

Machine Learning in Civil Engineering and Infrastructure Development

A Practitioner's Handbook



Edited by M.Z. Naser

Machine Learning in Civil Engineering and Infrastructure Development

This page intentionally left blank

Machine Learning in Civil Engineering and Infrastructure Development: A Practitioner's Handbook

Edited by M.Z. Naser

Published by Emerald Publishing Limited,

Floor 5, Northspring, 21-23 Wellington Street, Leeds LS1 4DL.

ICE Publishing is an imprint of Emerald Publishing Limited

Other ICE Publishing titles:

Digital Twins in the Built Environment: Fundamentals, principles and applications

Qiuchen Lu. ISBN 978-0-72776-580-2

Digital Twins for Smart Cities: Conceptualisation, challenges and practices

Qiuchen Lu. ISBN 978-0-7277-6600-7

A catalogue record for this book is available from the British Library.

ISBN 978-1-83662-867-5

© 2026 M.Z. Naser. Published under exclusive license by Emerald Publishing Limited.

Permission to use the ICE Publishing logo and ICE name is granted under licence to Emerald from the Institution of Civil Engineers. The Institution of Civil Engineers has not approved or endorsed any of the content herein.

All rights, including translation, reserved. Except as permitted by the Copyright, Designs and Patents Act 1988, no part of this publication may be reproduced, stored in a retrieval system or transmitted in any form or by any means, electronic, mechanical, photocopying or otherwise, without the prior written permission of the publisher, Emerald Publishing Limited, Floor 5, Northspring, 21-23 Wellington Street, Leeds LS1 4DL.

This book is published on the understanding that the author is solely responsible for the statements made and opinions expressed in it and that its publication does not necessarily imply that such statements and/or opinions are or reflect the views or opinions of the publisher. While every effort has been made to ensure that the statements made and the opinions expressed in this publication provide a safe and accurate guide, no liability or responsibility can be accepted in this respect by the author or publisher.

While every reasonable effort has been undertaken by the author and the publisher to acknowledge copyright on material reproduced, if there has been an oversight please contact the publisher and we will endeavour to correct this upon a reprint.

Cover photo: Shutterstock.com/g/chombosan

Commissioning Editor: Michael Fenton

Content Development Editor: Ryan Molyneux

Books Production Lead: Emma Sudderick

Typeset by KnowledgeWorks Global Limited

Index created by David Gaskell

Contents

Preface	ix
About the editor	xvii

Part I – Foundations and Modelling Philosophy 1

1	Overview of machine learning in civil engineering	3
	Vedprakash Maralapalle, Jayatheja Muktinutalapati, Bogireddy Chandra, Gangadhara Reddy Narala and Tammineni Gnananandarao	
	1.1. Introduction	3
	1.2. Fundamentals of machine learning	5
	1.3. Machine learning in structural engineering	9
	1.4. Machine learning in geotechnical engineering	10
	1.5. Machine learning in transportation engineering	14
	1.6. Machine learning in water resources engineering	15
	1.7. Machine learning in construction management	16
	1.8. Challenges and limitations of machine learning in civil engineering	19
	1.9. Future directions and emerging trends in machine learning for civil engineering	21
	1.10. Conclusion	23
2	Physics-informed machine learning: Applications in smart transportation	31
	Archie J Huang, Saumya Gupta and Shaurya Agarwal	
	2.1. Introduction	31
	2.2. Description of PIDL algorithm	32
	2.3. Case study I: PIDL for TSE with traffic sensing using CAVs	41
	2.4. Case study II: PIDL for TSE with traffic sensing using loop detectors	47
	2.5. Challenges and future work	49

3	Sustainable selection of construction materials using machine learning: A review	53
	Paul O Awoyera, Milica V Vasić, Kennedy Onyelowe and Sani Abba	
	3.1. Introduction	53
	3.2. Machine learning techniques in material selection	54
	3.3. Sustainability criteria for construction materials	56
	3.4. Application of machine learning for sustainable material selection	58
	3.5. Challenges and limitations	59
	3.6. Recommendations for future directions and opportunities	62
	3.7. Conclusion	62
	Part II – Structural Performance and Material Analysis	67
4	The power of carefully specified linear models: Steel fibre-reinforced concrete and its variability	69
	Emilio Garcia-Taengua	
	4.1. Introduction	69
	4.2. Preparation of the training dataset	70
	4.3. Modelling of SFRC residual flexural strength as a function of mix design	72
	4.4. Visualisation and interpretation of the model	76
	4.5. Analysis of the variability of SFRC residual flexural strength	84
	4.6. Summary	89
5	Machine learning-guided mechanical characterisation of 3D-printed plastic materials towards future optimisation of additive manufactured infrastructure components	91
	Rashmi Bhaila and Hadi Salehi	
	5.1. Introduction	91
	5.2. Literature review	93
	5.3. Data collection	94
	5.4. ML-guided materials design framework	98
	5.5. Results	105
	5.6. ML for 3D-printed plastic: limitations and future directions	110
	5.7. Conclusion	112

6	Deep learning-based surface crack detection in fibre-reinforced concrete exposed to temperature variations	117
	Diana Andrushia, Kanagaraj Balamurali and Nammalvar Anand	
	6.1. Introduction	117
	6.2. Materials	119
	6.3. Methods	119
	6.4. Results and discussion	122
	6.5. Conclusion	127
7	Machine learning-driven approach to understanding punching shear design in steel fibre-reinforced slabs	131
	Asad S Albostami and Rwayda Kh S Al-Hamd	
	7.1. Introduction	131
	7.2. Background and previous studies	132
	7.3. Current code provision for punching shear	135
	7.4. Description of machine learning (ML) techniques	139
	7.5. Results of the developed ML models	151
	7.6. Comparison with existing codes and developed equations	152
	7.7. Conclusions	159
	7.8. Challenges and considerations for new engineers in implementing ML models	160
	7.9. Codes	161
8	Training of ANN using Mountain Gazelle Optimiser for fire resistance of FRP-strengthened beams	171
	Nima Khodadadi, M.Z. Naser, Francisco De Caso, Antonio Nanni and Khalid M Mosalam	
	8.1. Introduction	171
	8.2. Construction of the model	173
	8.3. Results and discussion	180
	8.4. Conclusions	184

Part III – Systems, Infrastructure and Practice **187**

9 **SaltSpot: A convolutional neural network approach for classifying salt contamination damage on civil infrastructure** **189**
JA Guzmán-Torres, F J Domínguez-Mota, Gerardo Tinoco-Guerrero and EM Alonso-Guzmán

9.1. Introduction 189

9.2. Description of ML algorithm 191

9.3. A description of the dataset 194

9.4. Model development 195

9.5. Training process analysis and results 199

9.6. Conclusions 214

10 **Machine learning-driven assessment of embodied GHG emissions of structural systems** **219**
Ghada Karaki

10.1. Introduction 219

10.2. Source data and data processing 221

10.3. Classification model using machine learning 223

10.4. Results and analysis 228

10.5. Conclusions 236

11 **Synergising human expertise and AI in flood forecasting, management and resilience** **239**
Sun Yan Evans, Emma Wei and Sandra Stubenrauch

11.1. Introduction 239

11.2. Importance of coastal flood forecasting 241

11.3. Overview of Boston Barrier forecasting 242

11.4. Key components of coastal flood forecasting 242

11.5. Operational forecasting for the Boston Barrier 246

11.6. Machine learning – a layered approach to flood prediction 255

11.7. Key considerations and advice for practitioners 261

12 **What do AI chatbots think of civil and environmental engineering curricula? Insights into DFWs, JEDI, machine learning and modernisation strategies** **265**
Jamal Abdalla, M.Z. Naser and Saleh Al Ogla

12.1. Introduction 265

12.2. Approach and findings 268

12.3. Conclusions 298

Index 301

Preface

Machine learning (ML) no longer sits at the edges of civil engineering practice. Yet for many practising engineers, ML still feels like something that belongs to computer science or data science – a powerful but distant set of methods, rather than a natural extension of the modelling and empirical thinking they already use every day which are, in fact, embedded in various building codes.

Machine Learning in Civil Engineering and Infrastructure Development: A Practitioner's Handbook was conceived to narrow that gap. This is not a theoretical volume on algorithms, nor a collection of opaque code snippets. This handbook is a practitioner-oriented volume that shows, through diverse examples, how civil engineers can incorporate ML into real projects while remaining grounded in engineering judgement, physical understanding and professional responsibility.

The book rests on three straightforward premises. First, civil engineering is becoming irreversibly data-rich, as we continue to collect measurements from sensors, images from drones and phones, time-series data from environmental monitors, and large archives of test results and project records. Second, ML provides a flexible toolkit for extracting patterns and making predictions from this data – especially when we respect the role of physics, uncertainty and domain expertise. Third, engineers remain central, where ML should augment, not replace, the professional's ability to reason, critique results and make decisions that affect public safety and societal wellbeing.

To align with these premises, the chapters housed in this book are organised into three parts that move from foundations and modelling philosophy, through structural and material behaviour, to system-level applications and questions of practice, ethics and education. The progression is intentional: readers first encounter overarching concepts and mindsets, then see them applied to components and materials, and finally explore how these tools are implemented in infrastructure systems, risk management and the modernisation of the profession.

Part I – Foundations and Modelling Philosophy

The first part introduces core ideas and sets the tone for how this book treats machine learning: as a family of methods that must coexist with physics, good data and clear modelling goals.

The opening chapter, *Overview of machine learning in civil engineering*, provides the broad orientation many practitioners will need. This chapter walks through the main categories of ML by using civil engineering examples. The authors outline typical workflows: defining a problem, assembling and cleaning data, selecting appropriate input features, training and validating a model, and interpreting the results. For readers new to the area, this chapter offers an accessible but comprehensive entry point. For those with some experience, it provides a structured framework that helps place individual techniques within a bigger picture.

The second chapter, *Physics-informed machine learning: applications in smart transportation*, moves directly into one of the most important modelling philosophies in modern engineering: physics-informed machine learning (PIML). Herein, and rather than treating learning algorithms as black boxes, PIML embeds physical constraints, governing equations or conservation laws into the ML process. In the context of smart transportation, where safety, real-time decision-making and reliability matter, this hybrid approach can be particularly compelling. This chapter sends a clear signal by noting how ML is at its best when it works with, not against, our mechanistic understanding.

Part I concludes with *Sustainable selection of construction materials using machine learning: a review*, which extends foundational concepts into one of the most pressing themes in our field: sustainability. Material selection has always involved trade-offs among cost, performance, durability and constructability. Today, environmental impacts are also expected to be considered. Therefore, this chapter surveys how ML is being used to navigate these multi-criteria decisions. As a review, the chapter also identifies emerging trends and gaps, which can help guide practitioners and researchers toward areas where improved data, new models or enhanced decision frameworks are needed.

As can be seen, these three chapters define the intellectual ground of the book. More specifically, ML in civil engineering is not just about ML algorithms; it is about how we formulate problems, respect physical realities, and use data-driven tools to support broader societal goals.

Part II – Structural Performance and Material Analysis

The second part focuses more tightly on structural components, materials and damage detection, including behaviour under demanding or extreme conditions. What is new is how ML is used to interpret data, reduce testing burdens and interrogate existing design provisions.

The first chapter in this part, *The power of carefully specified linear models: steel fibre-reinforced concrete and its variability*, serves as a crucial reminder that ML does not automatically mean deep, opaque models. In fact, carefully designed linear models, built on a thoughtful selection and transformation of inputs, can capture variability and trends – with a case on steel fibre-reinforced concrete – remarkably well. This chapter encourages engineers to see linear and generalised linear models as transparent members of the ML family, particularly when combined with a solid understanding of materials and experimental design.

Building on that foundation, *Machine learning-guided mechanical characterisation of 3D-printed plastic materials towards future optimisation of additive manufactured infrastructure components* moves into the emerging area of additive manufacturing in civil engineering. The mechanical behaviour of 3D-printed plastics can be complex, influenced by printing parameters, material choices and geometry. The authors show how ML can suggest promising directions for optimising component performance. For practitioners, this chapter also offers a template for using ML to accelerate material characterisation when new technologies enter the field.

Damage detection and durability continue in the next chapter, *Deep learning-based surface crack detection in fibre-reinforced concrete exposed to temperature variations*. Here, image-based deep learning models are trained to identify and segment cracks in reinforced concrete subjected to different thermal environments. The chapter walks through data collection, labelling, model training and evaluation while highlighting the challenges of dealing with images. In doing so, it provides a practical example of how computer vision can complement traditional inspection and potentially lead to more objective assessments of surface damage.

The following chapter, *Machine learning-driven approach to understanding punching shear design in steel fibre-reinforced slabs*, shifts attention to ultimate limit states in design. Punching shear in slabs is a critical and often brittle failure mode that design codes must handle conservatively. Thus, by bringing together data with ML techniques, the authors explore how well existing design provisions capture observed behaviour, where they may be overly conservative or unconservative, and how alternative formulations might perform. The emphasis is not only on predictive accuracy, but also on extracting engineering insight.

Part II concludes with *Training of ANN using Mountain Gazelle Optimiser for fire resistance of FRP-strengthened beams*, which introduces readers to a more advanced algorithmic combination: artificial neural networks trained by way of a nature-inspired metaheuristic, applied to structural fire engineering. Fire resistance of FRP-strengthened beams involves complex interactions between temperature, material degradation and structural response. The chapter demonstrates how an optimised neural network can serve as a fast surrogate for more computationally expensive models, supporting design and assessment under fire scenarios. At the same time, it illustrates how evolutionary optimisation methods can be used to tune ML models in challenging design spaces.

Across these chapters, Part II shows ML at work in the heart of structural and materials engineering. For practitioners, this part offers examples of how ML can be integrated into familiar tasks: analysing test results, calibrating models, assisting inspections and supporting structural design.

Part III – Systems, Infrastructure and Practice

The final part of the book steps outward from components to infrastructure systems and professional practice. Here, the focus is on condition assessment at scale, system-level sustainability, human–AI collaboration in risk management, and the broader implications of ML tools for modernisation.

The first chapter in this part, *Saltspot: a convolutional neural network approach for classifying salt contamination damage on civil infrastructure*, uses computer vision to address the widespread durability issue of salt contamination (which can lead to significant deterioration of concrete and other materials, particularly in coastal or

winter-maintenance environments). Here, the authors demonstrate how training convolutional neural networks on images enables ML models to support automated classification in large-scale condition surveys. This can be helpful for agencies to prioritise inspections and interventions. This chapter complements earlier crack-detection work, but now emphasises system-level deployment.

Sustainability reappears in *Machine learning-driven assessment of embodied GHG emissions of structural systems*, which moves from material choices to whole-system environmental impact. Estimating embodied greenhouse gas emissions for different structural configurations can be time-consuming, especially when exploring multiple design alternatives. Thus, ML models, trained on detailed assessments, can provide rapid approximations of embodied emissions, enabling designers to compare options early in the design process. This chapter shows how such models can be integrated into conventional workflows, helping teams align structural decisions with climate objectives and regulatory requirements without treating sustainability as an afterthought.

Water-related risk and resilience take centre stage in *Synergising human expertise and AI in flood forecasting, management and resilience*. Flood risk management exemplifies a domain where data, physics, uncertainty and local experience must all come together. This chapter illustrates how ML can assist with forecasting, scenario analysis and real-time decision support, while emphasising that human expertise remains critical. It discusses not only technical aspects but also institutional and organisational considerations, including how teams adopt these tools, how responsibilities are shared, and how trust is established between human decision-makers and ML systems. For practitioners, this is an important reminder that successful deployments depend on people and processes as much as on algorithms.

The book concludes with *What do AI chatbots think of civil and environmental engineering curricula? Insights into DFWs, JEDI, machine learning and modernisation strategies*, which steps back to examine the role of ML tools, including large language models (LLMs), in the broader ecosystem of civil engineering. As chatbots become more common in classrooms, design offices and public agencies, they bring both opportunities and risks. This chapter critically evaluates how such tools perform when asked about diversity,

fairness, workforce strategies and modernisation within engineering contexts. It highlights issues of bias, transparency and accountability, and situates ML within ongoing discussions about justice, equity, diversity and inclusion (JEDI) in the profession. Ending the volume here is purposeful in order to invite readers to think not only about what ML can do technically, but also about how we use it, whose interests it serves, and how it might reshape professional norms.

Using this handbook

We anticipate that different readers will approach this handbook in different ways. Some may follow the parts sequentially: beginning with the conceptual overview and modelling philosophy of Part I, then moving through the structural and material applications of Part II, and finally exploring the system-level and practice-oriented chapters in Part III. Others may dip directly into the domain that most closely matches their work and then circle back to the foundational material. Educators may select individual chapters as case studies for courses on structural engineering, transportation, sustainability or infrastructure management, pairing them with hands-on exercises in Python or other platforms. Researchers may use the chapters as springboards for new datasets, hybrid modelling approaches or proposals to integrate machine learning more deeply into codes, standards and decision frameworks.

Throughout, the emphasis is on *practice*: not only what algorithms are, but how they are trained, validated, interpreted and integrated into real decision-making contexts. The reader will find examples where ML models serve as fast surrogates for complex simulations, where they complement visual inspections and monitoring, where they reveal structure in high-dimensional material data, and where they inform system-level strategies for emissions reduction and flood resilience. The reader may also find reminders that good engineering practice is as essential in ML as it is in any other analysis we perform.

Civil engineering has a long history of adopting new tools, from hand calculations to finite element analysis, from drawing boards to building information modelling, and from isolated measurements to sensor networks. Machine learning is the next such tool; powerful, sometimes over-hyped, but genuinely capable of improving how we design, assess and manage the built environment when used thoughtfully. If this handbook helps you see ML as a usable,

critique-able and adaptable part of your toolbox, then it will have achieved its goal.

A note from the editor

I am deeply grateful to all of the contributors to this volume, who generously shared their time, expertise and data to turn an idea into a coherent practitioner's handbook. Their chapters reflect not only technical proficiency but also a genuine commitment to advancing civil engineering in a responsible and practical manner. I would also like to thank the editorial and production teams at Emerald for their professionalism, patience and meticulous attention to detail throughout every stage of this project. In particular, my acquisition editor, Dr Michael Fenton, and Ryan Molyneux, whose guidance, encouragement and belief in the value of this book made the entire process not only possible but enjoyable, deserve my sincere appreciation. In addition, special thanks go to Prof Ghanim Kashwani for planting the seed for this handbook.

This page intentionally left blank

About the editor

Dr M.Z. Naser is a professional engineer and an assistant professor at the School of Civil and Environmental Engineering and Earth Sciences at Clemson University, SC, USA, and a faculty member of the AI Research Institute for Science and Engineering (AIRISE). Dr Naser serves as the current chair of the American Society of Civil Engineers' (ASCE) Task Committee on Machine Learning for Civil Engineering and was the former chair of the Advances in Information Technology (AIT) committee. He is a voting member of various national and international engineering institutions. Dr Naser's research develops causal, explainable machine learning methodologies to help us realise functional, sustainable and resilient infrastructure. He has co-authored over 150 peer-reviewed publications, including a textbook on machine learning and civil engineering, titled *Machine Learning for Civil and Environmental Engineers: A Practical Approach to Data-Driven Analysis, Explainability, and Causality*. He is listed in the company of the world's most impactful researchers by Elsevier and Stanford University, ranking among the world's top 2% of scientists since 2022.