Lecture Notes in Civil Engineering

Stefanus Adi Kristiawan
Buntara S. Gan
Mohamed Shahin
Akanshu Sharma *Editors*

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Editors
Stefanus Adi Kristiawan
Department of Civil Engineering
Universitas Sebelas Maret
Surakarta, Indonesia

Buntara S. Gan
College of Engineering
Nihon University
Tokyo, Japan

Mohamed Shahin
Department of Civil Engineering
Curtin University
Perth, WA, Australia

Akanshu Sharma
Institute of Construction Materials
University of Stuttgart
Stuttgart, Germany

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Foreword

The International Conference on Rehabilitation and Maintenance in Civil Engineering (ICRMCE) is a triennial conference that aims to provide a forum for researchers, academicians (professors, lecturers, and students), government agencies, consultants, and contractors to exchange experiences, technological advancement, and innovations in the world of civil engineering, specifically in the fields of rehabilitation and maintenance. The previous four ICRMCE conferences took place successfully in 2009, 2012, 2015, and 2018. Hundreds of researchers worldwide attended these events to present their scientific papers in various areas of civil engineering such as material engineering, structural engineering, geotechnical engineering, transportation engineering, and construction management.

This year's conference was organized by Sebelas Maret University in collaboration with Mataram University. The conference was initially scheduled offline in Mataram, Indonesia. However, due to the escalating coronavirus (COVID-19) outbreak and the need for social distancing, we decided to hold the conference online. Some reputable universities and institutions are participating in the current ICRMCE as partners. Among them are Nihon University, University of Stuttgart, National Taiwan University, TU Delft, Hiroshima University, Diponegoro University, Muhammadiyah University of Yogyakarta, Jenderal Soedirman University, University of Jember, UPN Veteran East Java, the National Center for Research on Earthquake Engineering (NCREE) Taiwan, Himpunan Ahli Konstruksi Indonesia (HAKI), and Himpunan Ahli Teknik Tanah Indonesia (HATTI).

The ICRMCE 2021 was successfully held on July 8–9. Presenters who joined this conference came from Japan, Singapore, Malaysia, China, Vietnam, Taiwan, England, the Netherlands, Kuwait, and Indonesia. Furthermore, several outstanding keynote speakers gave a presentation of the state-of-the-art findings in the field of civil engineering. Our esteemed speakers are Prof. Shyh-Jiann Hwang (National Taiwan University), Prof. Buntara Sthenly Gan (Nihon University), Dr. Edgar Bohner (VTT Technical Research Centre of Finland), and Prof. Mohamed Shahin (Curtin University).

In the process of organizing this conference, we received invaluable motivation, advice, and support from several individuals and institutions. I intend to express my gratitude and appreciation to all of them. First, my most profound appreciation goes to all organizing committee members who worked day and night preparing this conference. Special thanks to the conference and media partners for their generous support. We also express our gratitude to Prof. S.A. Kristiawan (Sebelas Maret University), Dr. Ing. Akanshu Sharma (University of Stuttgart), Prof. Mohamed Shahin (Curtin University), and Prof. Buntara Sthenly Gan (Nihon University) for their willingness to serve as the editors of the 5th ICRMCE proceedings.

Halwan Alfisa Saifullah
The 5th ICRMCE Chairman

Preface

Civil engineering infrastructures are the backbone for the continuous development of civilization. Managing these infrastructures is essential in keeping the quality of services they provide to the community. A decline in the performance of key infrastructure will have an impact on the quality of these services, which in turn can cause social and economic problems. A variety of factors affects the performance of infrastructure. In each case, the declining performance of infrastructure requires an appropriate and adaptive response to offer effective solutions. Protection, maintenance, repair, and retrofitting are part of the various solutions that can be implemented. All of these solutions are assisted by technological developments related to repair materials, methodologies, systems, management, and operational efficiency, as well as economic and social considerations.

Infrastructure performance is also inevitably affected by exposure to hazards originating from natural and environmental conditions such as earthquakes, landslides, and floods, among others. Therefore, hazard mitigation is also an interesting topic of discussion. In addition, risk reduction and safety are among the most important issues of infrastructure management. Finally, various perspectives on sustainability in civil engineering are also covered in this conference.

This book is a collection of papers presented at the 5th International Conference on Rehabilitation and Maintenance in Civil Engineering (ICRMCE) 2021 that deals with the issues stated above. The papers are grouped into sequential themes representing the structure of this book:

- Part I: Factors affecting performance of buildings and infrastructures
- Part II: Assessment, protection, maintenance, repair, and retrofitting of buildings and infrastructures
- Part III: Maintenance management of buildings and infrastructures
- Part IV: Hazard mitigation
- Part V: Risk reduction and safety management
- Part VI: Sustainability aspects in transportation engineering
- Part VII: Sustainability aspects in construction projects

- Part VIII: Sustainability aspects in water resources management
- Part IX: Construction materials for sustainable infrastructures

Postgraduate students, researchers, and practitioners who would like to update their knowledge on the topics above will find this book very useful.

Surakarta, Indonesia

Stefanus Adi Kristiawan
Chief Editor

Contents

Factors Affecting Performance of Buildings and Infrastructures

A Review on Application of Machine Learning in Building Performance Prediction

R. W. Triadji, M. A. Berawi, and M. Sari

Abstract Designers usually use Building Performance Simulation (BPS) to support decision making in facing design requirements and expected building performance. However, the fact is that BPS still experiences several limitations, such as BPS requires high computation time in assessing various design options. Machine learning is considered capable of solving the problem that the existing BPS has. Research on this problem has been conducted to provide solutions and prove the reliability of machine learning in predicting building performance. Therefore, this paper aims to discuss the research and overview of how machine learning has been used in predicting building performance. The results show that, performance prediction using machine learning has been developed on energy and environmental performance. Also, machine learning can significantly reduce the prediction time without reducing its accuracy.

Keywords Machine learning · Building performance · Energy performance · Environmental performance

1 Introduction

The importance of digital technology and automation systems in playing a role in industry 4.0 makes every device now equipped with machine learning [1]. As the core of artificial intelligence [2], machine learning is a process where machines can learn various things by themselves based on their experiences [3]. Machines learn the relationship between input and output data received as information and turn it

R. W. Triadji (✉) · M. A. Berawi · M. Sari
Civil Engineering Department, Faculty of Engineering, Universitas Indonesia, Depok, Indonesia
e-mail: rizka.wulan@ui.ac.id

M. A. Berawi
e-mail: maberawi@eng.ui.ac.id

M. Sari
e-mail: mustikasari01@ui.ac.id

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into an experience to offer solutions that can adapt according to given situations [4, 5]. Machine learning has been developed in the construction industry to solve complicated and difficult problems [6]. It is shown by the potential of machine learning in improving building performance [3].

Building performance is considered since the design stage; this step is taken as an effort for the building to perform its functions optimally when it is operating [7]. Designers usually use Building Performance Simulation (BPS) to support decision making in facing design requirements and expected building performance [8]. However, BPS is still experiencing several deficiencies in its application; first, BPS requiring a high computation time to assess various design options [8, 9]. Moreover, some factors have not been considered in implementing the simulation, thus making the predictions offered by BPS less accurate [7]. Machine learning is considered to have the potential and capability to answer these deficiencies [8]. Its ability to predict various designs in a second and incorporate factors not covered by existing BPS will improve the prediction results and replaced the existing Building performance Simulation [7, 9]. Below, we made the conceptual diagram to give a glance of insight (see Fig. 1). Building performance no longer predicts by the existing BPS; it replaced by machine learning and its algorithm to predict those predictions such as energy performance and environmental performance.

Therefore, this paper aims to examine studies related to machine learning in building performance and an overview of how machine learning has been used to predict building performance. The review expected can provide more extensive reference and insight in involving machine learning in the construction industry to enhance building performance prediction.

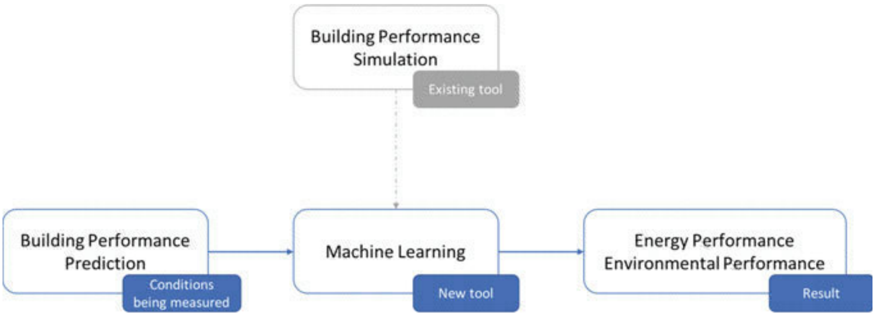

Fig. 1 Conceptual diagram of machine learning and existing BPS

2 Methods

In this study, we collected literature through Scopus as the central database for academic publications. The keywords used are “machine learning”, “building performance”, “energy performance”, “energy consumption”, “environment” “indoor environment”, “thermal comfort”, “visual comfort”, the selected documents are limited to journal articles and conference papers that have been published in the last ten years (2011–2021). The search structure example for Scopus is as follows:

> TITLE-ABS-KEY ("machine learning” AND "building performance") AND (LIMIT-TO (DOCTYPE, "ar”) OR LIMIT TO (DOCTYPE, "cp”)) AND (EXCLUDE (PUBYEAR, 2010))

The authors conducted the first screening by reviewing abstracts and matching predetermined keywords so irrelevant documents could be separated from the search results. 37 documents are deemed relevant to the topics we discussed. Then, the second screening will be carried out by reading the entire document. 17 papers were not selected to be discussed, after the second screening. Thus, 20 papers will be discussed and grouped based on two primary performances that become the main concern in a building: energy performance and environmental performance [10, 11]. The algorithm of machine learning in each paper will also be discussed in this review.

3 Result and Discussion

3.1 Energy Performance

Several building energy performance tools such as TrnSys, EnergyPlus, ESP-r, DOE-2 and Modellica have been widely used, but these tools still require high computation time for various designs with multiple inputs; this also makes simulation tools difficult in delivering precise result [9, 12, 13]. In this section, the discussion will be grouped into two main parts, which are thermal and electricity; due to the current study that we discussed in this section focuses on thermal performance and follows by electricity performance.

Thermal Energy

In previous studies, machine learning has been developed to predict the thermal (cooling and heating energy) performance of buildings using an Artificial Neural Network (ANN) [9, 12, 14–16]. Comesaña et al. [12] developed a machine learning model based on outdoor and indoor temperatures and radiation levels. Meanwhile, Geyer and Singaravel’s [14] model based on building components such as walls, windows and floors. Geyer and Singaravel [14] stated that the computation time to make predictions using machine learning is reduced drastically. In line with this, Ascione et al. [16] ensure a computation time savings of 98% can be achieved using machine learning, this has been proven in their research. They develop a model for predicting energy performance and the energy retrofitting scenario for each building element. Similarly, Seyedzadeh et al. [17] also made a model to predict energy performance and support decision-making about energy retrofit scenarios, the algorithm used is gradient boosted regression trees.

Singh et al. [9] make energy predictions by creating four schematic methods for making predictions. The first three using EnergyPlus, and the last method is using machine learning. The result is that machine learning can achieve the objectives of reducing computation time than EnergyPlus. Westermann et al. [18] using the Convolutional Neural Network (CNN) algorithm to develop a machine learning model to displace a building energy simulation tool. It can predict thermal energy based on input from various design and climate variations. The model is representative enough to be used in various climates of building locations and does not affect its accuracy. On the other hand, Ciulla and D'Amico [19] developed a model without the intention of replacing the existing simulation model. The model was developed with the Multiple Linear Regression algorithm, built as simple as possible, so even non-expert users can use it.

Chakraborty and Elzarka [20] developed their model using three different algorithms (XGBoost, ANN and Degree-day-based OLS regression); the result is XGBoost the most accurate algorithm in predicting thermal performance. In contrast to other studies, Attanasio et al. [21] developed a model only to predict heating energy by comparing four machine learning algorithms. Meanwhile, Yu et al. [13] combine two algorithms, genetic algorithm (GA) and back-propagation (BP), to optimize energy performance predictions and thermal comfort based on the building design and design envelope in residential building. Similarly, Robinson et al. [22] developed a model for commercial building using CBECS (Commercial Building Energy Consumption Survey) data released by the US Energy Information Administration (EIA). It is intended that the proposed model can be used in any city in the US.

Electricity Energy

Zeng et al. [23] developed machine learning to predict electrical energy consumption in a building using the Gaussian Process algorithm. The model developed is based on three types of buildings: offices, shopping centres, and hotels with various design configurations. Later, the model can be used in several kinds of buildings. Moreover, Pangaribuan et al. [24] also build a model to predict electrical energy using a support vector regression algorithm for residential homes.

3.2 Environmental Performance

Environmental performance is also one of the criteria that need to be considered in the design to balance each building's performance and achieve optimal sustainability goals [25, 26]. In this case, the environmental performance consists of an indoor or outdoor environment. The indoor performance focuses on the comfort of occupants in the building [13]. Meanwhile, outdoor performance pays more attention to the impact caused by buildings on the outdoor environment, such as CO_2 gas emissions [11]. Mazuroski et al. [27] developed a recurrent neural network-based model to predict indoor temperature based on density, specific heat and thermal conductivity of each building material that will be used. The same idea was done by Kamel et al. [28]. The difference between these two studies is the data used as input to predict indoor temperature, i.e. humidity, radiations, airspeed, door open/close status, and motion from sensors installed in the room. In their research, the model developed by Yu et al. [13] with GA-BP algorithm is not only to predict energy performance but also to predict thermal comfort.

On the other hand, Symonds et al. [29] used an artificial neural network to predict indoor environmental quality. The model developed can make predictions in overheating metric, PM2.5 ratio, relative humidity and heating energy use with a reasonable degree of accuracy. In his study, Chen [30] said that difference results between the building performance analysis predictions and reality could not be avoided. Machine learning was developed to improve the accuracy of green BIM by using an artificial neural network algorithm and daylight luminance level as an outcome of the prediction. The model can also predict climate analysis, thermal comfort, energy calculation, and other BPA dimensions. Chatzikonstantinou and Sariyildiz [31] focused their study on office space's visual comfort; a model developed can predict Daylight Glare Probability and Daylight Autonomy. Algorithms feed-forward networks (FFNs) were chosen as the algorithm with the highest level of accuracy compared to support vector machines (SVMs) and random forests (RFs).

While some of the studies focused on indoor performance, Feng et al. [11] developed a model to discover the environmental impact from the building design. They were using GWP/unit area as an indicator of environmental performance. The input of the model is the early design parameter, and fuzzy c means algorithm approach was used to perform the model. The model expected can help designers in testing several design scenarios and the resulting performance.

4 Conclusion

Machine learning has been used to predict buildings performance in terms of energy and the environment. From our review, energy performance is a performance that is widely used in developing machine learning models. Also, artificial neural networks are found as an algorithm that is widely used in model development. The potential of machine learning in predicting performance in a second and accurately can help designers make decisions of a wide variety of designs. It reveals that machine learning can be a promising and powerful tool, mainly when used at the design stage. However, while machine learning has promising potential, it still has its limitations. First, to make good predictive, machine learning requires big data to train the algorithm [3]. Moreover, some studies apply machine learning to only one building type, and this makes the model unable to be used for other building types. It is expected that with these reviews, the construction industry can take advantage of machine learning capabilities in predicting building performance.

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The Effect of P-Delta and P-Delta Plus Large Displacements Modelling on Lateral and Axial Displacement

Jonie Tanijaya and Robby S. Kwandou

Abstract The structural analysis programs have become increasingly sophisticated along with the advancement of science. However, engineers need to be more careful and understand the use of the options in the program. One program that can incorporate non-linear effects is SAP2000. In the SAP2000 program, non-linear modeling options are classified into two options, namely non-linear and non-linear plus large displacements. The SAP2000 program is a finite element-based program. The finite element method is a method that solves problems by dividing a large element into several small element segments or commonly referred to as meshing. The smaller the meshing segment used, the more accurate the output will be. However, its significance remains to be studied further. Therefore, this study was conducted to determine the significance of differences in modeling options (linear, non-linear, non-linear plus large displacements), as well as the effect of segment division in the analysis. The analysis results show that the linear model cannot capture the effect of the lateral displacement that changes due to the incremental of the compression force. The compression force has significant effect to moment value especially for the higher compression force. Therefore, the P-Delta effect should be analyzed carefully, especially for element with high compression force since the linear model could not capture this effect. The meshing by divide segment does not provide significance difference for both P-Delta and P-Delta plus large displacement model in this case.

Keywords P-Delta · P-Delta plus large displacements · Lateral displacement

J. Tanijaya (✉)
Civil Engineering Department, Universitas Kristen Indonesia Paulus Makassar, Makassar, Indonesia

R. S. Kwandou
Postgraduate Alumni of Hasanuddin University, Makassar, Indonesia

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1 Introduction

The structural analysis programs have become increasingly sophisticated along with the advancement of science. However, engineers need to be more careful and understand the use of the options in the program. The assumptions of modelling need to be considered carefully. The effect of lateral load on horizontal displacement should be checked in analysis. The elastic-linear analysis condition can produce an underestimated result, especially in the case of structural elements that experience large deformation, such as thin glass panel structures and mono-poles that are exposed to the wind load. A structural analysis that can take into account the large deformations effect will certainly provide a more accurate result. When using linear elastic analysis, the effect of changes in geometry due to large deflection cannot be taken into account in the analysis [1]. One program that can incorporate non-linear effects is SAP2000. In the SAP2000 program, non-linear modeling options are classified into two options, namely non-linear and non-linear plus large displacements. The SAP2000 program is a finite element-based program. The finite element method is a method that solves problems by dividing a large element into several small element segments or commonly referred to as meshing. The smaller the meshing segment used, the more accurate the output will be. Different output values would be provided when including the meshing effect. However, its significance remains to be studied further. Therefore, this study was conducted to determine the significance of differences in modeling options (linear, non-linear, non-linear plus large displacements), as well as the effect of segment division in the analysis.

2 Literature Review

The P-Delta effect occurs due to gravity load (P) that produces the increasing of horizontal displacement (Δ) [2]. The eccentricity of the gravitational load (P) against the column axis causes an increase in horizontal displacement when the structure is subjected to lateral loads. Thus, the P-Delta effect will cause an increase in the moment value as well as the structural drift [3]. Indonesia is surrounded by active tectonic faults so that the lateral load due to earthquakes needs to be considered [4]. The lateral force due to earthquake loads which is influenced by the P-Delta effect becomes critical, especially when the P-Delta effect needs to be considered in the analysis. Based on the research results of Isitono and Ramadhan, the increasing moment value is about 10% on the building structure model [2]. The average percentage increase in moment value that occurs due to P-Delta is between 19 and 27% based on the results of Suhana and Pello's research on a 15-story building [5].

P-Delta effect as one type of geometric nonlinearity, typically produce relatively small additional displacement due to large external force. If deformations become