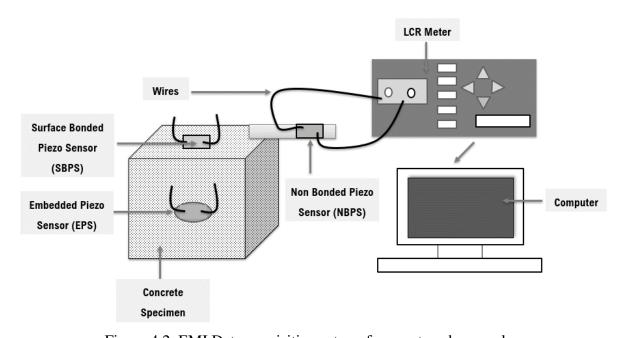


Figure 4.2. EMI Data acquisition setup of concrete cube sample

Figure 4.3 shows the baseline conductance signatures of LC³ concrete specimen using different piezo configurations (SBPS, EPS and NBPS). Conductance signatures of SPBS, EPS and NBPS configurations are different due to sensing adequacy of the sensors. On comparing the first resonance peak sensitivity of different piezo configurations were found in the frequency range of 190-210 kHz, 240-260 kHz, and 200-250 kHz, for SBPS, EPS and NBPS respectively. Figure 4.4 shows the baseline susceptance signatures of LC³ concrete specimen using different piezo configurations. Compared to conductance signatures, variation in susceptance signatures is comparatively flat with no peaks because of which conductance graphs are more widely used for damage prognosis due to their greater sensitivity to mechanical changes and lower susceptibility to environmental effects (Bhalla et al., 2012b; Lim and Soh, 2011; Park et al., 2003). Conductance and susceptance signatures of OPC concrete specimen using different piezo configurations (SBPS, EPS, and NBPS) are shown in Figure 4.5 and 4.6, respectively.

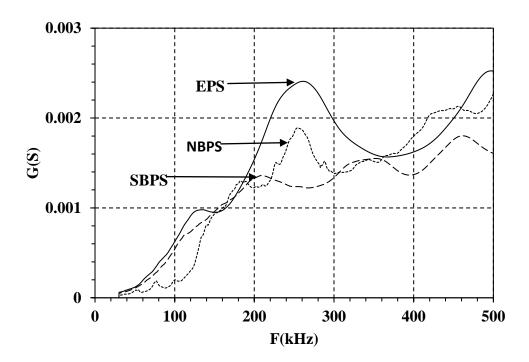


Figure 4.3: Baseline conductance signatures of LC³ specimen with different piezo configuration

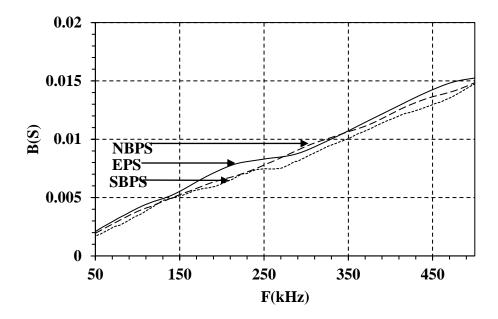


Figure 4.4: Baseline susceptance signatures of LC³ specimen with different piezo configuration

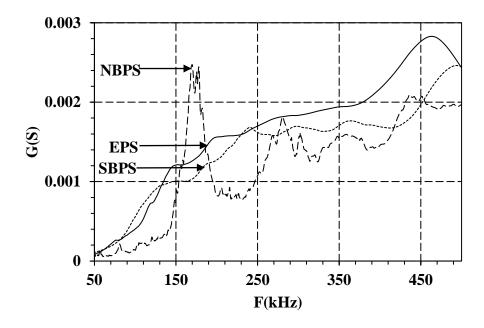


Figure 4.5: Baseline conductance signatures of OPC specimen with different piezo configuration

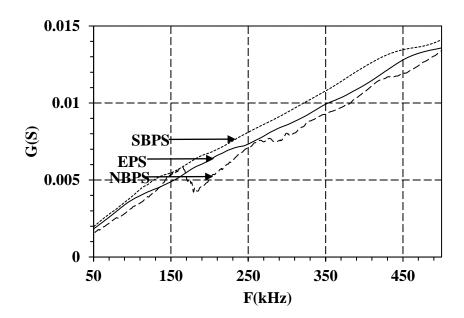


Figure 4.6: Baseline susceptance signatures of OPC specimen with different piezo configuration

Figure 4.7 shows the destructive result of time-dependent compressive strength of LC³ and OPC based concrete system, compressive strength increases in both the concrete specimens with the curing time as curing promotes the hydration reactions of the main phases of clinker phases present in the LC³ and OPC (Marangu, 2020). LC³ based concrete (calcined clay and limestone ratio is 2:1) exhibited lower compressive strength compared to the OPC based concrete in the present study, which was also noted by some of the researchers because of the variation in the ratios of calcined clay and limestone ratio as investigated by (Antoni, 2013; Nguyen et al., 2020) for the same LC³ based concrete system.

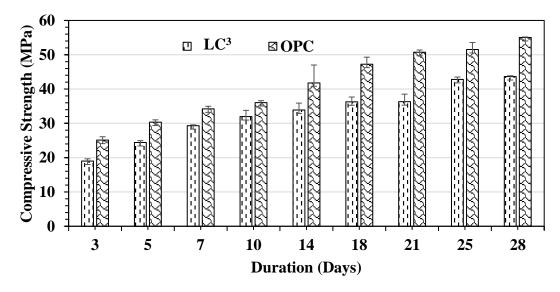
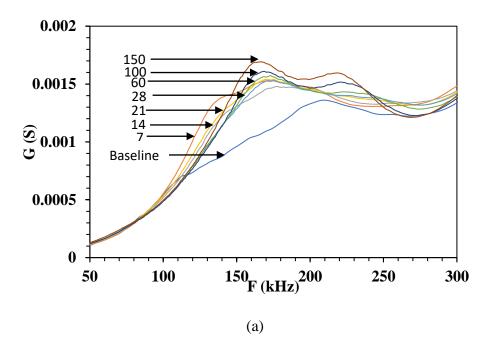


Figure 4.7: Destructive result of compressive strength vs curing time

Figure 4.8(a) shows the variation in conductance signature with curing time for a typical LC³ specimen in the frequency range of 100-300 kHz using SBPS configuration. It can be seen that the amplitude of signatures increases with increase in curing days when observed at the peak frequency in the range of 150-200 kHz (0.001 s to 0.0017 s). These peaks are called structural peaks which correspond to the structural vibration modes of SBPS in the experiment. It is also observed that the movement of structural peaks shifts upwards, which indicates stiffening of cementitious material during the curing process. RMSD and MAPD values were calculated to quantify the changes as shown in Figure 4.8(b). On comparing values of RMSD in different frequency ranges, the frequency range of 150-200 kHz is found to be reasonably good, providing an increasing trend with the curing days. At the age of 28 days, RMSD value was found to be 37.60 % with respect to baseline due to gain of strength in the concrete but thereafter attains almost constant values with time. In Figure 4.8(c), MAPD value at the age of 28 days was found to be 37.86 %, which is similar to RMSD value. Thus, from these observations, the optimal frequency range was found to be 150-200 kHz, which is also called as structural peak frequency range.



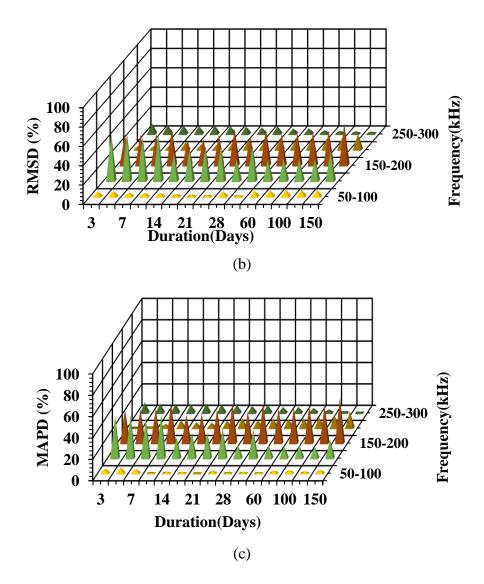
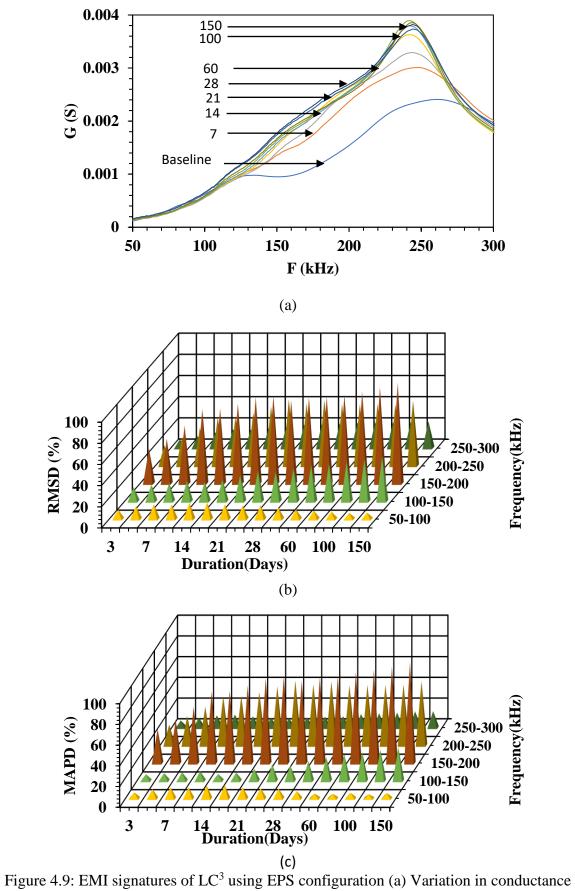


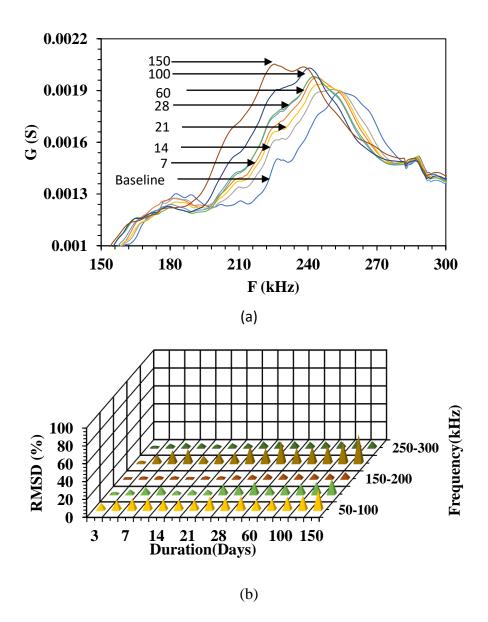
Figure 4.8: EMI signature of LC³ using SBPS configuration (a) Variation in conductance signature with frequency (b) RMSD (c) MAPD

Figure 4.9(a) shows variation of LC³ specimen in the frequency range of 50-300 kHz using EPS configuration. It is observed that the amplitude of signatures increases with curing days with a maximum increase at the structural resonance peaks in which the resonance peaks shift rightwards and upwards direction with an increase in curing time. The RMSD and MAPD values in the frequency range of 150-200 kHz at the age of 28 days are found to be 78.51 % and 79.86 %, as shown in Figure 4.9(b and c), respectively.



signature with frequency (b) RMSD (c) MAPD

For NBPS, as shown in Figure 4.10(a), it is seen that in the frequency range of 200-250 kHz, variation in resonance peaks is very minimal compared to the other two configurations since NBPS is not directly bonded to the structure due to which it reflects the structural signal response indirectly. The PZT patch first actuates the enclosure (aluminium foil), which in turn transfers the wave of vibrations through the aluminium foil to the host structures. From Figure 4.10(b and c), in the frequency range of 200 – 250 kHz, the RMSD value is 16.88 % at the age of 28 days, while the MAPD value is 16.24 %, which is much lower compared to other piezo configurations.



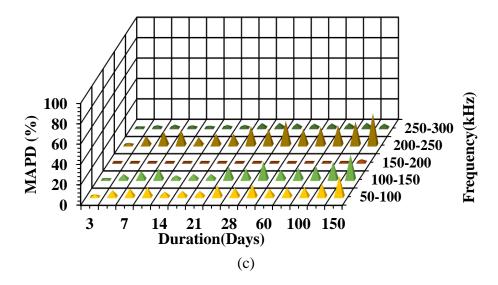


Figure 4.10: EMI signatures of LC³ using NBPS configuration (a) Variation in conductance signature with frequency (b) RMSD (c) MAPD

On comparing the raw signatures of SBPS, EPS and NBPS, it can be seen that the variation in resonance peak value of EPS configuration is higher as compared to SBPS and NBPS configurations which can also be seen in the variation of RMSD values. It is because the EPS sensor is embedded within the concrete and can detect changes more predominantly during the hydration process compared to SBPS and NBPS. Hence, it is concluded that the raw signatures from the EPS can provide a general idea about increase in compressive strength of concrete. Further in-detailed analysis of day-to-day strength gain in LC³ and OPC concrete, ESPs are extracted which would be beneficial than these raw signatures and statistical models covered in the next section.

4.3 ANALYSIS BASED ON EQUIVALENT STRUCTURAL PARAMETERS

In this analysis, the healthy state impedance plots of 'x vs f' and 'y vs f' in the frequency range of 150-200 kHz was found to be similar to an equivalent system consisting of spring (k), mass (m) and damper (c) element in series combination as discussed in Ch. 2. The x vs f and y vs f graphs are plotted for all the piezo configurations, whereas in the result, EPS configuration is shown in Figure 4.11.

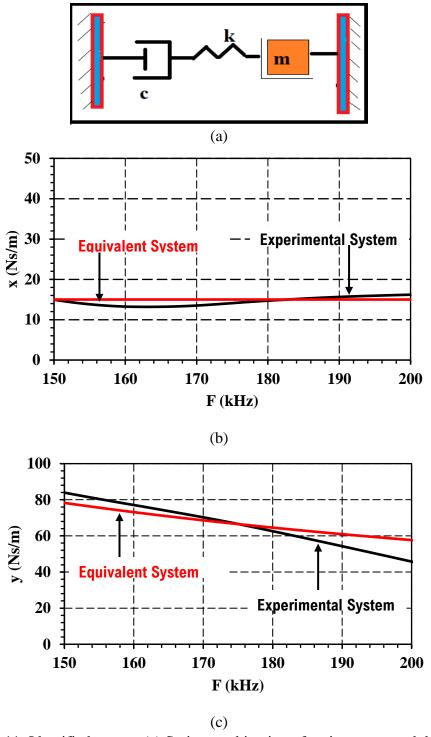


Figure 4.11: Identified system (a) Series combination of spring, mass and damper (b) variation of x vs f and (c) variation of y vs f

Figure 4.12 shows a variation in ESPs (stiffness and damping) with curing time for LC^3 specimen. It can be seen in Figure 4.12(a), equivalent stiffness (k) increases with curing time throughout the monitoring period. At the age of 28 days, the increase in k values from baseline was from 85-118 kNs/m. In Figure 4.12(b), it can be observed that equivalent damping (c) decreases with an increase in curing time because as the concrete gains its strength, the damping

starts decreasing. The same trend of increase in stiffness and reduction in damping for concrete was discussed in detail by Moharana and Bhalla (2019) while monitoring the strength gain of conventional concrete during the hydration process.

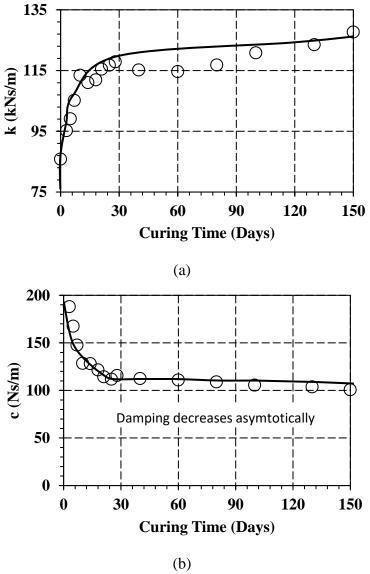


Figure 4.12: Equivalent structural parameter of LC³ concrete using piezo sensor data of EPS (a) Stiffness (b) Damping

The ESPs determined by using EMI signature data of SBPS configuration for LC³ specimen is shown in Figure 4.13. From this, it is observed that the k values increase throughout the monitoring of concrete strength gain during the hydration process. At the age of 28 days of curing time, increase in k value from baseline was 57-69 kN s/m while c values decreased asymptotically.

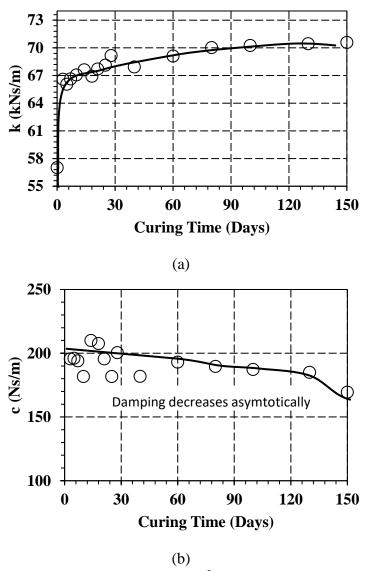


Figure 4.13: Equivalent structural parameter of LC³ concrete using piezo sensor data of SBPS (a) Stiffness (b) Damping

Figure 4.14 shows the variation in ESPs with curing time for LC³ specimen using NBPS configuration. It can be seen that the k values increase as the curing time increases and c values decrease asymptotically. The increase in k value from baseline was found to be 60-63 kN s/m. Figures 4.15 to 4.17 shows variation of k and c values of OPC concrete using SBPS, EPS and NBPS configurations, respectively. The increase in k value from baseline for OPC specimen using EPS, SBPS and NBPS configurations was found to be 75-117 kN s/m, 60-72 kN s/m and 55-61 kN s/m, respectively. During monitoring of the strength gain of conventional concrete, similar observations were made regarding k values (Soh and Bhalla, 2005a; Talakokula et al., 2018). When comparing the k value increase in different piezo configurations for both LC³ and OPC concrete, it is observed that the k value of EPS configuration is higher than the other two

piezo configurations.

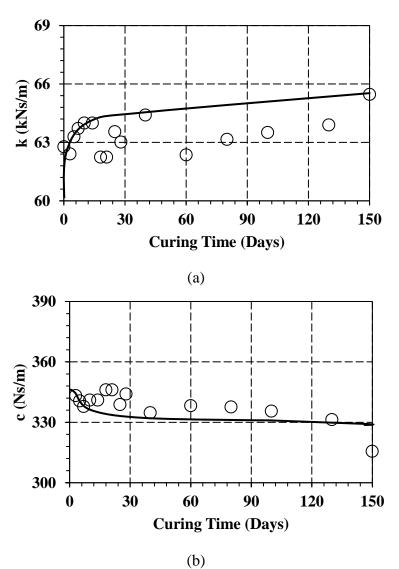
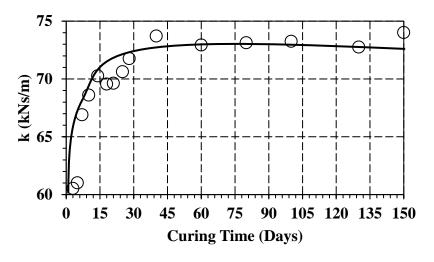


Figure 4.14. Equivalent structural parameter of LC³ concrete using piezo sensor data of NBPS (a) Stiffness (b) Damping



(a)

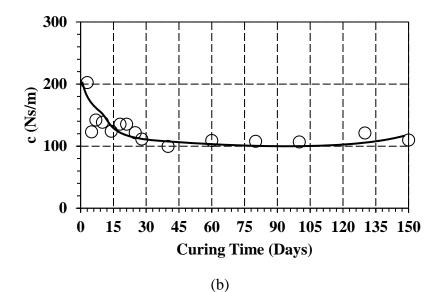
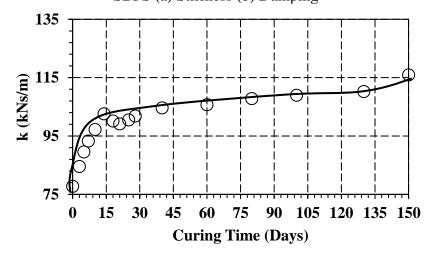
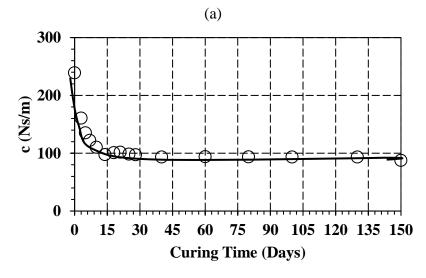
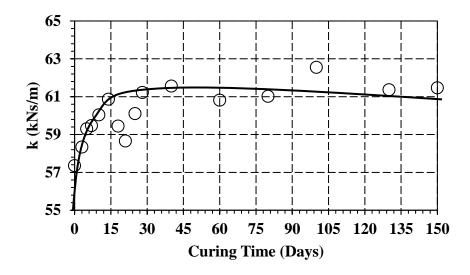


Figure 4.15: Equivalent structural parameter of OPC concrete using piezo sensor data of SBPS (a) Stiffness (b) Damping





(b)
Figure 4.16: Equivalent structural parameter of OPC concrete using piezo sensor data of EPS
(a) Stiffness (b) Damping



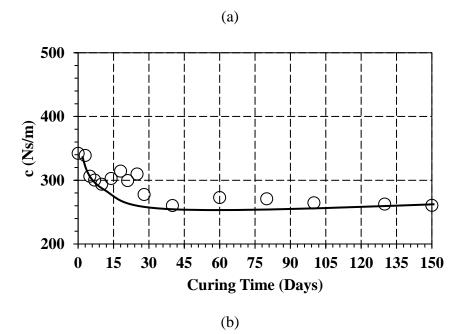


Figure 4.17: Equivalent structural parameter of OPC concrete using piezo sensor data of NBPS (a) Stiffness (b) Damping

Figure 4.18(a) shows day-to-day percentage increase in compressive strength values determined destructively for both OPC and LC^3 systems with respect to 3 day, it can be found that LC^3 system has higher increase as compared to OPC system, even though the overall strength is lower than OPC (as shown in Figure 4.7). Figure 4.18(b) shows day-to-day percentage increase in k values determined non-destructively for both OPC and LC^3 systems with respect to 3 day using EPS configuration. On comparing both the figures (Figure 4.18(a) and Figure 4.18(b)), it can be concluded that both the destructive and non-destructive analysis shows a similar trend. Thus, it can be established that not only the sensor gave the overall

impression of the changes in the strength but also provide insights into the day-to-day percentage increase in strength gain.

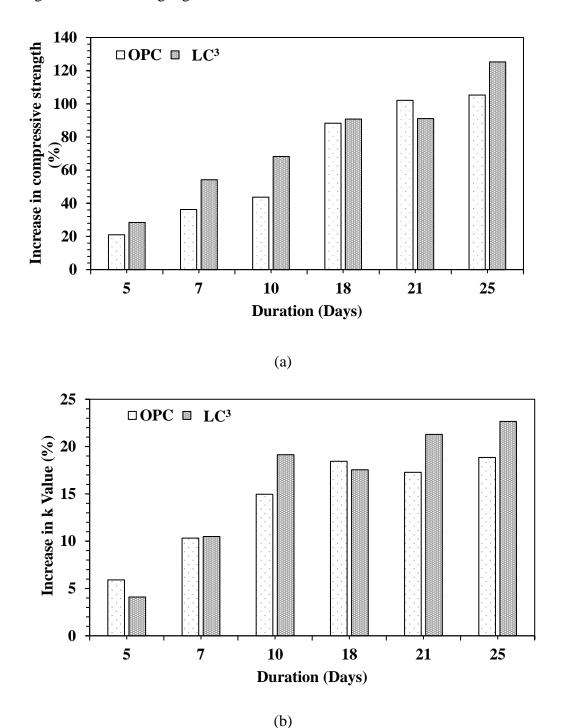


Figure 4.18: Comparison of destructive and non-destructive analysis (a) day-to-day percentage increase in compressive strength values (destructive) with respect to 3 day, and (b) day-to-day percentage increase in equivalent stiffness value (non-destructive) with respect to 3 day using EPS configuration

The sensitivity order of k value for various piezo configurations is EPS > SBPS > NBPS. In addition to this, the suitability of these three piezo configurations is described as follows: EPS configuration is suitable for monitoring the compressive strength of newly concrete structure because of its higher sensitivity and monitoring can be started from the moment concrete is cast; SBPS configuration is suitable for a condition where the sensor cannot be embedded, and NBPS configuration is suitable to monitor the strength of newly concrete structure in a reusable form. For real-life scenario, the applications of EPS configuration are corrosion monitoring in RC structure and strength monitoring of concrete structures; the application of SBPS configuration are damage detection in concrete structures, and loosening and tightening of bolt in industry, and the application of NBPS configuration are monitoring of pipeline corrosion, and assessment the condition of human bones, tissues, and other biomedical subjects.

4.4 PREDICTION OF COMPRESSIVE STRENGTH USING ML MODELS

In this study, firstly, EPS configuration dataset consisting of five features (independent variables) such as x, y, k, f, a and one response which is compressive strength (dependent variable) is choosen, where x is the real component of mechanical impedance, y is the imaginary part of mechanical impedance, k is the equivalent stiffness, f is the frequency and a is the age of the concrete. Each feature consists of 4500 data points of the ternary blended concrete system imported into the app in the form of predictor (x, y, k, f, a) and response (compressive strength). The entire workflow for training the regression model is explained in Ch. 3 (Section 3.23). After training the models, best-model is selected and then the other configurations dataset of different blended concrete system were trained and tested on the best-suited model. The performance of the model is estimated by using the equations (3.1 to 3.4) as mentioned in Ch. 3.

Table 4.1 shows the model performance comparison between different regression models used for prediction of compressive strength using EPS configuration dataset of LC^3 system. In this table, it is observed that the coefficients of multiple determination (R^2) value for linear regression, robust linear regression and linear SVM models is 0.94, coarse gaussian SVM is 0.97, interaction linear regression, stepwise linear regression, quadratic SVM, medium gaussian SVM models is 0.99 and cubic SVM, fine gaussian SVM is 1, which indicates that models predict the compressive strength variability with 94 %, 97 %, 99 %, and 100 % accuracy in

terms of \mathbb{R}^2 . Linear regression, robust linear regression and linear SVM have shown the lower value of \mathbb{R}^2 because these three models are linear models that consist of only linear terms. Cubic SVM and fine gaussian SVM model have shown the most admirable value of \mathbb{R}^2 but in terms of errors (RMSE and MAE), fine gaussian SVM perform the best followed by cubic SVM because fine gaussian SVM is a highly flexible model which allows rapid variations in the response function, while cubic SVM is medium flexible. Therefore, the best model chosen from all ML regression models is fine gaussian SVM model and it is named as CSM-1-EPS. The other fine gaussian SVM models are designated as CSM-1-SBPS, CSM-1-NBPS, CSM-2-EPS, CSM-2-SBPS, and CSM-2-NBPS in which CSM-1 and CSM-2 represents the dataset for ternary blended concrete and conventional concrete systems, respectively, EPS, SBPS, and NBPS represents the different piezo configurations, and CSM represent the compressive strength model.

Table 4.1: Comparison between different models

Model		RMSE			
Number	Model	(%)	\mathbb{R}^2	MSE (%)	MAE (%)
1	Linear Regression	1.74	0.94	3.04	1.36
2	Interactions Linear				
	Regression	0.88	0.99	0.78	0.61
3	Robust Linear				
	Regression	0.83	0.94	3.55	1.29
4	Stepwise Linear				
	Regression	0.83	0.99	0.68	0.56
5	Linear SVM	1.82	0.94	3.33	1.28
6	Quadratic SVM	0.86	0.99	0.75	0.59
7	Cubic SVM	0.47	1	0.22	0.46
8	Fine Gaussian SVM	0.46	1	0.21	0.44
9	Medium Gaussian SVM	0.59	0.99	0.35	0.49
10	Coarse Gaussian SVM	1.34	0.97	1.78	0.97

In CSM-1-EPS model, R², RMSE, MSE and MAE were found to be 1, 0.46 %, 0.21 % and 0.44 % respectively while for CSM-1-SBPS and CSM-1-NBPS models the values are 1, 0.47 %, 0.22 %, 0.45 % and 1, 0.42 %, 0.18 %, 0.39 % respectively as shown in Table 4.2. This implies

that the proposed model CSM-1-EPS, CSM-1-SBPS and CSM-1-NBPS predicts the compressive strength with an error of less than 1 %. The selected features are in good agreement with the value of MSE, MAE and RMSE since a higher value of R^2 corresponds to a smaller MSE, MAE and RMSE. Figure 4.19 (a, c, and e) represent the graph between response (compressive strength) and a record number of predicted value and true value. Figure 4.19 (b, d, and f) represent the graph between the predicted response and true response. From these figures, it is observed that data points are near the perfect prediction line, which indicates that the model predicts the compressive strength with good accuracy. Hence, it is concluded that the compressive strength models' prediction accuracy for the ternary blended concrete system exhibits a good correlation.

In CSM-2-EPS model, the R^2 , RMSE, MSE and MAE were found to be 0.99, 1.06 %, 1.21 % and 1.018 % respectively while for CSM-2-SBPS and CSM-2-NBPS models are 0.99, 1.033 %, 1.067 %, 0.976 % and 0.99, 1.020 %, 1.041 %, 0.981 % respectively as shown in Table 4.3. This implies that the proposed model CSM-2-EPS, CSM-2-SBPS and CSM-2-NBPS predicts the compressive strength with least error (less than 2 %). The plot of this model is represented in Figure 4.20. Hence, it is concluded that for a conventional concrete system, all the models exhibit satisfying correlation.

Table 4.2: Performance of the ML model for ternary blended concrete system

Parameter	CSM-1-EPS	CSM-1-SBPS	CSM-1-NBPS
RMSE	0.46	0.47	0.42
R-Squared	1	1	1
MSE	0.21	0.22	0.18
MAE	0.44	0.45	0.39

Table 4.3: Performance of the ML model for conventional concrete system

Parameter	CSM-2-EPS	CSM-2-SBPS	CSM-2-NBPS
RMSE	1.06	1.033	1.020
R-Squared	0.99	0.99	0.99
MSE	1.12	1.067	1.041
MAE	1.018	0.976	0.981

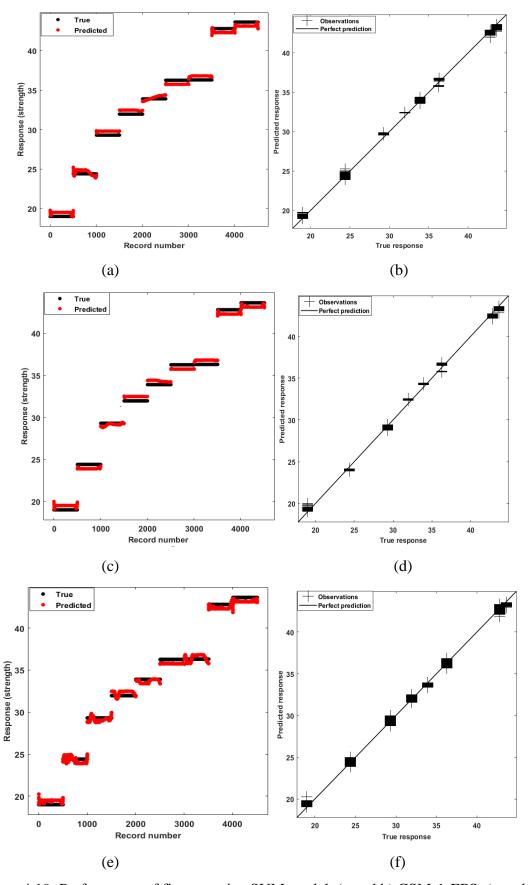


Figure 4.19: Performance of fine gaussian SVM model, (a and b) CSM-1-EPS, (c and d) CSM-1-SBPS, and (e and f) CSM-1-NBPS

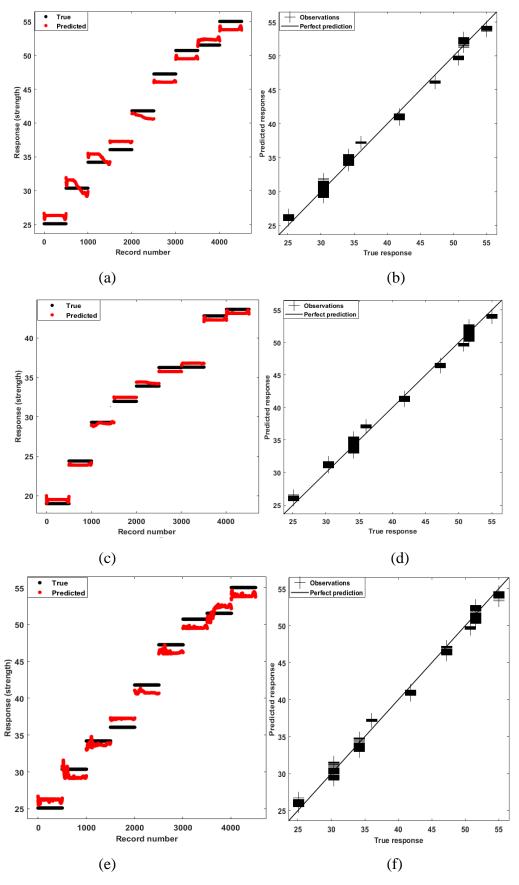


Figure 4.20: Performance of fine gaussian SVM model; (a and b) CSM-2-EPS, (c and d) CSM-2-SBPS, and (e and f) CSM-2-NBPS

On comparing the model performance of both the systems (conventional concrete and ternary blended concrete) it can be noticed that the proposed models provide a good correlation with the features in both the systems. By just using the EMI data in the form of x, y, f, k and a value as input to the model, it gives the output in the form of compressive strength. For the real-life field applications, just monitoring these five parameters using any of the three-sensor configurations, the contractor can predict the structure's compressive strength. Hence, the proposed fine gaussian SVM models (CSM-1-EPS, CSM-2-EPS, CSM-1-SBPS, CSM-2-SBPS, CSM-1-NBPS, and CSM-2-NBPS) are used for predicting the compressive strength of the structure non-destructively.

4.5 CONCLUDING REMARKS

This chapters presents the development of ML models to predict the strength of sustainable concrete blends using EMI data. Based on the raw EMI signature of different piezo configurations (EPS, SBPS, NBPS), it can be concluded that all the three piezo configurations could sense the changes during strength gain and their sensitivity is in the order of EPS > SBPS > NBPS. On comparing the day-to-day percentage increase in strength gain (destructively) with the day-to-day percentage increase in equivalent stiffness parameter (non-destructively), it can be concluded that equivalent structural parameter is a good indicator of strength and could be used in real-life scenario without any destructive testing. Furthermore, based on the prediction of compressive strength using ML models, it is concluded that the fine gaussian SVM models predict the compressive strength with excellent accuracy for ternary blended concrete and conventional concrete system, respectively. It is recommended that CSM-1-EPS and CSM-2-EPS models serves as the most suitable model for all newly developed constructions for predicting the strength of concrete from day 1, which helps in taking an on-spot decision on the removal of formwork, thus ensuring safety while minimizing unnecessary delay. CSM-1-SBPS and CSM-2-SBPS models are suitable for structures where the sensor cannot be installed inside the concrete, while CSM-1-NBPS and CSM-2-NBPS models are suitable where the accessibility is restricted. The models developed depend on the acquired data of piezo sensors which in turn depend on the type and size of the PZT patches, type and thickness of the bonding layer and the concrete system in which the sensor is embedded. Hence, these models cannot be considered as a universal one. Therefore, it is recommended that similar calibration should be first established in the laboratory for the particular concrete under investigation before using the method in the field.

CHAPTER-5

PREDICTION OF EMI DATA FOR DIFFERENT RC STRUCTURES SUBJECTED TO CORROSION

5.1 INTRODUCTION

Besides the early-age hydration and strength development in concrete structures, the durability of concrete is vital with regards to a reinforced structure's lifespan. As pointed out in Chapters 1 and 2, corrosion of steel bars in concrete is probably the most serious durability problem of RC structures in the modern time. The main corrosive agents i.e., the chlorides ions can ingress into concrete from several sources such as the use of groundwater/seawater in the mix or contaminated aggregates. When the sufficient amount of chloride ions reaches the steel/concrete surface, they may reduce the alkalinity of the pore solution thereby initiating corrosion. Initiated corrosion progresses rapidly and reaches a level that weakens the structural integrity (such as mass and stiffness) and load-bearing capacity, leading to failure of the structure and in turn huge amount of economic loss. This chapter covers durability experiments conducted on RC specimens followed by the development of ARIMA model based on EMI data of corrosion to predict baseline and future EMI data

5.2 PREPARATION OF CONCRETE SPECIMENS AND DATA ACQUISITION

In this study, cylindrical concrete specimens of 100 mm x 200 mm size were cast using three mixes, Mix A (conventional), Mix B (Fly ash with 35 % replacement of OPC), and Mix C (Fly ash-based geopolymer with 100 % replacement of OPC). Concrete specimens are prepared by adding cement, fine aggregate, coarse aggregate, and water according to the IS 10262:2009 standard. The details of all mix proportions are given in Table 5.1. The Water-to-cement ratio of various mix designs is kept at 0.43. The details of aggregate grading and sand zoning information are given in Table 5.2 to 5.4. High yield strength deformed (HYSD) steel bar of 16 mm diameter and 150 mm long was placed centrally before the cast in which 50 mm is projected out at one end of the cylinder. EPS is placed near the rebar at a horizontal and vertical distance of 20 mm and 50 mm, respectively, in all the specimens, as shown in Figure 5.1. The reason for choosing this distance is because the sensing area of a single PZT can vary anywhere from 0.4 m to 0.45 m (sensing radius) on the composite RC structure as explained by Park et al.

(2003). The same distance in reinforced concrete structures to detect the corrosion in rebar was used by Talakokula et al. (2015). The specimens are cured for 28 days at standard conditions (temperature: 20 ± 2 °C, relative humidity: ≥ 95 %) (Shi et al., 2019). After 28 days of curing, the baseline signature data were acquired at standard conditions using an LCR meter.

Table 5.1: Mix Proportion of Mix A, Mix B and Mix C

Materials	Mix A	Mix B	Mix C
w/c Ratio	0.43	0.43	-
Cement (kg/m ³)	482.55	313.66	-
Fine Aggregate (kg/m ³)	932.33	901.45	500.83
Coarse Aggregate (kg/m ³)	744.38	719.73	876.5
Water (kg/m ³)	207.5	207.5	-
Superplasticizer (% by weight of	0.3	0.3	-
cement)			
Fly ash (kg/m ³)	-	168.89	-
Ratio of Na ₂ SiO ₃ / NaOH	-	-	2.5
Fly ash +GGBS (kg/m ³)	-	-	550
Na ₂ SiO ₃ (kg/m ³)	-	-	239.64
NaOH (kg/m ³)	-	-	95.86

Table 5.2: Sieve analysis of Fine Aggregate

IS Sieve	Quantity Retained (Kg)	Percentage Retained (%)	Cumulative Percentage Retained (%)	Percentage Passing
4.75mm	0.012	1.2	1.2	98.8
2.36mm	0.047	4.7	5.9	94.1
1.18mm	0.162	16.2	22.1	77.9
600μ	0.210	21	43.1	56.9
300μ	0.289	28.9	72	28
150μ	0.222	22.2	94.2	5.8
Pan	0.04	-	-	-

Table 5.3: Physical properties of Fine Aggregate

S.No.	Property	Results
1	Max. sand size	4.75 mm
2	Zone	2
3	Specific Gravity	2.71
4	Water Absorption	2.04

Table 5.4: Sieve analysis of Coarse Aggregate

S.No.	IS Sieve	Weight	Percentage	Cumulative	Percentage
	size	Retained	Retained	Percentage	Passing
		(kg)	(%)	Retained (%)	
1	40 mm	0	0	0	100
2	20 mm	0.088	4.4	4.4	95.6
3	10 mm	0.882	44.1	48.5	51.5
4	4.75 mm	0.97	48.5	9.7	3
5	Pan	0.06	-		-

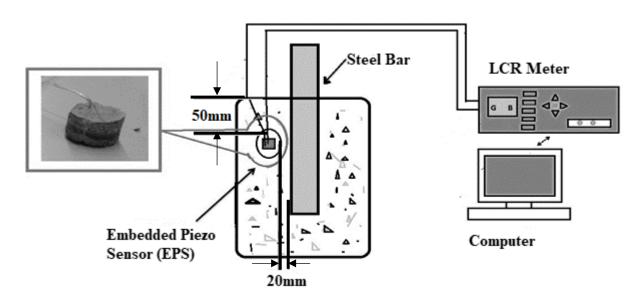


Figure 5.1: Experimental setup

The EMI signature for all the mixes was acquired multiple times until there is the repeatability of signatures to ensure that signatures are stable with respect to the hydration process.; after that, specimens were subjected to accelerated chloride laden environment (3.5 % NaCl solution) until failure as shown in Figure 5.2. The EMI data were frequently acquired from all the specimens during the exposure period to monitor the changes.

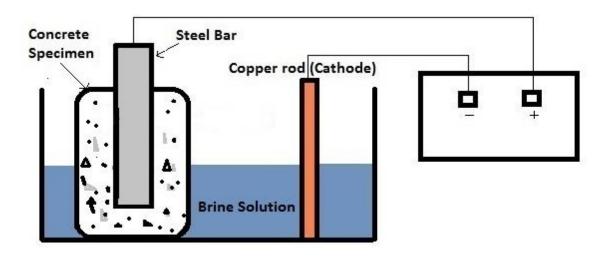
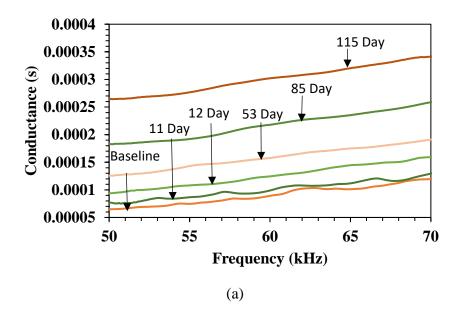


Figure 5.2: Accelerated corrosion setup

Figure 5.3 shows a variation of conductance signatures for 115 days of accelerated corrosion exposure for a typical specimen of Mix A, B and C. It can be observed that the conductance signature gradually shifts upwards with an increase in corrosion exposure days in all the mixes, thus sensing the changes occurring in the concrete systems due to corrosion.



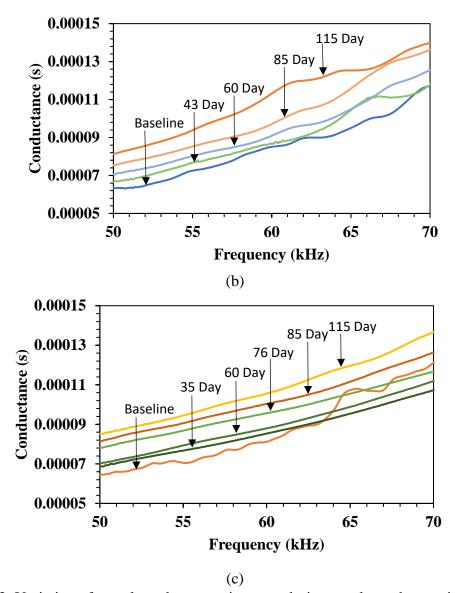


Figure 5.3: Variation of actual conductance signature during accelerated corrosion exposure (a) Mix A, (b) Mix B (c) Mix C

Figure 5.4 shows a variation of RMSD indices for Mix A, B, and C during an accelerated corrosion exposure period of 115 days in the frequency range of 50-70 kHz. Table 5.5 to 5.7 shows the interpretation of RMSD values with the correlation of visual inspection and variation in raw signatures during corrosion exposure for Mix A, B, and C. From this Figure 5.4 and tables 5.5 to 5.7, it is observed that the quantitative analysis of raw signatures using RMSD can be effectively used to identify the different phases of corrosion as given by Tuutti's model (1982).

Table 5.5: Interpretation of RMSD, visual inspection and raw signature for Mix A

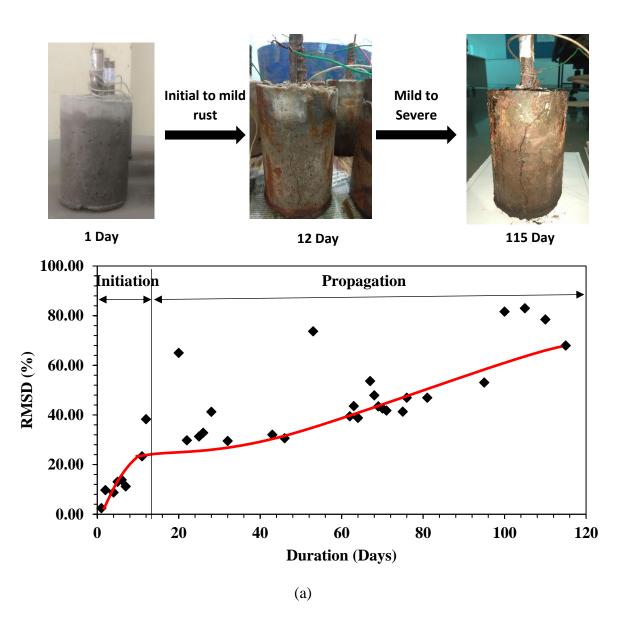
S.No.	RMSD Changes (%)	Observation based on Visual Inspection	Observation based on Acquired Signatures	Duration
Initiation Phase	0 to 23.35	No signs of corrosion	Deviation in conductance signature increases gradually	Until 11 days
First Crack	23.35 to 38.35	First corrosion- induced incipient crack	Sudden vertical shift in the signature	12 Day
Propagation Phase	38.35 to 68	Rust and corrosion products	Considerable vertical shift in the signature	12 to 115 Day

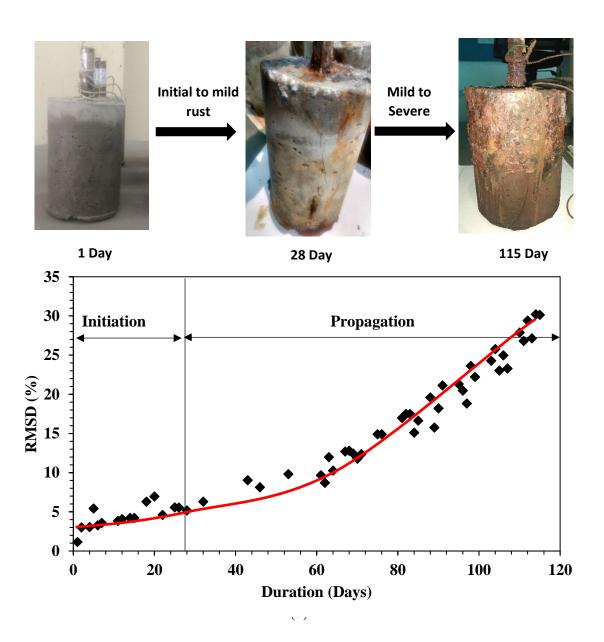
Table 5.6: Interpretation of RMSD, visual inspection and raw signature for Mix B

S.No.	RMSD Changes (%)	Observation based on Visual Inspection	Observation based on Acquired Signatures	Duration
Initiation Phase	0 to 5.16	No signs of corrosion	Deviation in conductance signatures are minimal	Until 28 days
First Crack	5.16 to 9.03	First corrosion- induced incipient crack	Considerable vertical shift in the signature	28 to 43 days
Propagation Phase	9.03 to 30	Highly voluminous corrosion products	Considerable vertical shift in the signature	28 to 115 days

Table 5.7: Interpretation of RMSD, visual inspection and raw signature for Mix C

S.No.	RMSD Changes (%)	Observation based on Visual Inspection	Observation based on Acquired Signatures	Duration
Initiation Phase	0 to 8	No signs of corrosion	Deviation in conductance signatures are minimal	Until 60 days
First Crack	8 to 17.68	Small-micro crack	Considerable vertical shift in the signature	60 to 76 days
Propagation Phase	17.68 to 23.75	Moderate rust formation	Considerable vertical shift in the signature	43 to 115 days





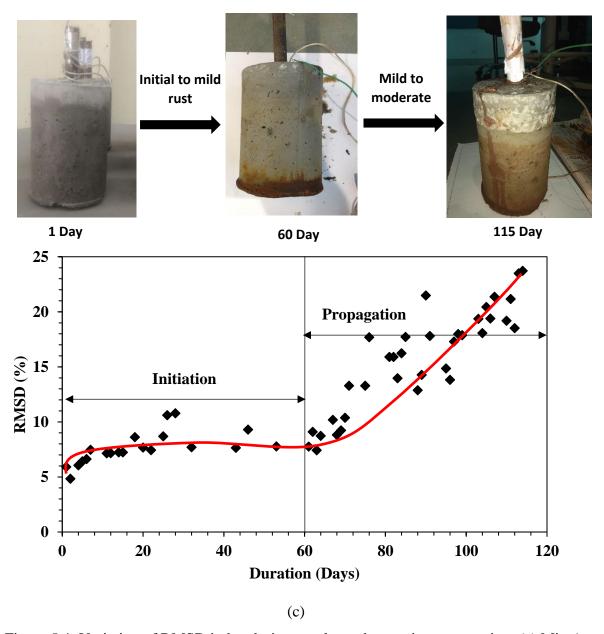


Figure 5.4: Variation of RMSD index during accelerated corrosion progression: (a) Mix A, (b) Mix B, (c) Mix C

From the above analysis, it can be concluded that the duration of the initiation phase is much higher in Mix C followed by Mix B and Mix A. Hence, it can be concluded that fly-ash blended concrete and geopolymer concrete have less permeability to water and chloride ions and exhibit good corrosion properties compared to the conventional concrete system, which is again reaffirmed non-destructively using the raw signature and RMSD indices analysis. Also, different phases of RC corrosion can also be identified non-destructively by using the quantitative analysis of raw signatures alone. However, this method is entirely based on the healthy baseline signature, which is a limitation when it needs to be applied for existing

structures. The healthy baseline signatures can be acquired for the new constructions without any difficulty by either using the surface-bonded piezo sensors or the EPS, but the problem exists for the already existing structures which are subjected to corrosion and their healthy baseline signature is not known to apply this technique. To overcome this limitation, a ML technique called ARIMA has been proposed to predict the structure's baseline and future EMI data.

5.3 DEVELOPMENT OF ARIMA MODEL

An ARIMA model is a class of statistical models for analyzing and predicting time series data. The steps involved in developing the ARIMA model are shown in Figure 5.5; first, conductance data is acquired from the EPS during the exposure of corrosion via EMI technique. The acquired conductance time series data has been checked for stationarity by determining the rolling statistics (rolling mean and rolling standard deviation) and Dickey-Fuller Test. If the data is not stationary, then d (where d is the difference order representing the number of times raw observations are differenced) is estimated to make the data stationarity. After the stationarity check, the ARIMA model has been established with (p, d, q) values using the following equations

$$\phi(D)(1-D)^d X(t) = \theta(D)a(t)$$
(5.1)

$$D = \frac{X(t-1)}{X(t)}$$
 (5.2)

$$\phi(D) = 1 - \phi_1 D - \phi_2 D^2 \dots \phi_{p-1} D^{p-1} - \phi_p D^p$$
(5.3)

$$\phi(D) = 1 - \phi_1 D - \phi_2 D^2 \dots \phi_{q-1} D^{q-1} - \phi_q D^q$$
 (5.4)

where, X(t) represents measured deviation for the moment t (t = 1, 2, 3, 4...115 days), while a(t) represents the residual errors at the same moment, which should satisfy the gaussian white noise process with a mean value of 0. $\phi_j(j = 1,2,3,4...q)$ indicates the parameters to be estimated, D is the difference operator, and p, d, and q are the autoregressive order, difference order, and moving average order of the model.

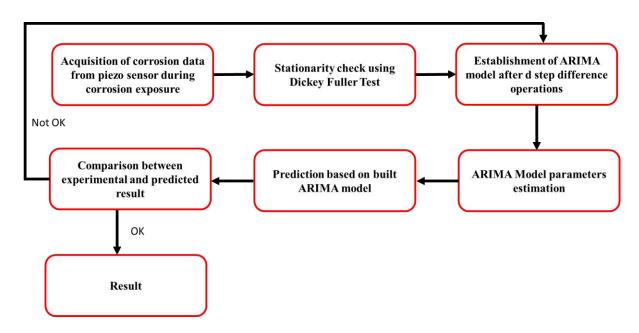


Figure 5.5: ARIMA model analysis process

The optimum value of (p, d, q) obtained from the above equations (5.1 to 5.4) are (0, 1, 0) for this dataset. Based on the obtained values, ARIMA model is developed which predicts tenth-step data and baseline EMI data. The details of the data used for training and prediction is shown in Table 5.8. The performance of the developed model has been done with the actual experimental data by determining mean absolute error (MAE), mean relative percentage error (MRPE), root mean absolute square error (RMSE) and root mean square mean relative error (RMSRE) as per the Eqs. (5.5 to 5.8)

$$MAE = \frac{1}{n_{te}} \sum_{i=1}^{n_{te}} |x_i - \overline{x_i}|$$
 (5.5)

$$MRPE = \frac{1}{n_{te}} \sum_{i=1}^{n_{te}} \left| \frac{x_i - \overline{x_i}}{x_i} \right| X 100\%$$
 (5.6)

$$RMSE = \sqrt{\frac{1}{n_{te}} \sum_{i=1}^{n_{te}} (x_i - \overline{x_i})^2}$$
 (5.7)

$$RMSRE = \sqrt{\frac{1}{n_{te}} \sum_{i=1}^{n_{te}} \left(\frac{x_i - \overline{x_i}}{x_i}\right)^2}$$
 (5.8)

where, n_{te} is the number of data for performance evaluation, $\overline{x_i}$ and x_i represents the predicted data and the measured data at the time t, respectively.

Table 5.8: ARIMA Model details

S.No	Data used for training	Prediction
	(Days)	
1	0-25	35th Day, 50 kHz - 70 kHz
3	0-75	85th Day, 50 kHz - 70 kHz
4	10-100	Baseline, 50 kHz – 70 kHz

In time-series analysis, uncertainties do play a vital role and it is obvious that uncertainty cannot be removed; the only thing that can be done is to minimize the uncertainty. In time-series analysis using the ARIMA model, two kinds of uncertainties are usually encountered, such as noise and seasonality.

(a) Uncertainty due to noise

Sometimes uncertainty can be found in a time-series data if the variables are independent and identically distributed with a mean of zero. Then it can be incorporated into the model by adding a noise factor (ϵ) in the equation below as

$$\phi(D) = 1 - \phi_1 D - \phi_2 D^2 \dots \phi_{q-1} D^{q-1} - \phi_q D^q + \epsilon$$
 (5.9)

where, ϵ is the white noise, which may be gaussian and non-gaussian.

In this study, the mean of the variables is not zero; hence this uncertainty is not included in the model.

(b) Uncertainty due to seasonality

Sometimes uncertainty can be found due to seasonality in the ARIMA model in which the data experiences any predictable fluctuation or pattern that repeats over a period. However, in this study, the data used for the prediction does not experience any change due to seasonality. Figure 5.6 shows the variation of conductance signature at a particular frequency (60 kHz) during corrosion exposure. From this figure 5.6, it is observed that the conductance value is different at different duration and there is no repetition in a period. Hence, this uncertainty is not included in the model. If the data experience any seasonality, then it can be incorporated into the model by subtracting the values from time cycle in which it was repeating. The equation of the ARIMA model with seasonality is changed as

$$\phi(D^S) = 1 - \phi_1 D^S - \phi_2 D^{2S} \dots \phi_{p-1} D^{(p-1)S} - \phi_p D^{pS}$$
(5.10)

$$\phi(D^s) = 1 - \phi_1 D^s - \phi_2 D^{2s} \dots \phi_{q-1} D^{(q-1)s} - \phi_q D^{qs}$$
 (5.11)

where S is the seasonality

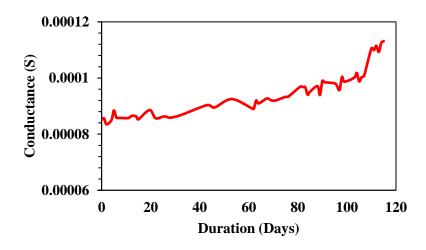


Figure 5.6: Variation of conductance signature during accelerated corrosion at 60 kHz frequency

5.4 ANALYSIS BASED ON ARIMA MODEL

To predict the baseline signature data, ARIMA model is developed for all the mixes by training the experimental data acquired from the piezo sensor during the corrosion exposure from days 10-100. From Figure 5.4, it can be observed that EMI data acquired from a piezo sensor varies with the exposure time (in days) and frequency (here from 50-70 kHz). Equations of the ARIMA model (Eq. 5.1-5.4) developed is a function of time, but the EMI data acquired from the sensors is both time and frequency dependent. Hence, to predict the baseline signature which is a backward prediction in time frequency is kept constant, and the respective data is predicted for a particular frequency. Using 10-100 days data, ARIMA model is trained for a particular frequency (for E.g. 50 kHz) and baseline data is predicted for the same frequency, in this manner the entire baseline data is predicted for the entire frequency range (50-70 kHz) by carrying out the loop multiple times. The entire predicted data is plotted to obtain the baseline signature for the frequency range of 50-70 kHz. Figure 5.7 compares predicted baseline signature using ARIMA model for all the mixes with respect to baseline signature acquired from the experiments. It can be observed that both the experimental and predicted signatures follow the same trend with an error of less than 6 % in Mix A, 5 % in Mix B and, 8.5 % in Mix C as calculated from MRPE and RMSRE shown in Table 5.9.

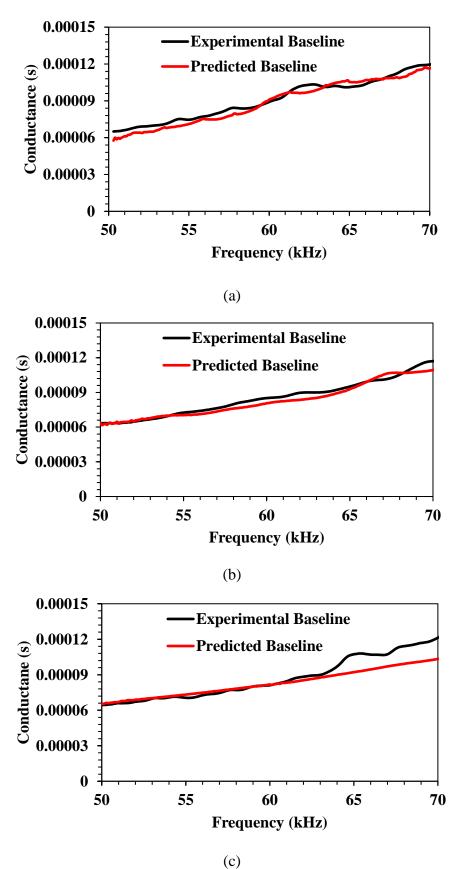


Figure 5.7: Experimental and predicted baseline signature comparison for (a) Mix A, (b) Mix B, and (b) Mix C

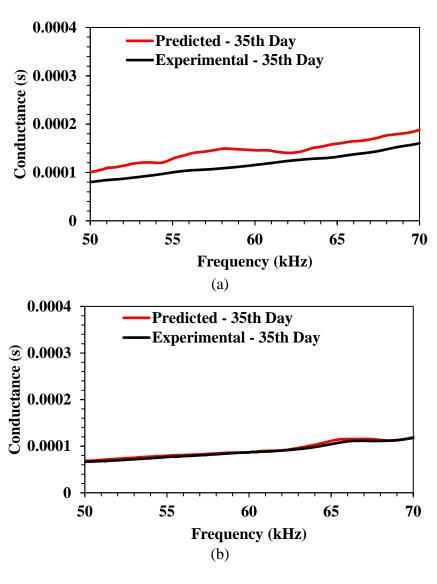
Table 5.9: Analysis of baseline predictions using 10 to 100 days training data

S No	Indices	Mix A	Mix B	Mix C
1	MAE	0.0000036	0.0000029	0.0000053
2	MRPE (%)	4.48	3.53	5.75
3	RMSE	0.0000039	0.0000035	0.0000078
4	RMSRE (%)	5.21	4.09	8.14

From the above observations, it can be concluded that ARIMA model performs best for all the mixes with an acceptable deviation of less than 8.5 %. Hence, it can be concluded that for existing structures, where the baseline data is not available, ARIMA model can be used to predict the same. To apply this model for any existing structure where the baseline data is missing, just bond the sensor on the structure and acquire the data from the same day onwards and predict the healthy state data by training the acquired data of several days/years. Once the baseline data is predicted for the existing structure, EMI technique can be effectively applied to timely assess the corrosion, take remedial measures, and prevent catastrophic failure in the future.

To predict the tenth step futuristic corrosion data which is a forward prediction, ARIMA model is developed by training the experimental data acquired from the piezo sensor during corrosion exposure from days 0 to 25 and 0 to 75 datasets respectively. Firstly, 0 to 25 days data of a particular frequency is used for training and predicting the tenth step (35th day) future data at the same frequency; similarly, 0 to 75 days data at a particular frequency is trained to predict the 85th day future data for the same frequency. In this manner, the loops are carried out for each frequency, and the entire future data is predicted for the total frequency range (50-70 kHz) with different datasets and plotted to get the conductance signature at 35th and 85th day. Figures 5.8 and 5.9 show a comparison between predicted 35th day and 85th day data with experimental data for all three mixes using 0 to 25 and 0 to 75 days datasets, respectively. It can be observed that for the predicted 35th day data, the performance of the model in terms of MRPE and RMSRE are 24.70 % and 25.68 % for Mix A, 2.95 % and 3.44 % for Mix B and 4.73 % and 5.11 % for Mix C, implies that except for the convention mix the errors for both fly-ash blended and geopolymer mix are within the acceptable range. For 85th day data prediction, the MRPE and RMSRE are found to be 8.55 % and 8.61 % for Mix A, 0.75 % and 0.93~% for Mix B and 5.25~% and 5.79~% for Mix C, respectively. Compared to the $35^{th}\,day$

prediction of conventional concrete, the MRPE and RMSRE value reduces from 24.70 % to 8.55 % and 25.68 % to 8.61 % for Mix A, and 2.95 % to 0.75 % and 3.44 % to 0.93 % for Mix B, respectively at 85th day prediction data which implies that the prediction using the model has improved once the training data is increased from 25 to 75 days. For Mix C, the MRPE and RMSRE value at 35th and 85th day prediction remains more or less same due to minimal deviation in the raw signatures. From Table 5.10 and 5.11, it could be seen that the values of the errors have dropped significantly for 85th day prediction for Mix A and B because the model contains a large amount of data for training (0 to 75 days). Hence, it can be concluded that predicted values are more accurate when the model is trained with large voluminous data because it is well-known that as the training data increases, the efficiency of the prediction model is also increase. In order to predict the future day corrosion data using this model, it needs to be ensured that the model contains a large number of days for training.



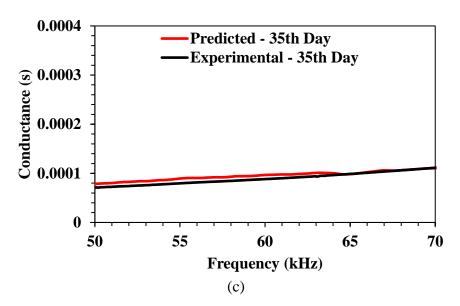
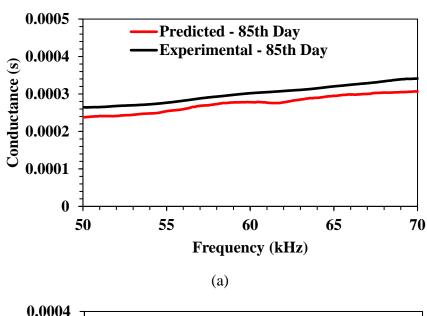
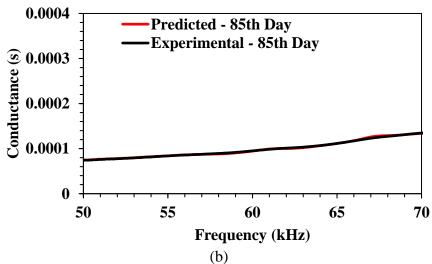


Figure 5.8: Comparison of predicted EMI with experimental EMI data using 0 to 25 days training data for (a) Mix A, (b) Mix B and (c) Mix C





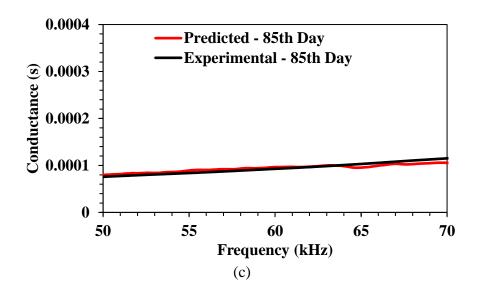


Figure 5.9: Comparison of predicted EMI with experimental EMI data using 0 to 75 days training data for (a) Mix A, (b) Mix B and (c) Mix C

Table 5.10: Analysis of tenth-step prediction using 0 to 25 days training data for all mixes

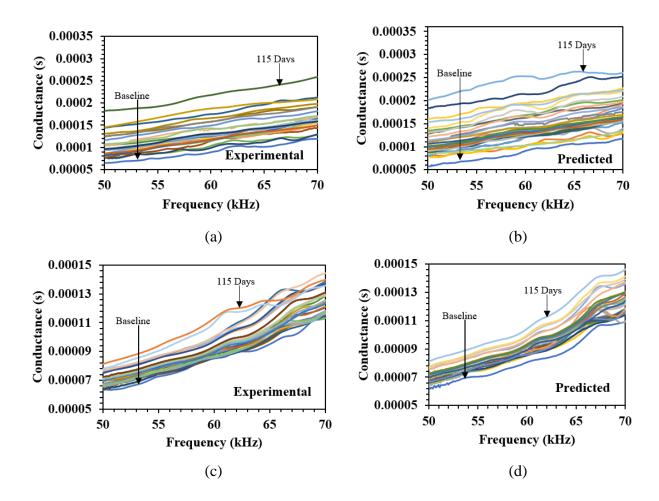
	Mix A	Mix B	Mix C
Indices	50-70kHz	50-70kHz	50-70kHz
MAE	0.0000277	0.0000025	0.0000044
MRPE (%)	24.70	2.95	4.73
RMSE	0.0000283	0.0000030	0.0000049
RMSRE (%)	25.68	3.44	5.11

Table 5.11: Analysis of tenth-step prediction using 0 to 75 days training data for all mixes

	Mix A	Mix B	Mix C
Indices	50-70kHz	50-70kHz	50-70kHz
MAE	0.000025	0.00000075	0.0000048
MRPE (%)	8.55	0.75	5.25
RMSE	0.000025	0.000001	0.0000051
RMSRE (%)	8.61	0.93	5.79

5.5 QUALITATIVE AND QUANTITATIVE VALIDATION OF PREDICTED AND EXPERIMENTAL DATA

In this section, qualitative and quantitative validation between experimental and predicted data has been carried out. For the qualitative and quantitative validation, first 5-day experimental conductance/RMSD data in the frequency range of 50 to 70 kHz has been used for training the ARIMA model and predict the 6th day data, then upto 6th day experimental data has been used and then predict the next day data. In this manner, upto 115 days data was predicted using the same ARIMA model. Figure 5.10 shows a qualitative comparison between experimental and predicted signature for a typical specimen of Mix A, B, and C. It can be observed from Table 5.12 that the conductance values predicted varies similarly with the values acquired experimentally during the corrosion exposure of 115 days. On comparing qualitatively, both the predicted and experimental signatures follow the same upward increasing trend in all the mixes; hence the qualitative representation, which is the first step in any SHM, ARIMA model provides absolute match which can aid for future diagnostics related to corrosion assessment.



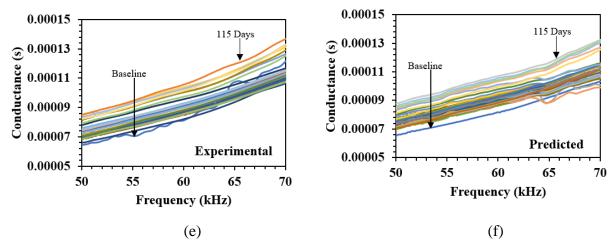


Figure 5.10: Comparison between experimental and predicted signature for (a) Mix A-experimental, (b) Mix A-predicted, (c) Mix B-experimental, (d) Mix B-Predicted, (e) Mix C-experimental, and (f) Mix C-predicted

Table 5.12: Comparison between experimental and predicted conductance values for all mixes

	Experimental		Predicted	
	Baseline 115th Day		Baseline	115th Day
	$(x 10^{-5} s)$	$(x 10^{-4} s)$	$(x 10^{-5} s)$	$(x 10^{-4} s)$
Mix A	5.00	2.6	5.65	2.6
Mix B	6.35	1.44	6.65	1.46
Mix C	6.43	1.36	6.53	1.32

Figure 5.11 shows the comparison of RMSD indices of experimental and predicted signatures for a typical specimen of Mix A, B, and C during corrosion exposure days. Table 5.13 shows the variation of the indices during the corrosion period of 115 days and their difference, it can be observed that the predicted values follow the same pattern as experimental with small difference, notable to see that the increase in the RMSD values of Mix A on 12th day, Mix B on 43rd day, and Mix C on 76th day (due to the formation of the incipient crack) can also be similarly seen in the predicted one. The phases of corrosion identified by the experimental indices can also be replicated in the predicted indices with the same duration and same increasing trends such as initiation phase till 11th day and propagation phase from 11th day to 115th day for Mix A, initiation phase till 28th day and propagation phase from 28th day to 115th day for Mix B, and initiation phase till 60th day and propagation phase from 60th day to 115th day for Mix C, respectively. Therefore, from the above results, it can be concluded that ARIMA model can be effectively applied for diagnosing the corrosion process of concrete via

predicting healthy state and future EMI data. With the help of predicting healthy state data for existing structures, EMI technique can be used to extract equivalent structural parameters such as stiffness, mass, and damping which would be useful to understand the in-depth phenomenon of material deterioration due to corrosion. As ARIMA model is data based, it can be implemented in various SHM applications such as material deterioration/damage assessment, deformation monitoring, strength monitoring, corrosion monitoring, and objectionable movements and geometry changes.

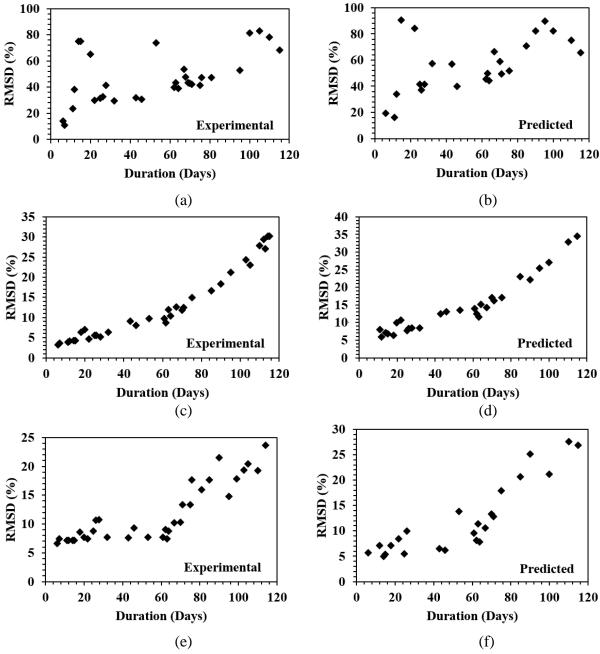


Figure 5.11: Comparison between experimental and predicted RMSD value for (a) Mix A-experimental, (b) Mix A- predicted, (c) Mix B- experimental, (d) Mix B- Predicted, (e) Mix C- experimental, and (f) Mix C- predicted

Table 5.13: Comparison between experimental and predicted RMSD values for all mixes

	Experimental		Predicted		Difference	
	1st Day	115th Day	1st Day	115th Day	1st Day	115th Day
	(%)	(%)	(%)	(%)	(%)	(%)
Mix A	11	68	16	65.6	-5	2.4
Mix B	3	30	5	34	-2	-4
Mix C	6	23	5	28	-1	-5

5.6 CONCLUDING REMARKS

This chapter presents the prediction of baseline and future EMI data of different blended RC structures subjected to chloride-laden environment using ARIMA model via EPS. From the EMI signature analysis, it can be concluded that the EPS is effective in sensing the changes during the corrosion process of RC structures and RMSD indices were found to be an effective statistical parameter for identifying the different phases of corrosion non-destructively. Based on the baseline and future prediction data using ARIMA model, it can be concluded that conductance signature of predicted and experimental ones follows the same trend with an acceptable error for all the mixes and 0-75 days training dataset performed the best to predict the tenth step future data with an agreement of good validation. The qualitative and quantitative analysis of predicted and experimental data is also done to show the efficiency of the ARIMA model which proved to be not only matching with the trend but also able to identify the onset of damage before the first cracks were visible to naked eye; thus, this technique provides a novel way for predicting the EMI data of RC structure subjected to chloride-laden environment which can be used for existing structures to predict the service life.

CHAPTER-6

DETERIORATION OF EQUIVALENT STRUCTURAL PARAMETERS IN PRESTRESSED CONCRETE SYSTEMS SUBJECTED TO CHLORIDE LADEN ENVIRONMENT

6.1 INTRODUCTION

In this chapter, the deterioration of structural parameters namely equivalent stiffness, mass and damping due to corrosion in PC structures using a SPPS via EMI technique is presented. The effectiveness of the SPPS was first demonstrated qualitatively by the change in the raw conductance signatures during the corrosion progression and different phases of corrosion (initiation, propagation, and cracking) was identified by the quantitative statistical damage indices. Assessment of material degradation under chloride-laden environment was done via deterioration of equivalent structural parameters identified by SPPS from the raw admittance signatures and demonstrated the possibility to calibrate with the corrosion rates.

6.2PREPARATION OF CONCRETE SPECIMENS AND DATA ACQUISITION

In this study, PC beams of size 500 mm x 100 mm x 100 mm were cast with OPC (43 grade) conforming to IS 8112 cement. The PC beam were casted using a prestressing steel wire of size 4mm placed at a distance of 20 mm above the bottom of the mould, which is then placed on the top of prestressing bed. An SPPS was attached to the prestressing wire at the center (as shown in Figure 6.1) using epoxy. prestressing wire was anchored at one end of the beam using an anchor plate and anchor bolt and the other end is used for applying the required amount of prestressing force, the entire experimental setup is shown in Figure 6.2. A stress level of $0.6f_{\rm ptk}$, where $f_{\rm ptk}$ is the ultimate tensile strength, was applied using the hydraulic jacking system. SPPS configuration was used because of the limitation in surface bonding the sensor on to the thin prestressing wire and the embedded sensor was not considered as the focus of monitoring was to assess the deterioration of the prestressing wire. After the SPPS was installed, concrete was poured into the mould and the prestressing wire was cut after tenth-day with the help of motorized electronic steel cutter (in which the one end of the wire is fully cut, and another end kept 100 mm outside). The curing was done by wet jute bag for 28 days at standard temperature, baseline signatures were acquired using LCR meter after the curing period until the signatures

were found stable with respect to the curing process. After the baseline signature was acquired, PC specimens were subjected to accelerated chloride environment by immersing them in a brine solution (3.5 % NaCl) and applying a constant current until the specimens cracked. The exposed length of the specimens is 325 mm (65 % of the beam length) and the size of the prestressing wire is 4 mm. A constant current of 150 mA/cm² was applied using an electrical loop between the prestressing wire (acting as an anode) and copper bar (acting as a cathode) to accelerate the corrosion process. During the accelerated corrosion exposure, the admittance signatures (conductance and susceptance) were acquired periodically from the SPPS instrumented in all specimens, signatures were recorded after removing them from the brine solution and drying the specimens for half an hour at standard conditions (temperature: 20 ± 2 °C, relative humidity: ≥ 95 %) in a lab environment.

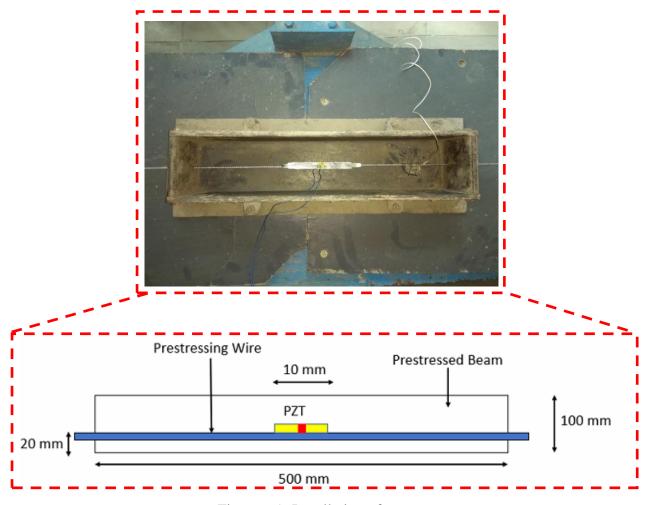


Figure 6.1: Installation of sensor

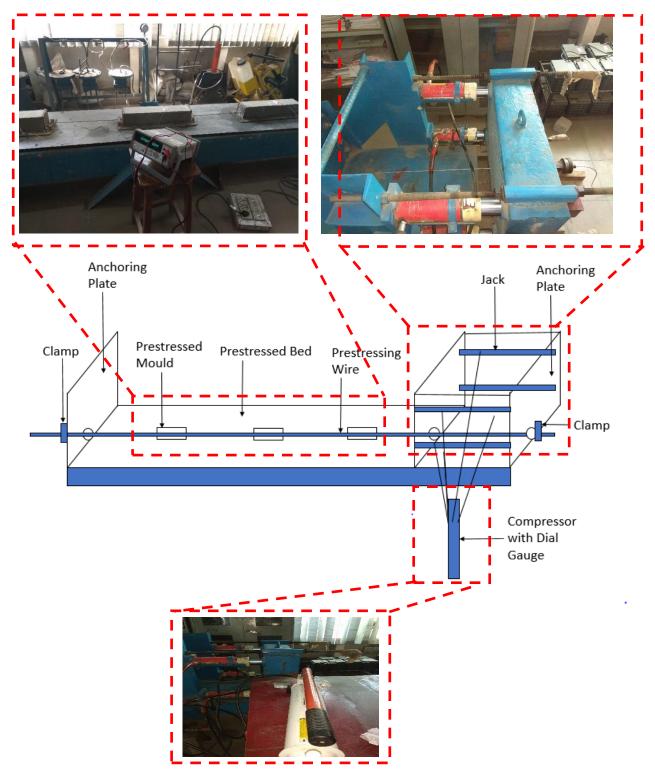


Figure 6.2: Experimental setup of prestressed concrete structures

Equivalent structural parameters (stiffness, mass, and damping) were extracted from the raw signatures of the SPPS for assessing the deterioration of structural parameters. For the specimens in this study, an equivalent system consisting of the spring element (k)-mass element (m) and damper (c) in series combination as shown in Figure 6.3(a) is choosen based on the match betwee the experimental and equivalents plots of "x" and "y" of the extracted ipedance

plots, which can be seen in Figure 6.3(b) and (c) for the selected frequency rangeof 220 kHz-270 kHz.

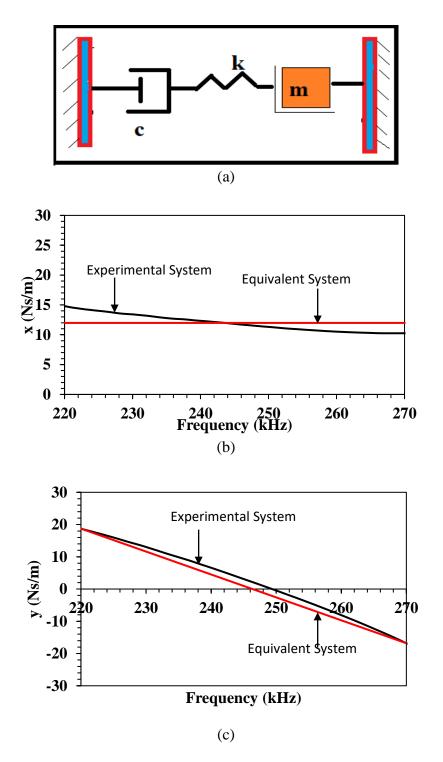


Figure 6.3: Identified system (a) Series combination of spring, mass, and damper (b) variation of x vs f and (c) variation of y vs f

6.3 RESULTS AND DISCUSSION

The variation of conductance vs frequency for a typical specimen acquired at 7th day as compared with the pristine stage is shown in Figure 6.4 (a). A visible deviation in the signature can be observed after 7 days of exposure, however, there were no observable rust signs visible to the naked eye on the surface of the specimens (as shown in Figure 6.4 (a)). Figure 6.4 (b) shows all signatures at various days during the corrosion exposure, on 11th day a substantial downward vertical shift can be seen in the signature. At this stage when the specimen was visually observed, signs of rust were seen throughout the portion of the specimen which was immersed in a brine solution. It is worth mentioning that at this stage, there was no visible damage appeared to the naked eye in the form of cracks. When the specimen was further exposed to the accelerated corrosion until 21 days, the signatures acquired at 19th day and 20th day shows a considerable upward vertical shift even though cracks were not visible to the naked eye. On the 21st day, visible cracks were seen on the specimen running throughout the immersed portion, at this stage the corrosion exposure was stopped, and the final signature was acquired. On observing the 19th, 20th and 21st-day signature, it could be seen that the SPPS could detect the approaching failure state way before any signs of it was visible to the naked eye. The approaching damage state identification using piezo sensors is also reported by Chalioris et al. (2015, 2016, 2020). The major upward vertical shift in signature just before the cracks was indicative of the serious nature of damage inflicted on the specimen at the previous days. Ultimately at the 21st day, the SPPS was damage due to cracks in the specimens and the signatures significantly shift downwards. Thus, from the raw signatures, it can be concluded that the SPPS can effectively detect the flaw/damage in the neighbourhood of the sensor qualitatively due to corrosion.

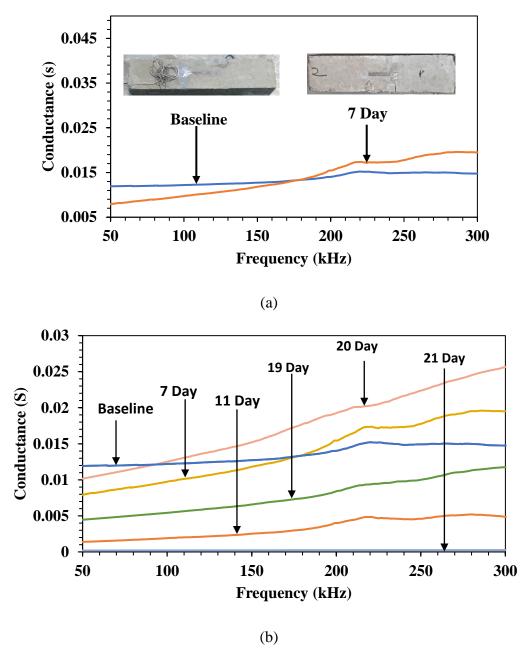


Figure 6.4: Variation of conductance vs frequency for a typical specimen (a) 7th Day vs baseline, (b) signature at various days during corrosion exposure

Figure 6.5 shows the variation of the RMSD index with the corrosion exposure in days in the frequency range 50-300 kHz. Until 7th day the increase in RMSD was around 20 % thereafter, there was a sudden increase in the value to about 40 % on 11th day, on the 21st day to 98 % where visible cracks have appeared on the specimen.

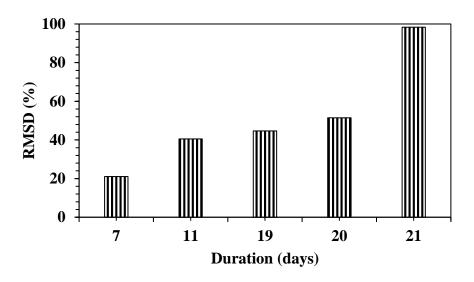
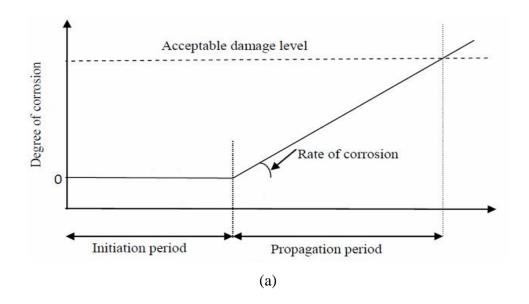
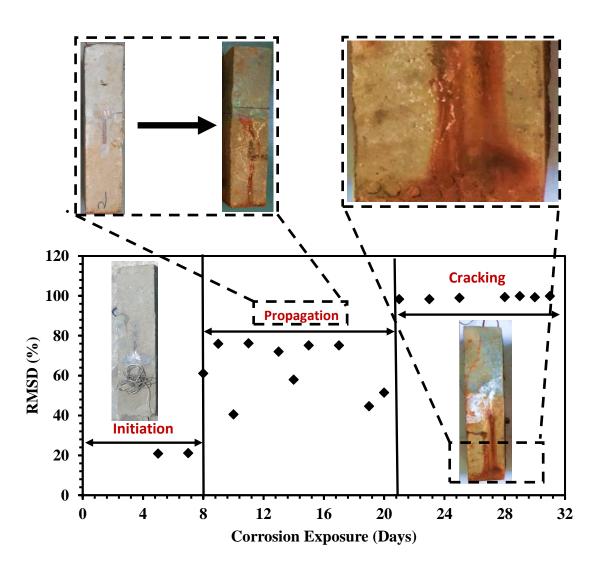


Figure 6.5. Variation of RMSD index with corrosion exposure

On comparing the visual inspection in correlation with the raw signature data and RMSD index, it can be concluded that until 7th day, deviation in the raw signatures were minimal with RMSD value up to 20%, visual observation of the specimen also shows no signs of corrosion (see Figure 6.6(b)), hence this phase can be termed as the first phase of corrosion namely 'corrosion initiation'. This followed by the second phase, corrosion propagation ranging from 8-20 days during which considerable vertical shifts in the signatures can be noticed and RMSD values were also seen in an increasing trend (from 21 % - 51 %). Visual observation also shows mild to severe rust formations as shown in Figure 6.6(b). After initiation of corrosion, chlorides ions break down the passive layer and starts corroding the prestress bar. The accumulation of the highly voluminous corrosion products creates internal stress which results in cracking, hence the phase three, cracking stage started after 20th day where the signature has a sudden downward shift and RMSD index recorded a value of 98 %, and several cracks along the length of the bar can be seen during visual observations as shown in Figure 6.6(c). The concept of Initiation, Propagation and cracking periods can be illustrated by famous Tuutti's model (1982) as shown in Figure 6.6(a), the same can be illustrated using the RMSD index as shown in Figure 6.6(b) which indicates that during the initiation phase ranging from 0-7 days, RMSD values slightly increased up to 20 %, followed by propagation phase ranging from 8-19 days, an increase in the RMSD indices up to 98 % can be seen and finally cracking phase started after 21 days during in which the RMSD values remained constant due to failure of the specimen by cracking as shown in Figure 6.6(c). Hence the SPPS can be effectively utilized for identifying the relevant phases of corrosion via raw signatures (qualitatively) and RMSD indices (Quantitatively).





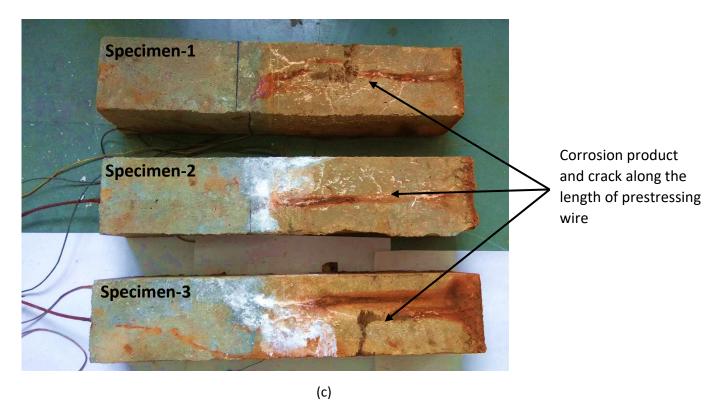
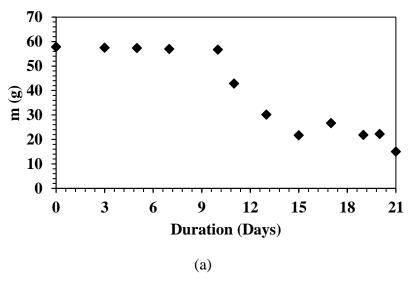


Figure 6.6: Initiation, propagation, and cracking phase (a) Tutti's Model, (b) Identification of corrosion phases based on RMSD, (c) Specimen condition in cracking phase

Figure 6.7 shows the variation of equivalent structural parameters such as mass, stiffness and damping during corrosion progression. The effect of deterioration due to corrosion is clearly evident in the figure, with corrosion progression, mass and stiffness can be seen to reduce and the damping to increase. During the initiation phase, structural stiffness and the mass parameter was found to reduce by 1.55 % and damping increased by 7.02 %, while in propagation phase, structural stiffness and mass parameter were found to reduce gradually from 1.55-61.56 %, damping increased from 7.02-155.39 %.



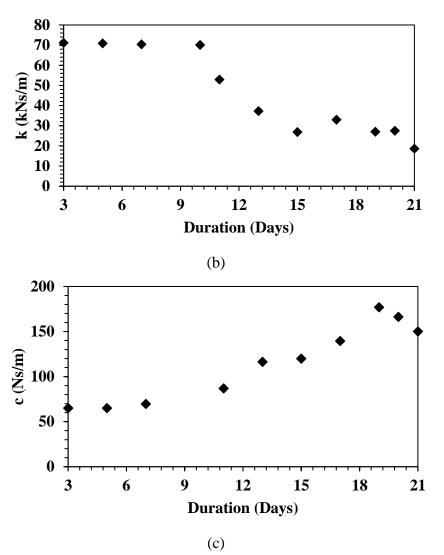


Figure 6.7: Identified equivalent structural parameter during corrosion exposure (a) Identified mass, (b) Identified stiffness, (c) Identified damping

It is noteworthy to mention that the above structural parameters which are identified by the SPPS are based on the equivalent system identified by the sensor and not the actual mass, stiffness, and damping. To calibrate these structural parameters with the actual ones, the actual initial mass of the specimen was measured before embedding and final mass after completion of the experiment by splitting the specimen. Knowing the SPPS identified initial and final mass and the actual (initial and final) mass, both are related with a non-dimensional constant (Λ_m) which was found to be 0.57. This correlation will be useful in calculating the corrosion rates of the rebar because measuring the actual mass loss in real-life structures is not possible as a prestress bar is placed inside the concrete. Knowing Λ_m , actual mass loss of the specimen for all days during corrosion progress was calculated and the corrosion rates were determined using gravimetric mass loss technique ASTM G1 (ASTM, 2012). Figure 6.8 shows a plot between

the corrosion rates calculated and the equivalent spring stiffness k identified by SPPS. Following empirical relation was found between the two using the regression analysis.

Corrosion rate =
$$-2x10^{-08}k^2 + 0.0008k + 30.742$$
 (6.1)

At higher corrosion rates it can be seen that the SPPS identified stiffness is lowest and this relation demonstrates to calibrate the corrosion rates of the PC members non-destructively using equivalent spring stiffness k identified by SPPS which can be employed in real-life structures were measuring the actual stiffness loss is difficult. The proposed method can only be applicable to the newly developed structures. For applicability on an existing structure, the EMI technique can be utilized by bonding the sensor on the surface of the structure externally (surface bonding the PZT patches) or in non-bonded fashion using non-bonded piezo sensor (Chalioris et al., 2016; Voutetaki et al., 2016). As the EMI technique is based on the healthy state signature data which for an existing structure is not available, hence, to monitor such structures, the first day signature after bonding the patch is considered as the baseline data and monitoring is done based on this. However, to overcome the baseline signature problem for an existing structure, ARIMA model developed in Ch. 5 can be used to predict the baseline signature from the future data by developing machine learning model. Once the healthy state/baseline has been predicted, the proposed EMI method can be effectively applied to an existing structure.

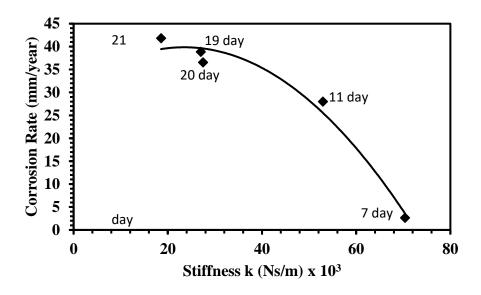


Figure 6.8: Corrosion rate vs equivalent stiffness

6.4 CONCLUDING REMARKS

This chapter presented a simplified SPPS for diagnosing the corrosion progression and assessing the deterioration of structural parameters in PC members. The research shows the effectiveness of SPPS in sensing the changes occurred during the corrosion progression (namely initiation, propagation, and cracking phases) non-destructively without any a prior information related to the host structure, which could be very useful and successfully applied to large-scaled existing PC structures for detection of the onset of the damage and for the approaching material failure way before any sign of it was visible to the naked eye. SPPS can be installed easily on the prestress bar of any diameter in comparison to the surface bonded sensor which requires the machined surface of the prestress bar to bond which would be difficult in these cases as the diameter of the bars are usually small to bond the sensor. SPPS based assessment is not only simple to apply and analyze but at the same time provides an essence of the associated damage mechanism.

CHAPTER-7

MONITORING THE DURABILITY OF DIFFERENT CONCRETE SYSTEMS SUBJECTED TO COMBINED ENVIRONMENTAL AND MECHANICAL LOADING

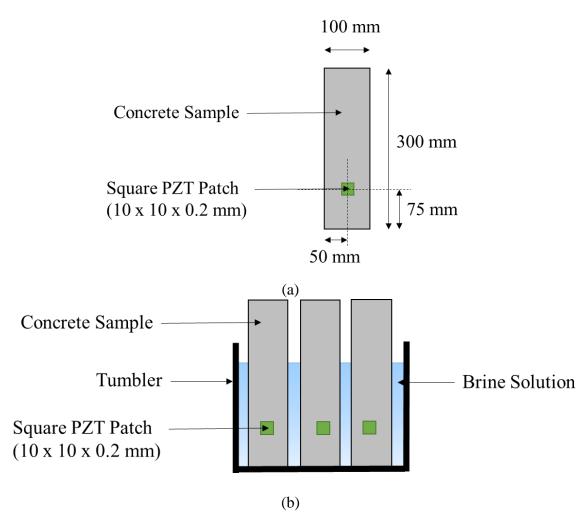
7.1 INTRODUCTION

This chapter compares durability aspects of two different concrete systems namely LC³ and conventional OPC subjected to combined effect of chloride-induced corrosion and compression loading with ideal chloride effect using piezo sensors. These are the pioneering studies on application of EMI technique for diagnosing and assessing the health of two concrete systems subjected to the combined mechanical and environmental loading condition. Chloride penetration, chloride profiles, diffusion coefficient and surface concentrations were the various parameters considered for evaluation of durability performance. Further, an equivalent structural parameter (mass, stiffness, and damping) model has been proposed to identify the deterioration in these two systems and an empirical relation between equivalent stiffness and surface concentration is established.

7.2 SAMPLE PREPARATION AND METHODOLOGY

In this study, concrete prisms with dimensions $100 \text{mm} \times 100 \text{mm} \times 300 \text{mm}$ were prepared for experimental analysis using the same mix design followed in the earlier chapters. After 24 hours of casting, the prisms are cured at standard conditions (temperature: $20 \pm 2^{\circ}\text{C}$, relative humidity: $\geq 95\%$) for 28 days before subjected to testing environment. The cured specimens were sealed at bottom with wax so that chloride penetrates only from the sides when subject to combined effect. For monitoring this effect, a square PZT patch of size $10 \text{ mm} \times 10 \text{ mm} \times 0.2 \text{ mm}$ was surface bonded on the prisms at the vertical distance of 75mm from the bottom and 50 mm from the side face, as shown in Figure 7.1(a). The thickness of the epoxy is maintained at $1/3^{\text{rd}}$ of the thickness of the PZT patch so the shear lag effect is negligible. After the specimens were cured, they were placed vertically in a stainless-steel tumbler containing brine solution of 3% concentration, as shown in Figure 7.1(b). The entire setup consisting of tumbler with specimens dipped in solution is placed under a compressive test rig and the desired stress level for combined environmental and mechanical loading test was applied on the specimens. It is ensured that the sealed wax surface is placed at the bottom. The level (60 % of the height of the

prism which is 180mm) of the brine solution in the tumbler was maintained properly so that exposure of chloride penetration is uniform throughout the experimental period. Before placing the specimens in the brine solution, the compressive strength of the prisms was determined destructively based on which the desired stress level for the combined application is calculated. The average value of compressive strength with standard deviation for both the systems are shown in Figure 7.2. The compressive stress ratio of 0 and 0.3 (30% of breaking load, for OPC 90 kN and for $LC^3 = 86$ kN) was used for the application of mechanical loading on the prisms, as shown in Figure 7.1 (c). The prisms were unloaded after exposure time of 6 and 10 weeks for measuring the chloride profiles. During the entire exposure period, EMI signatures were also acquired from the bonded PZT patch throughout the experiment as shown in Figure 7.3.



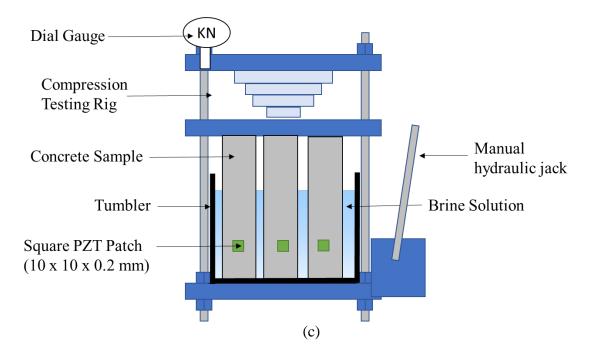


Figure 7.1: Schematic representation of: (a) Concrete sample, (b) tumbler with filled solution, and (c) setup for chloride diffusion into concrete under compression

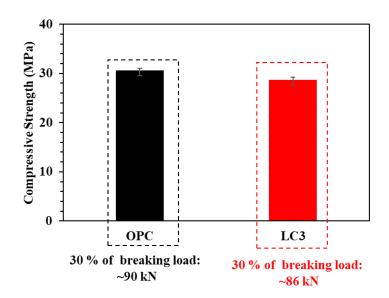


Figure 7.2: Average compressive strength

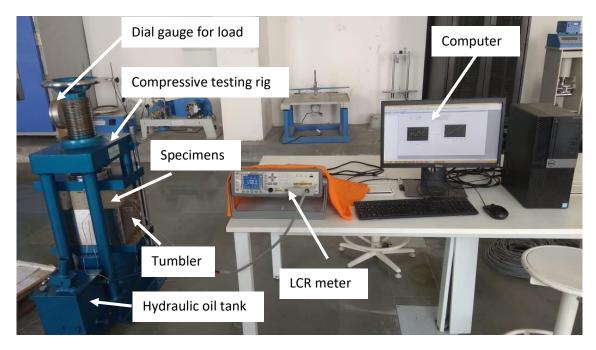


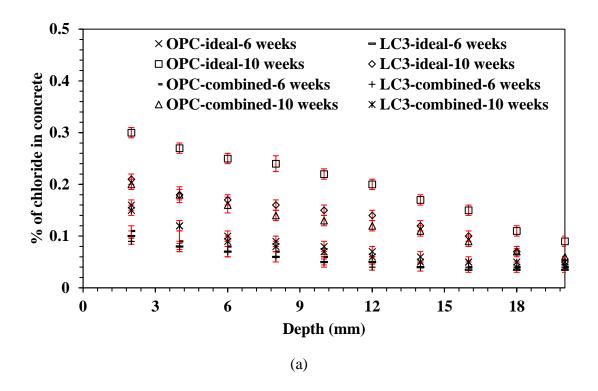
Figure 7.3: Experimental Setup

7.3 DETERMINATION OF CHLORIDE PROFILE

The first step for obtaining the chloride profile from the concrete samples is sampling, which is an essential part of this study. Generally, three types of methods are used for obtaining the samples such as dry drilling, dry grinding, and dry cutting. In dry drilling method, a rotary hammer is used for obtaining the powder. In the dry grinding method, the exposed surface of the concrete is grinding at different depths by using mechanical devices. In dry cutting method, saw slices from the concrete core are cut at certain depths and subsequently crushed to obtain the powder. Among all the methods mentioned above, it is observed that the dry drilling method is economical and quicker. Hence, the dry drilling method was used to obtain the powder from the concrete specimens in this study, as suggested by climent et al. (2001). Firstly, the concrete prims were taken out from the tumbler after releasing the applied load and the powder sample was collected from the exposed surface at 2 mm intervals up to a penetration depth of 20mm which is then kept in a small plastic container to protect it from environmental effects. It must be ensured that the concrete surface must be protected from drying before the drilling process, as the drying process will change the chloride profile. The chemical analysis of the powder sample collected is performed according to the recommendation of RILEM TC-178 (Testing and modelling chloride penetration in concrete).

7.4 RESULTS AND DISCUSSION

The chloride profiles of OPC and LC³ concrete systems under ideal chloride and combined effect for 6 and 10 weeks are shown in Figure 7.4(a). It can be observed that the chloride profiles show a gradual decrease in chloride content with increasing distance from the surface in both the concrete systems. The percentage of chloride penetration into concrete increased with the exposure period (6 to 10 weeks). Figure 7.4(b) shows the schematic representation of how chloride concentration decreases with increasing depth (Sun et al., 2012) because of various mechanism (capillary absorption, chemical reactions with the porous matrix, and sorption processes) which effect the transport of ions through the pore space of hydrated concrete surface (Yao et al., 2017). On comparing the chloride profiles of both the concrete systems, it can be seen that LC³ system exhibits lower chloride content than OPC system as LC³ system produces more Friedel's salt than that of OPC paste and has better binding capacity as reported by (Sui et al., 2019; Shi et al., 2017 and Maraghechi et al., 2018). On comparing the combined environmental and mechanical effect with that of ideal chloride effect, the percentage of chloride penetration into concrete is significantly less in combined effect. It is due to the fact that the compression force applied tend to compress the pore space between the concrete matrix; thus making it difficult for the ions to penetrate inside it.



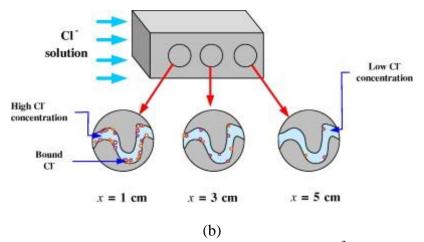


Figure 7.4: (a) Chloride profiles comparison between OPC and LC³ during ideal chloride and combined effect and (b) schematic representation of chloride concentration decreases with increasing depth (Sun et al., 2012)

Regression analysis were performed on these measured chloride profiles using the errorfunction solution to Fick's 2^{nd} law using Equation 7.1 to obtain the apparent chloride diffusion coefficients (D) and surface concentrations (*Cs*) as per BS EN 12391-15:2015

$$c_x = c_i + (c_s - c_i) \cdot (1 - erf \left[\frac{x}{2\sqrt{D.t}}\right])$$
 (7.1)

where, C_i is the initial chloride content (%), C_s is the surface concentration (%), x is depth at which the chloride content measured (m), D is the apparent chloride diffusion coefficient (m²/s), t is the exposure time in (s), and C_x is the chloride content measure at x distance.

Figure (7.5(a) and 7.6) shows the apparent chloride diffusion coefficient and surface concentrations of different concrete systems at 6 and 10 weeks for ideal chloride and combined effect. It can be observed that the apparent chloride diffusion coefficient under ideal chloride and combined effect decreases, and surface concentration significantly increases with the increase in exposure period (6 to 10 weeks). Similar findings were also reported by Yao et al. (2017) while calculating the diffusion coefficients and surface concentrations at different time intervals. The decrease in apparent chloride diffusion coefficient is due to the fact that only free chlorides dissolved in the pore solution continue to penetrate through concrete and are responsible for initiating the corrosion process, remaining chlorides are either dissolved in the pore solution or chemically/ physically bound to the cement hydrates along their diffusion path. The amount of free chloride ions are thus reduced by this binding mechanisms; therefore, the rate of chloride ionic transport in concrete is also reduced as explained by Sun et al. (2012). Figure 7.5(b) shows the schematic representation of chloride diffusion coefficient decreasing

with increasing time. Also, LC³ concrete exhibited lower apparent chloride diffusion coefficients and surface concentrations than OPC concrete in both the effects. The lower apparent chloride diffusion coefficient of LC³ concrete can be attributed to its improved chloride binding capacity as well as refinement of pore solution and pore structure. The excellent chloride ion transport resistance in mortar and paste mixtures of LC³ was also reported by Maraghechi et al. (2018). The lower alkali ions content in pore solution of LC³ sample than that of OPC sample led to a lower chloride diffusion coefficient as reported by Sui et al. (2019). Hence, it can be concluded that LC³ concrete system exhibits high chloride diffusion resistance than that of OPC system. In terms of effects, the chloride diffusion and surface concentration are lower in combined effect than that of ideal chloride effect. The next section deals with the real-time monitoring and deterioration of concrete under ideal chloride and combined effect using piezo sensor-based EMI technique.

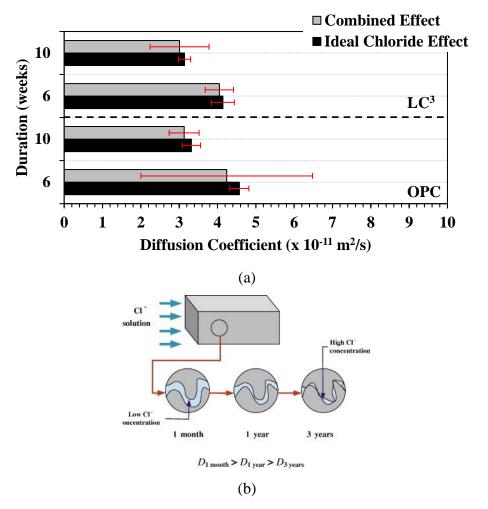


Figure 7.5: (a) Apparent chloride diffusion coefficient of different concrete system at 6 and 10 weeks of ideal chloride and combined effect and (b) schematic representation of chloride diffusion coefficient decreases with increasing time (Sun et al., 2012)

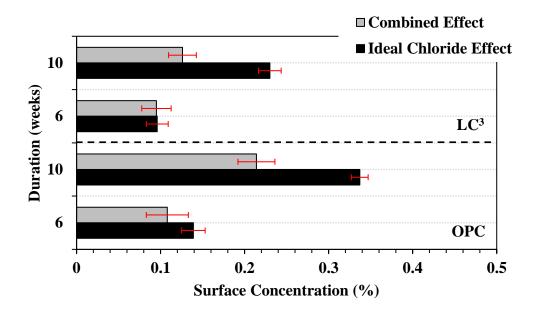


Figure 7.6: Surface concentrations value of different concrete system at 6 and 10 weeks of ideal chloride and combined effect

Figure 7.7 shows the baseline conductance signature of a typical OPC and LC³ concrete systems during ideal chloride and combined effect. It can be observed that the magnitude and the frequency of the resonance peak shift upwards under the influence of applied load in both the concrete systems. The similar observation was reported by Lim and Soh (2013) in case of damage detection and characterization using EMI technique under varying axial load.

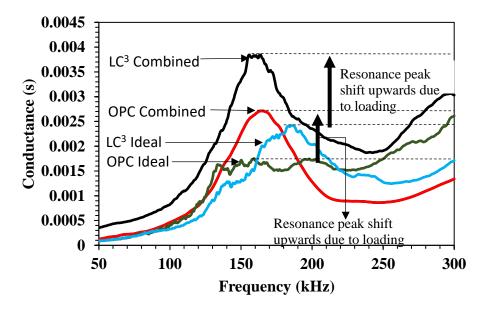
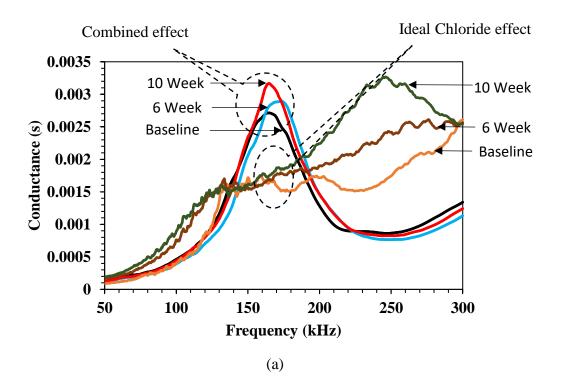


Figure 7.7: Baseline conductance signature of OPC and LC³

Figure 7.8 shows the comparison of variation in conductance signature due to ideal chloride and combined effect for a typical OPC and LC³ concrete specimen at different time intervals in a frequency range of 50-300 kHz. It can be observed that amplitude and frequency of the conductance signatures at resonance peak shift in the upward direction, which shows that the changes due to both the effects have been captured well by the attached SBPS. In both the systems, the results indicate that the combined effect attains lesser variation in conductance signature than ideal chloride effect. This can be due to compression of pore space between the concrete matrix, resulting in significantly lower chloride penetration into concrete under combined effect. Figure 7.9 shows the RMSD values of different concrete system at 6 and 10 weeks for ideal chloride and combined effect. It can be observed that until 6 weeks, the average RMSD values of OPC concrete system under ideal chloride and combined effect was found to be 34.15% and 16.82%, respectively. This signifies the significant deviation of RMSD value in ideal chloride than combined effect. As the exposure period increases to 10 weeks, the RMSD values increases from 34.15% to 53.20% and 16.82% to 19.79%. In LC³ concrete system, the average RMSD values under ideal chloride and combined effect was found to be 31.76% and 13.56%, respectively. This indicates that LC³ concrete system exhibited lower RMSD values than OPC concrete system which concur with the earlier observations of chloride profiles and diffusion coefficients.



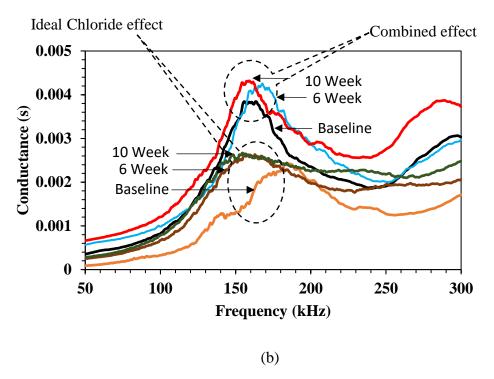


Figure 7.8: Comparison of variation in conductance signature due to ideal chloride and combined effect for a typical concrete specimen (a) OPC and (b) LC³

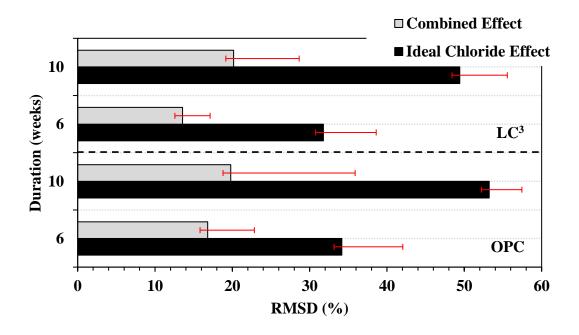


Figure 7.9: RMSD value of different concrete system at 6 and 10 weeks of ideal chloride and combined effect

To identify the deterioration of the structural parameters, equivalent system consisting of spring element (k), mass element (m) and damper element (c) in parallel combination is identified based on the impedance as shown in Figure 7.10.

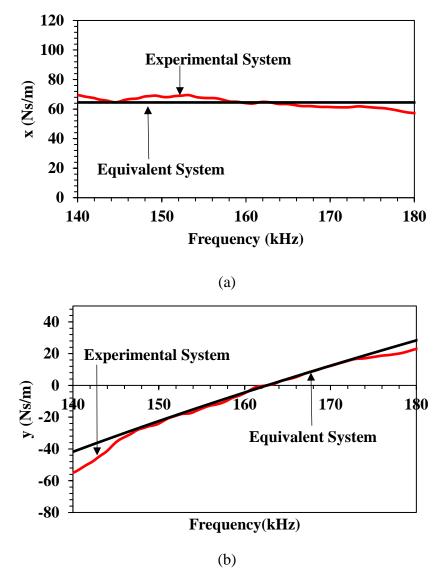


Figure 7.10: Comparison between experimental and identified equivalent structural system: (a) x vs frequency and (b) y vs frequency

The identified equivalent stiffness variation of OPC and LC³ concrete systems during ideal chloride and combined effect for a typical specimen is shown in Figure 7.11. It can be observed that the identified equivalent stiffness value decreases with increase in exposure duration. It is due to the fact that as the chloride penetrates into the concrete, the porosity inside the matrix of the concrete structure increases due to that the compressive strength decreases, thus the equivalent stiffness parameter decreases which is effectively captured by the attached SBPS.

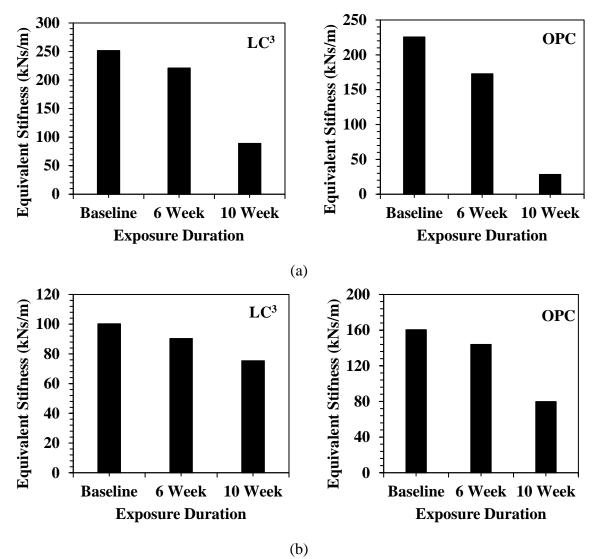


Figure 7.11: Equivalent stiffness variation for different concrete system (a) ideal chloride attack and (b) combined attack

Figure 7.12 shows the stiffness loss variation for different concrete systems under ideal chloride and combined effect for a typical specimen. The value of stiffness loss for different concrete system for different effects are shown in Table 7.1. It can be observed that the deterioration in terms of stiffness loss is significantly less in combined effect than ideal chloride. This findings concur with the observations reported by Yao et al. (2017) that significantly less chloride penetrates in the concrete under the influence of a given applied load. Also, the stiffness loss in LC³ concrete system is less than OPC concrete system, due to the synergy effect between calcined clay and limestone which can react with the tri-calcium aluminate (C₃A) from the clinker to form extra aluminates in the form of hemicarboaluminate (Hc) and

monocarboaluminate (Mc) phases, thus producing more Friedel's salt than that of OPC paste which has better chloride binding capacity as reported by Sui et al. (2019).

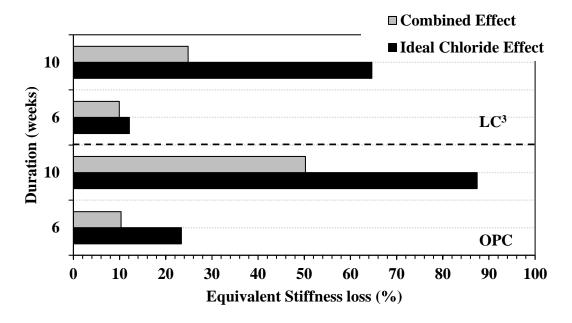


Figure 7.12: Equivalent stiffness loss for different concrete system at 6 and 10 weeks of ideal chloride and combined effect for a typical specimen

Table 7.1: Equivalent stiffness loss of different concrete system at 6 and 10 weeks of ideal chloride and combined effect

	Ideal Chloride Attack		Combined Attack	
	LC^3	OPC	LC ³	OPC
Initial stiffness (kNs/m)	251.58	225.65	100.249	160.46
Equivalent Stiffness at 6 weeks (kNs/m)	221.07	172.86	90.29	143.86
Equivalent Stiffness at 10 weeks (kNs/m)	88.96	28.30	75.35	79.82
Stiffness loss after 6 weeks (%)	12.12	23.39	9.93	10.33
Stiffness loss after 10 weeks (%)	64.63	87.45	24.83	50.25

Figure 7.13 shows the correlation between the equivalent stiffness and surface concentration with exposure for both the concrete systems under ideal chloride and combined effect. It can be observed that the equivalent stiffness parameter decreases, and surface chloride concentration increases as the exposure period increases. It is due to the fact that the chloride penetration and deposition makes the chloride higher and higher in the surface layer and leaching of cement hydrates makes higher surface porosity and higher pore network connectivity, thus higher the surface chloride concentration (Liu et al., 2014). Also, due to this higher porosity, the compressive strength of the concrete decreases, thus the equivalent stiffness parameter decreases.

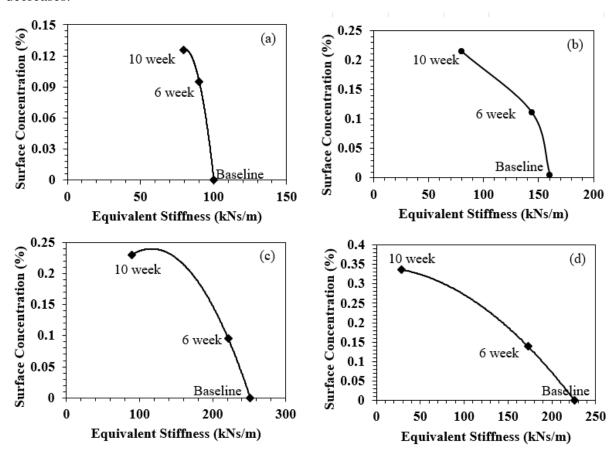


Figure 7.13: Correlation between equivalent stiffness and surface concentration with exposure duration for both concrete system (a) LC³-C, (b) OPC-C, (c) LC³-I, and (d) OPC-I

Based on the values of equivalent stiffness and surface concentration for both the concrete systems and effects, an empirical relation was developed for predicting the surface concentration in terms of k using the best-fit curve. The empirical relation for estimating the C_s for both concrete systems and effects namely, LC³-C, OPC-C, LC³-I, OPC-I are given by the Eqs. (7.2) - (7.5), respectively, in which I represent the ideal chloride effect and C represent the combined. Based on the empirical relations, it can be concluded that by just monitoring the

k value, one can directly get the value of surface concentration non-destructively, without measuring actual surface concentration, but more comprehensive investigations need to be performed on the effectiveness and reliability of the proposed empirical relations.

$$C_s = -3x10^{-4}(k)^2 + 0.0516(k) - 1.9479$$
(7.2)

$$C_s = -6x10^{-5}(k)^2 + 0.0118(k) - 0.3446$$
(7.3)

$$C_s = -1x10^{-5}(k)^2 + 0.0031(k) + 0.0624$$
(7.4)

$$C_s = -6x10^{-6}(k)^2 + 8x10^{-5}(k)^2 + 0.3444$$
(7.5)

7.5 CONCLUDING REMARKS

This chapter presents the durability aspects of OPC and ternary blended concrete made with LC³ under ideal chloride and combined effect (chloride-induced corrosion and compression loading) using the piezo sensor-based EMI technique. From the analysis of experimental results in this work, following conclusions can be drawn:

- 1) Based on the chloride profiles, diffusion coefficients and surface concentrations analysis, it is concluded that the deterioration of concrete under the combined effect is significantly less than ideal chloride effect and LC³ concrete system exhibits higher chloride resistance compared to the OPC concrete system.
- 2) The chloride diffusion coefficient under ideal chloride and combined effect significantly decreased and surface concentration increased with increase in the exposure period in both the concrete systems.
- 3) The raw EMI signature obtained from SBPS during the ideal chloride and combined effect at different time intervals reflects the changes sensed by the sensor.
- 4) The equivalent stiffness parameter derived from the EMI signature is very effective in monitoring the mechanical changes under the ideal chloride and combined effect.
- 5) Correlation between the equivalent stiffness and surface concentration with exposure duration under ideal chloride and combined effect indicates that the equivalent stiffness parameter is inversely proportional to the surface concentration and provides good insights into the material deterioration.

CHAPTER-8

CONCLUSIONS AND RECOMMENDATIONS

8.1 INTRODUCTION

This thesis embodies finding from the research work carried out on developing ML models for monitoring the strength and durability aspects of different concrete systems using piezo based impedance monitoring. The major novelty includes extensive experimental studies conducted on different concrete systems to acquire voluminous data related to strength and durability for developing the robust ML models. Pioneering studies on combined environmental and mechanical loading were conducted on sustainable concrete systems to depict real life exposure to the specimens in the laboratory.

8.2 RESEARCH CONCLUSIONS

The major research conclusions are summarized as follows

- Firstly, for different sustainable cementitious systems, comparison of EMI analysis
 with that of conventional Vicat's needle and micro-structural analysis (FTIR, XRD,
 and SEM) resulted in a correlation during the early ages. The resonance peak shift and
 amplitude variation serves as a most suitable indicator for monitoring the hydration
 process
- 2. The equivalent stiffness parameter extracted from the impedance spectra during the later curing ages is in good agreement with the maturity identified compressive strength in all the systems. The equivalent stiffness calculated from the maturity method and the one extracted from impedance show similar increasing trend with age for all the systems.
- 3. Further, for predicting the strength of cementitious systems, the cubic SVM and medium gaussian model predicts with excellent accuracy for OPC, FA-based binder system and LC³- based binder system respectively.
- 4. The feasibility of using different piezo configurations for monitoring the strength is studied in concrete systems, on comparing different sensor configurations, it can be concluded that all the three piezo configurations could sense the changes during strength gain and their sensitivity is in the order of EPS > SBPS > NBPS. The

- equivalent stiffness parameter from EPS not only provides an overall impression of the changes in the strength but also gives insights into the day-to-day percentage increase in strength gain.
- 5. Related to applications of different sensor configurations in real-life applications, EPS configuration is suitable for monitoring the compressive strength of new concrete structures since monitoring can be started from the moment concrete is cast; SBPS configuration is suitable for a condition where the sensor cannot be embedded, i.e for existing structures, and NBPS configuration is suitable to monitor the strength of newly concrete structure in a reusable form.
- 6. Fine gaussian SVM model provide a good correlation with the features in both (conventional and ternary blended) the concrete systems. Thus, the model can be effectively applied in real-life scenario for predicting the compressive strength of the structure non-destructively.
- 7. Durability studies on concrete system subjected to chloride environment, EPS is effective in sensing the changes during the corrosion process and RMSD indices were found to be an effective statistical parameter for identifying the different phases of corrosion non-destructively.
- 8. The ARIMA model developed for predicting both the backward EMI data and the future EMI data of corrosion was accurate, and its accuracy increased with large training data. The qualitative and quantitative analysis of predicted and experimental data show the efficiency of the ARIMA model which not only match the trend but also identifies the onset of damage before the first cracks were visible to naked eye.
- 9. The experiments conducted on PC concrete systems subjected to chloride environment with SPPS identifies different corrosion phases (namely initiation, propagation, and cracking phases) non-destructively without any a prior information related to the host structure. The physical models developed for monitoring the structural parameter deterioration (stiffness, mass, and damping) were effective in assessing the material degradation. Thus, the SPPS can be effectively employed in real-life scenario for diagnosing the PC structures subjected to corrosion.
- 10. Pioneering studies on OPC and LC³ systems subjected to environmental and mechanical loading resulted in concluding that the combined effect results in decreased levels of chloride profiles, diffusion coefficients and surface concentrations analysis.
 Under ideal chloride and combined effects, the equivalent stiffness parameter and

surface concentration indicates inverse corelation between them. Thus, the empirical relations can be effectively employed in real-life scenario for monitoring the surface concentration of the structures subjected to ideal chloride and combined effect.

- 11. Further, this research aimed at rigorously calibrating the impedance parameters with corrosion for more meaningful applications in real-life scenario.
- 12. The pioneering studies on combined environmental and mechanical loading experiments resulted in developing enhanced physical models for corrosion monitoring and diagnosis.

8.3 LIMITATIONS

The ML models developed depend on the acquired data of piezo sensors depend on the type and size of the PZT patches, type and thickness of the bonding layer and the concrete system in which the sensor is embedded. Hence, these models cannot be considered as a universal one. Therefore, it is recommended that similar calibration should be first established in the laboratory for the concrete system under investigation before using the method in the field. The developed ARIMA model for prediction of baseline and futuristic EMI data of corrosion is difficult to predict turning points like resonance peak in the conductance data, cannot be used for seasonal time series data, there is quite a bit of subjectivity involved in determining (p, d, q) order of the model, and also not suitable for long-term forecasts. Also, comprehensive investigations need to be performed on the effectiveness and reliability of the developed empirical relations for the surface concentration and equivalent stiffness.

8.4 SIGNIFICANT CONTRIBUTIONS

The significant contribution of this research work can be summarized as follows:

The different ML models have been developed using the EMI data to predict the
compressive strength of different cementitious systems based on the features such as
compressive strength, real component of mechanical impedance, imaginary part of
mechanical impedance, equivalent stiffness, frequency and curing age. The developed
ML model has been further applied to predict the compressive strength of concrete
systems, which enables the models more robust.

- 2. A detailed study on sensitivity of different piezo configurations for strength monitoring of different concrete systems has been carried out and suggesting its suitability for real-life applications.
- A new ML model (ARIMA) has been developed to predict baseline and futuristic EMI
 data of corrosion for different reinforced concrete systems under chloride laden
 environment.
- 4. A detailed study has been carried out on prestressed concrete (PC) structure subjected to chloride laden environment using piezo sensor. To identify the different phases of corrosion and assess the deterioration, RMSD indices has been calculated and equivalent structural parameters have been derived based on the raw signature EMI data.
- 5. At last, physical models have been developed for assessing the deterioration of structural parameters in different concrete systems subjected to combined environmental and mechanical loading using piezo sensor.

8.5 RECOMMENDATIONS FOR THE FUTURE WORK

Based on the author's limited expertise and knowledge in the field of SHM, NDT&E, and ML the present research work may be extended in future for...

- 1. The basic strength prediction ML model developed for the laboratory data and for controlled laboratory condition can be extended to real life applications by incorporating field data and field condition to make it more robust.
- 2. The ARIMA model for prediction of backward and future corrosion data can be extended for other SHM applications such as material deterioration/damage assessment, deformation monitoring, strength monitoring, and objectionable movements and geometry changes. Also, the ARIMA model developed for low frequency ranges can be further extended for high-frequency ranges near the resonance for actual field data.
- 3. The physical models for strength deterioration in PC structures can be extended in posttensioned members with various piezo configurations.
- 4. Monitoring the durability of different concrete systems subjected to combined loading using piezo sensors can be further extended for complex loading such as vibrations together with the degradation (oxidation, aging and so on).

5. Based on the deterioration of the structural parameters, the remaining service life models can be developed based on the laboratory data already acquired for various durability aspects.

The author strongly believes that the ML models for strength and corrosion prediction using the EMI data acquired from piezo sensor has great as a NDE technique, which can be possibly provide better monitoring the RC structures during the construction stage as well as throughout its service condition. These models have potential to provide the remaining service life of the structure under inspection.

LIST OF PUBLICATIONS

INTERNATIONAL JOURNALS

- Hanne Vanoutrive,......Tushar Bansal......Visalakshi Talakokula... (2022) "Report of RILEM TC 281-CCC: Outcomes of a round robin on the resistance to accelerated carbonation of Portland, Portland-fly ash and blast-furnace blended cement", *Materials* and Structures, 55(99), Springer- SCIE, (IF: 3.428), https://doi.org/10.1617/s11527-022-01927-7
- 2. **Tushar Bansal,** Visalakshi Talakokula and Prabhakar Sathujoda, (2021) "A machine learning approach for predicting the electro-mechanical impedance data of blended RC structures subjected to chloride laden environment", *Smart Materials and Structures*, 31(1):015036, IOP Science-SCI, https://doi.org/10.1088/1361-665X/ac3d6f, (IF: 3.585)
- 3. **Tushar Bansal,** Visalakshi Talakokula and Kaliyan Mathiyazhagan, (2021) "Equivalent structural parameters based non-destructive prediction of sustainable concrete strength using machine learning models via piezo sensor", *Measurement: Journal of the International Measurement Confederation*, 187(12):110202, Elsevier SCIE, https://doi.org/10.1016/j.measurement.2021.110202, (IF: 3.927)
- 4. **Tushar Bansal** and Visalakshi Talakokula, (2021) "Deterioration of structural parameters due to corrosion in prestressed concrete identified by smart probe-based piezo sensor", *Engineering Research Express*, 3(1):015011, IOP Science ESCI, https://doi.org/10.1088/2631-8695/abded9
- 5. **Tushar Bansal**, Visalakshi Talakokula and Prabhakar Sathujoda, (**Under Review**) "Durability Aspects of Blended Concrete Systems Subjected to Combined Environmental and Mechanical Loading Using Piezo Sensor", Construction and Building Materials, Elsevier, SCIE (IF: 6.14)
- 6. **Tushar Bansal**, Visalakshi Talakokula and Prabhakar Sathujoda, (**Submitted**) "Monitoring of Very Early-Age Hydration Process and Strength Development of Different Blended Cementitious Systems using Embedded Piezo Sensor: A Comparative Study", Structural Control and Health Monitoring, Wiley, SCIE (IF: 4.819)

INTERNATIONAL CONFERENCES AND POSTER

- Tushar Bansal and Visalakshi Talakokula, "Piezo based monitoring of blended concrete under combined chloride induced corrosion and compression loading" 75th RILEM Annual Week Merida, Mexico, 2021. (Poster Presentation in Conference) (Awarded RILEM PhD Support Grant)
- Tushar Bansal and Visalakshi Talakokula, "Durability of concrete systems under combined loading using piezo sensor" 74th RILEM Annual Week and 40th Cement and Concrete Science Conference Sheffield, UK, 31 August - 4 September 2020. (Awarded RILEM PhD Grant)
- 3. **Tushar Bansal**, Visalakshi Talakokula and Suresh Bhalla, "Model based corrosion assessment in rebars of different fly ash concrete using piezo sensors", Proceedings of the 7th-Asia-Pacific workshop on structural health monitoring (APWSHM-2018), Hong Kong, SAR, P.R. China, November 12-15, 2018, pg-991-1002
- 4. **Tushar Bansal**, Visalakshi Talakokula and Suresh Bhalla, "Rebar corrosion assessment comparison of different piezo configurations in blended concrete", Proceedings of the 7th-Asia-Pacific workshop on structural health monitoring (APWSHM-2018), Hong Kong, SAR, P.R. China, November 12-15, 2018, pg-1003-1014
- Tushar Bansal, Shubhranshu Singh, Visalakshi Talakokula and Shilpa Pal, "Corrosion assessment in rebars of normal and geopolymer concrete using piezo sensors", International conference and expo (CORCON), 30th sept – 3rd Oct, 2018, RCC-26

BOOK CHAPTERS

- Tushar Bansal and Visalakshi Talakokula, "Study of durability aspects of limestone calcined clay cement using different piezo configurations", 3rd International Conference on Calcined Clays for Sustainable Concrete, New Delhi, 15-17 Oct 2019. https://doi.org/10.1007/978-981-15-2806-4_80, Springer- (Scopus Indexed)
- Tushar Bansal and Visalakshi Talakokula, "Monitoring strength development of cement substituted by limestone calcined clay using different piezo configurations", 3rd International Conference on Calcined Clays for Sustainable Concrete, New Delhi, 15-17 Oct 2019. https://doi.org/10.1007/978-981-15-2806-4_62, Springer- (Scopus Indexed)

AWARDS

- 1. RILEM PhD Support Grant award in the 75^{th} RILEM Week and International Conference on Advances in Sustainable Construction Materials and Structures, Mexico, Merida, 30^{th} August -3^{rd} September 2021
- 2. RILEM PhD Grant award in the 74th RILEM Week and 40th Cement & Concrete Science Conference, Sheffield, UK, 31^{st} August -4^{th} September 2020

REFERENCES

- [1].Adhikari, S., & Bhalla, S. (2019). Modified dual piezo configuration for improved structural health monitoring using electro-mechanical impedance (EMI) technique. *Experimental Techniques*, 43(1), 25-40.
- [2]. Agilent Technologies. (2012) www. Home.agilent.com.
- [3].Akande, K. O., Owolabi, T. O., Olatunji, S. O., & Abdul Raheem, A. (2017). A hybrid particle swarm optimization and support vector regression model for modelling permeability prediction of hydrocarbon reservoir. *Journal of Petroleum Science and Engineering*, 150, 43-53.
- [4].Amini, K., Jalalpour, M., & Delatte, N. (2016). Advancing concrete strength prediction using non-destructive testing: Development and verification of a generalizable model. *Construction and Building Materials*, 102, 762-768.
- [5].An, Y., Spencer Jr, B. F., & Ou, J. (2015), "A test method for damage diagnosis of suspension bridge suspender cables", *Computer-Aided Civil and Infrastructure Engineering*, 30(10), 771-784.
- [6].Andrade Perdrix, C. (2002). Rilem TC 178-TMC: Testing and modelling chloride penetration in concrete'-Analysis of total chloride content in concrete.
- [7]. Annamdas, V. G. M., & Rizzo, P. (2010, March). Monitoring concrete by means of embedded sensors and electromechanical impedance technique. In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems* 2010 (Vol. 7647, p. 76471Z). International Society for Optics and Photonics.
- [8].Antoni, M. (2013). *Investigation of cement substitution by blends of calcined clays and limestone* (Ph.D. Thesis). EPFL.

- [9].ASTM C1074. (2017). Standard test method for estimate concrete strength by maturity method. West Conshohocken, USA: American Society for Testing and Materials.
- [10].ASTM C42/C42M. (2012). Standard test method for obtaining and testing drilled cores and sawed beams of concrete, West Conshohocken, USA: American Society for Testing and Materials.
- [11].ASTM C587. (2016). Standard test method for pulse velocity through concrete, West Conshohocken, USA: American Society for Testing and Materials.
- [12].ASTM C803/C803M. (2018). Standard test method for penetration resistance of hardened concrete, West Conshohocken, USA: American Society for Testing and Materials.
- [13].ASTM C805/C805M. (2013). Standard test method for rebound number of hardened concrete, West Conshohocken, USA: American Society for Testing and Materials.
- [14].ASTM C900. (2019). Standard test method for pull out strength of hardened concrete, West Conshohocken, USA: American Society for Testing and Materials.
- [15].ASTM G I -03 (2012). Standard Practice for Preparing, Cleaning and Evaluating Corrosion Test Specimens. *West Conshohocken*, PA.
- [16].Bedekar, V., Inman, D. and Priya, S. (2008). Detection of Corrosion Using Impedance Spectroscope. *Ferroelectrics letter section* 35, 7-16.
- [17].Bhalla, S., & Kiong Soh, C. (2003). Structural impedance based damage diagnosis by piezo-transducers. *Earthquake engineering & structural dynamics*, 32(12), 1897-1916.
- [18].Bhalla, S., & Moharana, S. (2013). A refined shear lag model for adhesively bonded piezo-impedance transducers. *Journal of Intelligent Material Systems and Structures*, 24(1), 33-48.
- [19].Bhalla, S., & Soh, C. K. (2004). Structural health monitoring by piezo-impedance transducers. I: Modeling. *Journal of Aerospace Engineering*, 17(4), 154-165.

- [20].Bhalla, S., & Soh, C. K. (2004). Structural health monitoring by piezo–impedance transducers. II: Applications. *Journal of Aerospace Engineering*, 17(4), 166-175.
- [21].Bhalla, S., Gupta, S., Bansal, S. and Garg, A. (2009). Ultra low cost adaptation of electro-mechanical impedance for structural health monitoring. *Journal of Intelligent Material System and Structure*, 20, 991-999.
- [22].Bhalla, S., Soh, C. K., Tseng, K. K. H., & Naidu, A. S. (2001, December). Diagnosis of incipient damage in steel structures by means of piezoceramic patches. In *Proceedings of 8th East Asia-Pacific conference on structural engineering and construction, Singapore* (pp. 5-7).
- [23].Bhalla, S., Vittal, A. P. R. and Veljkovic, M. (2012). Piezo-impedance transducers for residual fatigue life assessment of bolted steel joints. *Journal of Structural Health Monitoring*, 11(6), 733-750.
- [24].Bhalla, S., Vittal, P. A., & Veljkovic, M. (2012). Piezo-impedance transducers for residual fatigue life assessment of bolted steel joints. *Structural Health Monitoring*, 11(6), 733-750.
- [25].Bhalla. (2001). Smart system based automated heath monitoring of structures. *MEngg Thesis*, School of Civil and Environmental Engineering, Nanyang Technological University, Singapore.
- [26].Bhalla. (2004). A mechanical impedance approach for structural identification, health monitoring and non-destructive evaluation using piezo-impedance transducers. *PhD Thesis, School of Civil and Environmental Engineering, Nanyang Technological University*, Singapore.
- [27].Cassagnabère, F., Diederich, P., Mouret, M., Escadeillas, G., & Lachemi, M. (2013). Impact of metakaolin characteristics on the rheological properties of mortar in the fresh state. *Cement and Concrete Composites*, *37*, 95-107.

- [28].Chalioris, C. E., Karayannis, C. G., Angeli, G. M., Papadopoulos, N. A., Favvata, M. J., & Providakis, C. P. (2016). Applications of smart piezoelectric materials in a wireless admittance monitoring system (WiAMS) to Structures—Tests in RC elements. *Case Studies in Construction Materials*, 5, 1-18.
- [29]. Chalioris, C. E., Voutetaki, M. E., & Liolios, A. A. (2020). Structural health monitoring of seismically vulnerable RC frames under lateral cyclic loading. *Earthquakes and Structures*, 19(1), 29-44.
- [30].Chou, J. S., & Ngo, N. T. (2016). Time series analytics using sliding window metaheuristic optimization-based machine learning system for identifying building energy consumption patterns. *Applied energy*, 177, 751-770.
- [31].Chou, J. S., & Pham, A. D. (2013). Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength. *Construction and Building Materials*, 49, 554-563.
- [32].Chou, J. S., Ngo, N. T., & Chong, W. K. (2017). The use of artificial intelligence combiners for modeling steel pitting risk and corrosion rate. *Engineering Applications of Artificial Intelligence*, 65, 471-483.
- [33].Choudhary, H. K., Anupama, A. V., Kumar, R., Panzi, M. E., Matteppanavar, S., Sherikar, B. N., & Sahoo, B. (2015). Observation of phase transformations in cement during hydration. *Construction and Building Materials*, *101*, 122-129.
- [34].Climent, M. A., de Vera, G., & Viqueira, E. (2001). Bit shape geometric considerations when sampling by dry drilling for obtaining chloride profiles in concrete. *Materials and Structures*, *34*(3), 150-154.
- [35].Daniyal, M., & Akhtar, S. (2020). Corrosion assessment and control techniques for reinforced concrete structures: a review. *Journal of Building Pathology and Rehabilitation*, 5(1), 1-20.

- [36].Dhandapani, Y., Sakthivel, T., Santhanam, M., Gettu, R., & Pillai, R. G. (2018). Mechanical properties and durability performance of concretes with Limestone Calcined Clay Cement (LC3). *Cement and Concrete Research*, 107, 136-151.
- [37].Divsholi, B. S., & Yang, Y. (2009, March). Application of reusable PZT sensors for monitoring initial hydration of concrete. In *Sensors and Smart Structures Technologies* for Civil, Mechanical, and Aerospace Systems 2009 (Vol. 7292, p. 729222). International Society for Optics and Photonics.
- [38].Dugnani, R. (2009). Dynamic behavior of structure-mounted disk-shape piezoelectric sensors including the adhesive layer. *Journal of Intelligent Material Systems and Structures*, 20(13), 1553-1564.
- [39].El-Sebakhy, E. A. (2009). Forecasting PVT properties of crude oil systems based on support vector machines modeling scheme. *Journal of Petroleum Science and Engineering*, 64(1-4), 25-34.
- [40].Erdal, H., Erdal, M., Simsek, O., & Erdal, H. I. (2018). Prediction of concrete compressive strength using non-destructive test results. *Computers and Concrete*, 21(4), 407-417.
- [41].Fauzi, A., Nuruddin, M. F., Malkawi, A. B., & Abdullah, M. M. A. B. (2016). Study of fly ash characterization as a cementitious material. *Procedia engineering*, *148*, 487-493.
- [42].Feng, D. C., Liu, Z. T., Wang, X. D., Chen, Y., Chang, J. Q., Wei, D. F., & Jiang, Z. M. (2020). Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. *Construction and Building Materials*, 230, 117000.
- [43].Ghafari, E., Yuan, Y., Wu, C., Nantung, T., & Lu, N. (2018). Evaluation the compressive strength of the cement paste blended with supplementary cementitious

- materials using a piezoelectric-based sensor. *Construction and Building Materials*, 171, 504-510.
- [44]. Giurgiutiu, V., Reynolds, A. and Rogers, C. A. (1999). Experimental investigation of e/m impedance health monitoring for spot-welded structural joints. *Journal of Intelligent Material Systems and Structures*, 10(10), 802-812.
- [45].Goel, A., & Pal, M. (2009). Application of support vector machines in scour prediction on grade-control structures. *Engineering Applications of Artificial Intelligence*, 22(2), 216-223.
- [46].Gretchen Jacobson NACE-International Report (2016). International measures of prevention, application, and economics of corrosion technologies study. NACE International Houston, Texas, USA.
- [47].Hixon, E. L. (1988). Mechanical Impedance Shock and Vibration Handbook edited by C. M. Harris, 3rd edition, *Mc Graw Hill Book Co*, New York.
- [48].Huo, L., Li, C., Jiang, T., & Li, H. N. (2018). Feasibility study of steel bar corrosion monitoring using a piezoceramic transducer enabled time reversal method. *Applied Sciences*, 8(11), 2304.\
- [49]. Ikeda, T. (1990). Fundamentals of piezoelectricity. Oxford University Press, Oxford.
- [50].IS 1786-1985. Indian standard specification for high strength deformed steel bars and wires for concrete reinforcement. *Bureau of Indian Standards*, New Delhi.
- [51].IS: 10262-2009. Indian standard concrete mix proportioning-guidelines. *Bureau of Indian Standards*, New Delhi.
- [52].IS: 383-1970. Indian standard specification for coarse and fine aggregates from natural sources for concrete. *Bureau of Indian Standards*, New Delhi.
- [53].IS: 456-2000 Indian Standard Plain and Reinforced Concrete-Code of Practice, *Bureau* of *Indian Standards*, New Delhi.

- [54].IS: 516-1959. Indian standard methods of tests for strength of concrete. *Bureau of Indian Standards*, New Delhi.
- [55].IS: 8112-2013. Indian standard ordinary Portland cement, 43 grade specification, Bureau of Indian Standards, New Delhi.
- [56].Jothi Saravanan, T., Balamonica, K., Bharathi Priya, C., Gopalakrishnan, N., & Murthy, S. G. N. (2017). Piezoelectric EMI–based monitoring of early strength gain in concrete and damage detection in structural components. *Journal of Infrastructure Systems*, 23(4), 04017029.
- [57].Jung, H., Jo, H., Kim, S., Lee, K., & Choe, J. (2018). Geological model sampling using PCA-assisted support vector machine for reliable channel reservoir characterization. *Journal of Petroleum Science and Engineering*, 167, 396-405.
- [58].Karayannis, C. G., Chalioris, C. E., Angeli, G. M., Papadopoulos, N. A., Favvata, M. J., & Providakis, C. P. (2016). Experimental damage evaluation of reinforced concrete steel bars using piezoelectric sensors. *Construction and Building Materials*, 105, 227-244.
- [59].Karayannis, C. G., Voutetaki, M. E., Chalioris, C. E., Providakis, C. P., & Angeli, G. M. (2015). Detection of flexural damage stages for RC beams using Piezoelectric sensors (PZT). Smart Structures and Systems, 15(4), 997-1018.
- [60].Karina, C. N., Chun, P. J., & Okubo, K. (2017). Tensile strength prediction of corroded steel plates by using machine learning approach. *Steel Compos. Struct*, 24(5), 635-641.
- [61].Kaur, N., Bhalla, S., Shanker, R., & Panigrahi, R. (2016). Experimental evaluation of miniature impedance chip for structural health monitoring of prototype steel/RC structures. *Experimental Techniques*, 40(3), 981-992.
- [62].Keshtegar, B., Meng, D., Ben Seghier, M. E. A., Xiao, M., Trung, N. T., & Bui, D. T. (2021). A hybrid sufficient performance measure approach to improve robustness and

- efficiency of reliability-based design optimization. *Engineering with Computers*, *37*(3), 1695-1708.
- [63].Khan, M. S., Nguyen, Q. D., & Castel, A. (2020). Performance of limestone calcined clay blended cement-based concrete against carbonation. *Advances in Cement Research*, 32(11), 481-491.
- [64].Kim, J., Kim, J. W., & Park, S. (2014, July). Early-age concrete strength estimation technique using embedded piezoelectric self-sensing impedance. In *EWSHM-7th* european workshop on structural health monitoring. Inria.
- [65].Kim, J., Lee, C., & Park, S. (2017). Artificial neural network-based early-age concrete strength monitoring using dynamic response signals. *Sensors*, *17*(6), 1319.
- [66].Kloprogge, J. T., Schuiling, R. D., Ding, Z., Hickey, L., Wharton, D., & Frost, R. L. (2002). Vibrational spectroscopic study of syngenite formed during the treatment of liquid manure with sulphuric acid. *Vibrational Spectroscopy*, 28(2), 209-221.
- [67].Kong, Q., Hou, S., Ji, Q., Mo, Y. L., & Song, G. (2013). Very early age concrete hydration characterization monitoring using piezoceramic based smart aggregates. *Smart Materials and Structures*, 22(8), 085025.
- [68].Lalande, F., Childs, B., Chaudhry, Z. and Rogers, C. A. (1996). High frequency impedance analysis for nde of complex precision parts. *Conference on Smart Structures and Materials, Proceedings of SPIE* 2717:237-245.
- [69].Lee, C. J., Lee, J. C., Shin, S. W., & Kim, W. J. (2012). Investigation of setting process of cementitious materials using electromechanical impedance of embedded piezoelectric patch. *Journal of the Korea Institute of Building Construction*, 12(6), 607-614.

- [70].Li, W., Liu, T., Gao, S., Luo, M., Wang, J., & Wu, J. (2019). An electromechanical impedance-instrumented corrosion-measuring probe. *Journal of Intelligent Material Systems and Structures*, 30(14), 2135-2146.
- [71].Li, W., Liu, T., Zou, D., Wang, J., & Yi, T. H. (2019). PZT based smart corrosion coupon using electromechanical impedance. *Mechanical Systems and Signal Processing*, 129, 455-469.
- [72].Li, W., Wang, J., Liu, T., & Luo, M. (2020). Electromechanical impedance instrumented circular piezoelectric-metal transducer for corrosion monitoring: modeling and validation. *Smart Materials and Structures*, 29(3), 035008.
- [73].Liang, C., Sun, F. P. and Rogers, C. A. (1994). Coupled electro-mechanical analysis of adaptive material systems- determination of the actuator power consumption and system energy transfer. *Journal of Intelligent Material Systems and Structures*, 5, 12-20.
- [74].Liang, C., Sun, F. P., & Rogers, C. A. (1994). An impedance method for dynamic analysis of active material systems.
- [75].Lim, Y. Y., & Soh, C. K. (2011). Fatigue life estimation of a 1D aluminum beam under mode-I loading using the electromechanical impedance technique. *Smart Materials and Structures*, 20(12), 125001.
- [76].Lim, Y. Y., & Soh, C. K. (2013). Damage detection and characterization using EMI technique under varying axial load. *Smart Struct. Syst*, 11(4), 349-364.
- [77].Lim, Y. Y., Smith, S. T., Padilla, R. V., & Soh, C. K. (2021). Monitoring of concrete curing using the electromechanical impedance technique: review and path forward. *Structural Health Monitoring*, 20(2), 604-636.

- [78].Liu, J., Tang, K., Pan, D., Lei, Z., Wang, W., & Xing, F. (2014). Surface chloride concentration of concrete under shallow immersion conditions. *Materials*, 7(9), 6620-6631.
- [79].Liu, Z. G., & Mu, Z. T. (2011). Research on aircraft LY12CZ Aluminum Alloy corrosion damage prediction based on ARIMA Model. In *Advanced Materials Research* (Vol. 308, pp. 1016-1022). Trans Tech Publications Ltd.
- [80].Lu, X., Lim, Y. Y., & Soh, C. K. (2018). A novel electromechanical impedance—based model for strength development monitoring of cementitious materials. *Structural Health Monitoring*, 17(4), 902-918.
- [81].Lu, X., Lim, Y. Y., Izadgoshasb, I., & Soh, C. K. (2020). Strength development monitoring and dynamic modulus assessment of cementitious materials using EMI-Miniature Prism based technique. *Structural Health Monitoring*, 19(2), 373-389.
- [82].Maraghechi, H., Avet, F., Wong, H., Kamyab, H., & Scrivener, K. (2018).

 Performance of Limestone Calcined Clay Cement (LC 3) with various kaolinite contents with respect to chloride transport. *Materials and structures*, *51*(5), 1-17.
- [83].Marangu, J. M. (2020). Physico-chemical properties of Kenyan made calcined clay-limestone cement (LC3). *Case Studies in Construction Materials*, *12*, e00333.
- [84].Matthews, S. L., & Morlidge, J. R. (2008). Performance based rehabilitation of reinforced concrete structures. In *Concrete Repair, Rehabilitation and Retrofitting II* (pp. 295-296). CRC Press.
- [85].Mijwel, M. M. (2018). Artificial neural networks advantages and disadvantages. Retrieved from LinkedIn https://www.linkedin.com/pulse/artificial-neuralnet Work.

- [86].Moharana, S., & Bhalla, S. (2019). Development and evaluation of an external reusable piezo-based concrete hydration-monitoring sensor. *Journal of Intelligent Material Systems and Structures*, 30(18-19), 2770-2788.
- [87].Na, U. J., Park, T. W., Feng, M. Q., & Chung, L. (2009). Neuro-fuzzy application for concrete strength prediction using combined non-destructive tests. *Magazine of Concrete Research*, 61(4), 245-256.
- [88].Narayanan, A., Kocherla, A., & Subramaniam, K. V. (2017). Embedded PZT sensor for monitoring mechanical impedance of hydrating cementitious materials. *Journal of Nondestructive Evaluation*, 36(4), 1-13.
- [89].Naskar, S., & Bhalla, S. (2016). Metal-wire-based twin one-dimensional orthogonal array configuration of PZT patches for damage assessment of two-dimensional structures. *Journal of Intelligent Material Systems and Structures*, 27(11), 1440-1460.
- [90].Oh, T. K., Kim, J., Lee, C., & Park, S. (2017). Nondestructive concrete strength estimation based on electro-mechanical impedance with artificial neural network. *Journal of advanced concrete technology*, 15(3), 94-102.
- [91].Omotoso, O. E., Ivey, D. G., & Mikula, R. (1998). Containment mechanism of trivalent chromium in tricalcium silicate. *Journal of hazardous materials*, 60(1), 1-28.
- [92].Palomo, A., Blanco-Varela, M. T., Granizo, M. L., Puertas, F., Vazquez, T., & Grutzeck, M. W. (1999). Chemical stability of cementitious materials based on metakaolin. *Cement and Concrete research*, 29(7), 997-1004.
- [93].Pan, H. H., & Huang, M. W. (2020). Piezoelectric cement sensor-based electromechanical impedance technique for the strength monitoring of cement mortar. *Construction and Building Materials*, 254, 119307.

- [94].Panigrahi, R., Bhalla, S., & Gupta, A. (2010). A low-cost variant of electro-mechanical impedance (EMI) technique for structural health monitoring. *Experimental Techniques*, 34(2), 25-29
- [95].Parashar, A., & Bishnoi, S. (2021). Hydration behaviour of limestone-calcined clay and limestone-slag blends in ternary cement. *RILEM Technical Letters*, 6, 17-24.
- [96].Park, G., Sohn, H., Farrar, C. R., & Inman, D. J. (2003). Overview of piezoelectric impedance-based health monitoring and path forward. *Shock and vibration digest*, 35(6), 451-464.
- [97].Park, S. and Park, S. K. (2010). Quantitative corrosion monitoring using wireless electromechanical impedance measurements. *Research in Non Destructive Evaluation*, 21, 184-192.
- [98].Park, S., Benjamin, L. G., Inman, J. and Yun, C. B. (2007). MFC-based structural health monitoring using a miniaturized impedance measuring chip for corrosion detection. *Research in Non-destructive Evaluation* 18:139-150.
- [99].Priya, C. B., Saravanan, T. J., Balamonica, K., Gopalakrishnan, N., & Rao, A. R. M. (2018). EMI based monitoring of early-age characteristics of concrete and comparison of serial/parallel multi-sensing technique. *Construction and Building Materials*, 191, 1268-1284.
- [100]. Providakis, C. P., Liarakos, E. V., & Kampianakis, E. (2013). Nondestructive wireless monitoring of early-age concrete strength gain using an innovative electromechanical impedance sensing system. *Smart Materials Research*, 2013.
- [101].Qian, L., Liu, C., Yi, J., & Liu, S. (2020, November). Application of hybrid algorithm of bionic heuristic and machine learning in nonlinear sequence. In *Journal of Physics:*Conference Series (Vol. 1682, No. 1, p. 012009). IOP Publishing.

- [102].Qin, L., & Li, Z. (2008). Monitoring of cement hydration using embedded piezoelectric transducers. *Smart materials and structures*, *17*(5), 055005.
- [103].Qin, L., Gao, X., & Zhang, A. (2018). Potential application of Portland cement-calcium sulfoaluminate cement blends to avoid early age frost damage. *Construction and Building Materials*, 190, 363-372.
- [104].Qing, X. P., Chan, H. L., Beard, S. J., Ooi, T. K., & Marotta, S. A. (2006). Effect of adhesive on the performance of piezoelectric elements used to monitor structural health. *International Journal of Adhesion and Adhesives*, 26(8), 622-628.
- [105].Quinn, W., Kelly, G., & Barrett, J. (2012). Development of an embedded wireless sensing system for the monitoring of concrete. *Structural Health Monitoring*, 11(4), 381-392.
- [106].Quinn, W., Kelly, G., & Barrett, J. (2012). Development of an embedded wireless sensing system for the monitoring of concrete. *Structural Health Monitoring*, 11(4), 381-392.
- [107].Raju, J., Bhalla, S., & Visalakshi, T. (2020). Pipeline corrosion assessment using piezo-sensors in reusable non-bonded configuration. *NDT & E International*, 111, 102220.
- [108].Saravanan, T. J., Balamonica, K., Priya, C. B., Reddy, A. L., & Gopalakrishnan, N. (2015). Comparative performance of various smart aggregates during strength gain and damage states of concrete. *Smart Materials and Structures*, 24(8), 085016.
- [109].Seghier, M. E. A. B., Keshtegar, B., Tee, K. F., Zayed, T., Abbassi, R., & Trung, N.
 T. (2020). Prediction of maximum pitting corrosion depth in oil and gas pipelines. *Engineering Failure Analysis*, 112, 104505.
- [110].Shi, W., Chen, Y., Liu, P., & Xu, D. (2019). Corrosion investigation of reinforced concrete based on piezoelectric smart materials. *Materials*, *12*(3), 519.

- [111].Shi, Z., Geiker, M. R., De Weerdt, K., Østnor, T. A., Lothenbach, B., Winnefeld, F., & Skibsted, J. (2017). Role of calcium on chloride binding in hydrated Portland cement—metakaolin—limestone blends. *Cement and Concrete Research*, 95, 205-216.
- [112].Shin, S. W., & Oh, T. K. (2009). Application of electro-mechanical impedance sensing technique for online monitoring of strength development in concrete using smart PZT patches. *Construction and Building Materials*, 23(2), 1185-1188.
- [113].Shin, S. W., Qureshi, A. R., Lee, J. Y., & Yun, C. B. (2008). Piezoelectric sensor based nondestructive active monitoring of strength gain in concrete. *Smart Materials and Structures*, 17(5), 055002.
- [114].Simmers, G. E. (2005). Impedance-based structural health monitoring to detect corrosion. *MS Thesis*, *Department of Mechanical Engineering*, *Blacksburg*, *Virginia*.
- [115].Sirohi, J., & Chopra, I. (2000). Fundamental behavior of piezoceramic sheet actuators. *Journal of Intelligent Material Systems and Structures*, 11(1), 47-61.
- [116].Snellings, R., Chwast, J., Cizer, Ö., De Belie, N., Dhandapani, Y., Durdzinski, P., ... & Lothenbach, B. (2018). RILEM TC-238 SCM recommendation on hydration stoppage by solvent exchange for the study of hydrate assemblages. *Materials and Structures*, 51(6), 1-4.
- [117].Soh, C. K., & Bhalla, S. (2005). Calibration of piezo-impedance transducers for strength prediction and damage assessment of concrete. *Smart materials and structures*, 14(4), 671.
- [118].Soh, C. K., Tseng, K. K., Bhalla, S., & Gupta, A. (2000). Performance of smart piezoceramic patches in health monitoring of a RC bridge. *Smart materials and Structures*, 9(4), 533.

- [119].Sriramadasu, R. C., Lu, Y., & Banerjee, S. (2019). Identification of incipient pitting corrosion in reinforced concrete structures using guided waves and piezoelectric wafer transducers. *Structural Health Monitoring*, *18*(1), 164-171.
- [120].Stepkowska, E. T., Blanes, J. M., Real, C., & Perez-Rodriguez, J. L. (2005). Hydration products in two aged cement pastes. *Journal of thermal analysis and calorimetry*, 82(3), 731-739.
- [121].Su, Y. F., Han, G., Amran, A., Nantung, T., & Lu, N. (2019). Instantaneous monitoring the early age properties of cementitious materials using PZT-based electromechanical impedance (EMI) technique. *Construction and Building Materials*, 225, 340-347.
- [122].Sui, S., Georget, F., Maraghechi, H., Sun, W., & Scrivener, K. (2019). Towards a generic approach to durability: Factors affecting chloride transport in binary and ternary cementitious materials. *Cement and Concrete Research*, 124, 105783.
- [123].Sun, F. P., Chaudhry, Z., Liang, C., & Rogers, C. A. (1995). Truss structure integrity identification using PZT sensor-actuator. *Journal of Intelligent material systems and structures*, 6(1), 134-139.
- [124].Sun, Y. M., Liang, M. T., & Chang, T. P. (2012). Time/depth dependent diffusion and chemical reaction model of chloride transportation in concrete. *Applied Mathematical Modelling*, 36(3), 1114-1122.
- [125].Talakokula, V., & Bhalla, S. (2015). Reinforcement corrosion assessment capability of surface bonded and embedded piezo sensors for reinforced concrete structures. *Journal of Intelligent Material Systems and Structures*, 26(17), 2304-2313.
- [126].Talakokula, V., Bhalla, S., & Gupta, A. (2014). Corrosion assessment of reinforced concrete structures based on equivalent structural parameters using electro-mechanical

- impedance technique. *Journal of Intelligent Material Systems and Structures*, 25(4), 484-500.
- [127].Talakokula, V., Bhalla, S., & Gupta, A. (2018). Monitoring early hydration of reinforced concrete structures using structural parameters identified by piezo sensors via electromechanical impedance technique. *Mechanical Systems and Signal Processing*, 99, 129-141
- [128].Talakokula, V., Bhalla, S., Ball, R. J., Bowen, C. R., Pesce, G. L., Kurchania, R., ...
 & Paine, K. (2016). Diagnosis of carbonation induced corrosion initiation and progression in reinforced concrete structures using piezo-impedance transducers. Sensors and Actuators A: Physical, 242, 79-91.
- [129]. Tawie, R., & Lee, H. K. (2010). Monitoring the strength development in concrete by EMI sensing technique. *Construction and Building Materials*, 24(9), 1746-1753.
- [130]. Tawie, R., & Lee, H. K. (2010). Piezoelectric-based non-destructive monitoring of hydration of reinforced concrete as an indicator of bond development at the steel–concrete interface. *Cement and Concrete Research*, 40(12), 1697-1703.
- [131]. Tawie, R., & Lee, H. K. (2011). Characterization of cement-based materials using a reusable piezoelectric impedance-based sensor. *Smart Materials and Structures*, 20(8), 085023.
- [132]. Thomas, D. and Welter, J. (2004). Corrosion damage detection with piezoelectric wafer active sensors. SPIE's 11th Annual International Symposium on Smart Structures and Materials and 9th Annual International Symposium on NDE for Health Monitoring and Diagnostics, 14-18 March 2004, San Diego, CA: 5394-2.
- [133].Tuutti, K. (1982). Corrosion of steel in concrete. *CBI research report no* 4.82, Swedish *Cement and Concrete Research Institute*, Stockholm, Sweden.)

- [134]. Vagenas, N. V., Gatsouli, A., & Kontoyannis, C. G. (2003). Quantitative analysis of synthetic calcium carbonate polymorphs using FT-IR spectroscopy. *Talanta*, *59*(4), 831-836.
- [135]. Visalakshi. (2014). Corrosion assessment in rebars of reinforced concrete structures using equivalent parameters extracted from piezo-patches. *PhD Thesis*, *Department of Civil Engineering, Indian Institute of Technology Delhi*, New Delhi.
- [136]. Voutetaki, M. E., Papadopoulos, N. A., Angeli, G. M., & Providakis, C. P. (2016). Investigation of a new experimental method for damage assessment of RC beams failing in shear using piezoelectric transducers. *Engineering Structures*, 114, 226-240.
- [137].Wang, D. S., Li, Q. C., Zhu, H. P., & Jing, K. (2009, December). Experimental study on waterproof technology of piezoelectric impedance tranducers in concrete. In 2009 Symposium on Piezoelectricity, Acoustic Waves, and Device Applications (SPAWDA 2009) (pp. 37-37). IEEE.
- [138].Wang, D., & Zhu, H. (2011). Monitoring of the strength gain of concrete using embedded PZT impedance transducer. *Construction and Building Materials*, 25(9), 3703-3708.
- [139]. Wang, D., Song, H., & Zhu, H. (2014). Embedded 3D electromechanical impedance model for strength monitoring of concrete using a PZT transducer. *Smart Materials and Structures*, 23(11), 115019.
- [140].Wen, Y. F., Cai, C. Z., Liu, X. H., Pei, J. F., Zhu, X. J., & Xiao, T. T. (2009). Corrosion rate prediction of 3C steel under different seawater environment by using support vector regression. *Corrosion Science*, *51*(2), 349-355.
- [141].Wen, Y. F., Cai, C. Z., Liu, X. H., Pei, J. F., Zhu, X. J., & Xiao, T. T. (2009). Corrosion rate prediction of 3C steel under different seawater environment by using support vector regression. *Corrosion Science*, *51*(2), 349-355.

- [142].Yang, Y., Divsholi, B. S., & Soh, C. K. (2010). A reusable PZT transducer for monitoring initial hydration and structural health of concrete. *Sensors*, *10*(5), 5193-5208.
- [143].Yao, Y., Wang, L., Wittmann, F. H., De Belie, N., Schlangen, E., Alava, H. E., ... & Cao, Y. (2017). Test methods to determine durability of concrete under combined environmental actions and mechanical load: final report of RILEM TC 246-TDC. *Materials and Structures*, 50(2), 1-13.
- [144].Yidong, X. (2016). Use of time series models to forecast the evolution of corrosion pit in steel rebars. *Functional materials*.
- [145].Ylmén, R., Jäglid, U., Steenari, B. M., & Panas, I. (2009). Early hydration and setting of Portland cement monitored by IR, SEM and Vicat techniques. *Cement and Concrete Research*, 39(5), 433-439.
- [146]. Yousuf, M., Mollah, A., Hess, T. R., Tsai, Y. N., & Cocke, D. L. (1993). An FTIR and XPS investigations of the effects of carbonation on the solidification/stabilization of cement based systems-Portland type V with zinc. *Cement and Concrete Research*, 23(4), 773-784.
- [147].Zhang, C., Panda, G. P., Yan, Q., Zhang, W., Vipulanandan, C., & Song, G. (2020).
 Monitoring early-age hydration and setting of portland cement paste by piezoelectric transducers via electromechanical impedance method. *Construction and Building Materials*, 258, 120348.
- [148].Zhou, S. W., Liang, C., & Rogers, C. A. (1996). An impedance-based system modeling approach for induced strain actuator-driven structures.

ANNEXURE-I

The solution of Model number 1, 4, and 7 of equivalent system paramters such as stiffness k', mass m' and damping c'.

Model 1: Parallel combination of spring and damper

For this combination, the given equation of x and y are

$$x = c (a)$$

$$y = -\frac{k}{\omega} \tag{b}$$

The system parameters can be determined, by algebraic manipulations, as

$$c = x$$
 (c)

$$k = -\omega y$$
 (d)

Model 4: Parallel combination of spring, mass and damper

For this combination, the given equation of x and y are

$$x = c$$
 (e)

$$y = m\omega - \frac{k}{\omega} \tag{f}$$

The angular frequency at which y=0 is denoted by ω_0 . The system parameters can be determined, by algebraic manipulations, as

$$c = x$$
 (g)

$$m = \frac{y\omega}{(\omega^2 - \omega_o^2)} \tag{h}$$

$$k = \frac{y\omega \,\omega_o^2}{(\omega^2 - \omega_o^2)} \tag{i}$$

Model 7: Series combination of spring, mass and damper

For this combination, the given equation of x and y are

$$x = \frac{c^{-1}}{c^{-2} + \left(\frac{\omega}{k} - \frac{1}{\omega m}\right)^2}$$
 (j)

$$y = \frac{-\left(\frac{\omega}{k} - \frac{1}{\omega m}\right)^2}{c^{-2} + \left(\frac{\omega}{k} - \frac{1}{\omega m}\right)^2}$$
 (k)

The angular frequency at which y=0 is denoted by ω_o . The system parameters can be determined, by algebraic manipulations, as

$$m = \frac{(\omega_o^2 - \omega^2)(x^2 + y^2)}{\omega \omega_o^2 y} \tag{1}$$

$$k = \frac{(\omega_o^2 - \omega^2)(x^2 + y^2)}{\omega y}$$
 (m)

$$c = \frac{(x^2 + y^2)}{x} \tag{n}$$

The solution is valid for y > 0 and $|\omega| < \omega_0$ or y < 0 and $|\omega| > \omega_0$.

ANNEXURE-II

ARIMA Model code for prediction of EMI baseline data

```
import pandas as pd
from statsmodels.tsa.arima_model import ARIMA
data = pd.read_csv('./newFile1new.csv')
data.head()
type(data)
pandas.core.frame.DataFrame
import numpy as np
import matplotlib.pylab as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15, 6
# fvsb=pd.read_csv('./FvsB_daywisenew.csv')
fvsg=pd.read_csv('./FvsG_daywise1new.csv')
prediction = pd.DataFrame()
def test_stationarity(timeseries):
       #Determing rolling statistics
      rolmean = pd.rolling_mean(timeseries, window=4)
rolstd = pd.rolling_std(timeseries, window=4)
      #Plot rolling statistics:
      orig = plt.plot(timeseries, color='blue',label='Original')
mean = plt.plot(rolmean, color='red', label='Rolling Mean')
std = plt.plot(rolstd, color='black', label = 'Rolling Std')
      plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation')
      plt.show(block=False)
      #Perform Dickey-Fuller test:
print ('Results of Dickey-Fuller Test:')
      dftest = adfuller(timeseries['6'], autolag='AIC')
dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value
      print (dfoutput)
for z in range(0,2701) :
      #fvsb1 = fvsb.iloc[2350,:]
fvsg1 = fvsg.iloc[z,:]
#fvsb1=pd.DataFrame(fvsb1)
       fvsg1=pd.DataFrame(fvsg1)
      fvsg1.head()
      #b_value=[]
       g_value=[]
      for i in range(84,-1,-1):
             if(i%2==1):
                  #b_value.append(fvsb1.iloc[i,0])
      g_value.append(fvsg1.iloc[i,0])
#b_value
       #b_value=np.array(b_value).reshape(-1,1)
      #g_value=np.array(g_value).reshape(-1,1)
dataset=pd.DataFrame(g_value)
       #data1=pd.DataFrame(g_value)
      #type(data)
#dataset.head()
      #IndexedDataset
```

```
dataset = pd.concat([dataset,data],axis=1)
dataset.columns = ['G','Dates']
#dataset
dataset['Dates'] = pd.to_datetime(dataset['Dates'],infer_datetime_format=True)
IndexedDataset = dataset.set_index(['Dates'])
IndexedDataset.dropna(inplace=True)
#IndexedDataset.head()
# plt.xlabel("Date")
# plt.ylabel("B")
# plt.plot(IndexedDataset,color='blue',label='G')
#plt.plot(data1,color='blue',label='G')
#Determing rolling statistics
rolmean = IndexedDataset.rolling(window=4).mean()
rolstd = IndexedDataset.rolling(window=4).std()
#print(rolmean,rolstd)
 #Plot rolling statistics:
##tot rotting statistis:
# orig = plt.plot(IndexedDataset, color='blue',label='Original')
# mean = plt.plot(rolmean, color='red', label='Rolling Mean')
# #std = plt.plot(rolstd, color='black', label = 'Rolling Std')
# plt.legend(loc='best')
# plt.title('Rolling Mean & Standard Deviation')
# plt.show(block=False)
 #Perform Dickey-Fuller test:
#Perform DicRey-Fuller test:
# from statsmodels.tsa.stattools import adfuller
# print('Results of DicRey-Fuller Test:')
# dftest = adfuller(IndexedDataset['G'], autolag='AIC')
# dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', '#Lags Used', 'Number of Observations Used'])
# for key, value in dftest[4].items():
# dfoutput['Critical Value (%s)'%key] = value
# print(dfoutput)
 # print(dfoutput)
 #Estimating Trends
 indexedDataset_logScale = np.log(IndexedDataset)
indexedDataset_logScale.dropna(inplace=True)
#print(indexedDataset_logScale)
 # plt.plot(indexedDataset_logScale)
movingAverage = indexedDataset_logScale.rolling(window=4).mean()
movingSTD = indexedDataset_logScale.rolling(window=4).std()
# plt.plot(indexedDataset_logScale)
# plt.plot(movingAverage, color='red')
datasetLogScaleMinusMovingAverage = indexedDataset_logScale - movingAverage
 #datasetLogScaleMinusMovingAverage.head(12)
 #removing nan values
datasetLogScaleMinusMovingAverage.dropna(inplace=True)
#datasetLogScaleMinusMovingAverage.head(10)
#this is done in order to visualize that mean is increasing with propagation of trend in graph in upward direction exponentialDecayWeightedAverage = indexedDataset_logScale.ewm(halflife=12,min_periods=0,adjust=True).mean() exponentialDecayWeightedAverage.dropna(inplace=True)
 # plt.plot(indexedDataset_logScale)
# plt.plot(exponentialDecayWeightedAverage,color='red')
datasetLogScaleMinusMovingExponentialDecayAverage = indexedDataset_logScale - exponentialDecayWeightedAverage
datasetLogScaleMinusMovingExponentialDecayAverage.dropna(inplace=True)
# test_stationarity(datasetLogScaleMinusMovingExponentialDecayAverage)
\label{logDiffShifting} \mbox{ = indexedDataset\_logScale - indexedDataset\_logScale.shift() } \mbox{ = } \mbox{ indexedDataset\_logScale.shift() } \mbox{ = } \mbox{ indexedDataset\_logScale - indexedDataset\_logScale - indexedDataset\_logScale.shift() } \mbox{ = } \mbox{ indexedDataset\_logScale - indexedDa
datasetLogDiffShifting.dropna(inplace=True)
# test_stationarity(datasetLogDiffShifting)
 # #ACF and PACF plots:
# from statsmodels.tsa.stattools import acf, pacf
# lag_acf = acf(datasetLogDiffShifting, nlags=20)
# lag_pacf = pacf(datasetLogDiffShifting, nlags=20)
# #Plot ACF:
 # plt.subplot(121)
 # plt.plot(lag_acf)
# plt.axhline(y=0,linestyle='--',color='gray')
# plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
# plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
 # plt.title('Autocorrelation Function')
# #PLot PACF:
```

```
# plt.subplot(121)
      # plt.plot(lag acf)
     # ptt.pcb(lag_dr)
# ptt.axhline(y=0,linestyle='--',color='gray')
# ptt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
# ptt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
# ptt.title('Autocorrelation Function')
      # #PLot PACF:
      # plt.subplot(122)
      # plt.plot(lag_pacf)
     # plt.axhline(y=0,linestyle='--',color='gray')
# plt.axhline(y=0,linestyle='--',color='gray')
# plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
# plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
      # plt.title('Partial Autocorrelation Function')
     # plt.tight_layout()
           \label{eq:model} \begin{array}{ll} model = ARIMA(indexedDataset\_logScale, \ order=(0,\ 1,\ 0)) \\ results\_ARIMA = model.fit(disp=-1) \end{array}
           # plt.plot(datasetLogDiffShifting)
           # plt.plot(results_AR.fittedvalues, color='red')
# plt.title('RSS: %.4f'% sum((results_AR.fittedvalues-datasetLogDiffShifting['G'])**2))
# print('Ploting AR model')
           predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues,copy=True)
# print(predictions_ARIMA_diff)
           predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
           # print(predictions ARIMA diff_cumsum)
           #predictions_ARIMA_log
           predictions_ARIMA = np.exp(predictions_ARIMA_log)
            #prediction_ARIMA_my = np.log(predictions_ARIMA)
           # plt.plot(IndexedDataset)
           # plt.plot(predictions_ARIMA)
           x=results_ARIMA.forecast(steps=10)
           mean=np.exp(x[0])
           mean=pd.DataFrame(mean)
prediction=prediction.append(mean.T)
           print("EXCEPTION OCCUR AT " + str(z))
print(prediction)
```

BIOGRAPHY OF TUSHAR BANSAL

Tushar Bansal received his B.Tech + M.Tech degree in Civil Engineering with specilization in Structural Engineering from Gautam Buddha University, India in 2016. From August 2016 to December 2017, he worked as an assistant professor in the Department of Civil Engineering at Skyline Institute of Engineering and Technology, Greater Noida, India. He is currently pursuing Ph.D degree in Civil Engineering from Bennett University, Greater Noida, Uttar Pradesh. His research interest are machine learning based structural health monitoring of civil structures, smart materials and structures, non-destructive evaluation, corrosion assessment in reinforced concrete and prestressed concrete structures and vibration analysis of structures. He is also a technical member of international committees of Union of Laboratories and Experts in Construction Materials, Systems and Structures (RILEM) and involved in several technical committees (TCs) of RILEM such as TC-293-CCH: Stress Corrosion Cracking and Hydrogen Embrittlement of Concrete-Reinforcing Steels, TC-281-CCC: Carbonation of concrete with supplementary cementitious materials, TC-282-CCL: Calcined Clays as Supplementary Cementitious Material and TC-289-DCM: Long-term durability of structural concretes in marine exposure conditions.