A COMPRESSIVE CONCRETE STRENGTH PREDICTION MODEL USING ARTIFICIAL NEURAL NETWORKS

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Abstract (English)

A building is at a high risk of destruction if the compressive concrete strength does not meet the required specification. Thus, the prediction of compressive concrete strength has become an important research area. Previous prediction models are based on fix numbers of attributes. Consequently, when the number of attributes increase or decrease, the models could not be used. Thus, a compressive concrete strength prediction model which can work with different numbers of attribute is needed. The purpose of this study is to develop compressive concrete strength prediction models using different combinations of attributes. This study includes five stages: data collection, normalization, parameters identification, model construction and evaluation. The employed data set consists of nine attributes: water, cement, fine aggregate, coarse aggregate, age, fly ash, super plasticizer, blast furnace slag and compressive concrete strength. This study produced eight prediction models where each model has different combination of attributes. It also identified appropriate weights, learning rate, momentum and number of hidden nodes for each of the proposed model, and design a general artificial neural network (ANN) architecture. Model eight of the study produced a higher correlation coefficient (i.e., 0.973) than the existing study (i.e., 0.953). This study has successfully produced eight concrete strength prediction models with good coefficient correlation. The compressive strength prediction models would benefit civil engineers as they can use the models to identify the suitability of additional materials in concrete mix.

Keywords: Compressive concrete strength, Different combinations of attributes, Artificial neural networks, Prediction models.

Abstrak (Bahasa malaysia)

Sesebuah bangunan adalah berisiko tinggi untuk runtuh jika kekuatan mampatan konkrit tidak memenuhi spesifikasi yang dikehendaki. Oleh itu, ramalan kekuatan mampatan konkrit telah menjadi satu topik penyelidikan yang penting. Model ramalan sebelum ini adalah berasaskan kepada bilangan atribut yang tetap. Akibatnya, apabila berlaku peningkatan atau penurunan bilangan atribut, model tersebut tidak boleh digunakan. Oleh itu, model ramalan kekuatan mampatan konkrit yang boleh berfungsi dengan bilangan atribut yang berlainan adalah diperlukan. Tujuan kajian ini adalah untuk membangunkan model ramalan kekuatan mampatan konkrit yang menggunakan kombinasi atribut berlainan. Kajian ini merangkumi lima peringkat: pengumpulan data, penormalan, pengenalpastian parameter, pembinaan model dan penilaian. Data set yang digunakan terdiri daripada sembilan atribut: air, simen, agregat halus, agregat kasar, usia, abu terbang, *super plasticizer*, sanga relau bagas dan kekuatan mampatan konkrit. Kajian ini menghasilkan lapan model ramalan yang mana setiap model mempunyai kombinasi atribut yang berbeza. Kajian itu juga mengenalpasti berat, kadar pembelajaran, momentum dan bilangan nod tersembunyi yang sesuai untuk setiap model ramalan yang dicadangkan, dan rekabentuk umum seni bina rangkaian neural buatan (ANN). Model lapan dalam kajian ini menghasilkan pekali korelasi yang lebih tinggi (0.973) daripada kajian yang sedia ada (0.953). Kajian ini telah berjaya menghasilkan lapan model ramalan kekuatan mampatan konkrit dengan pekali korelasi yang baik. Model ramalan kekuatan mampatan konkrit ini akan memberi manfaat kepada jurutera awam untuk mengenal pasti kesesuaian bahan tambahan untuk campuran konkrit.

Kata Kunci: Kekuatan konkrit mampatan, Kombinasi sifat-sifat, Rangkaian neural buatan, Model ramalan.

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Table of Contents

List of Tables

List of Figures

List of Appendices

CHAPTER ONE

INTRODUCTION

1.1 Background

Concrete is one of the most indispensable building and engineering material in the world. It has been used for more than 10 decades (Aggarwal, Kumar, Sharma, & Sharma, 2015). Concrete becomes more and more popular in the world because of its capabilities. For example, it can take up any shape before it becomes hard, and strengthens when it hardens. This construction material is widely used in buildings, bridges, roads, runways, docks, military engineering, nuclear power stations and so on (Wankhade & Kambekar, 2013). If there is a high quality building, it must have a strong compressive strength of concrete. Because of this, compressive concrete strength becomes an important element building construction. If the compressive concrete strength do not meet the required specification for a building then there will a high risk of destruction when unfortunate incidents happened such as natural disasters or damages caused by humans. For example on May 12, 2008, an earthquake of magnitude 7.9, struck western Sichuan province causing many buildings to be destroyed and casualties. Many experts agree that casualties and damages could have been avoided if the buildings were built using high quality components. The question is, how quality is the buildings? Obviously, when such catastrophic incident occur, the buildings can said to be below the quality standard – that is, the compressive concrete strength was below than the standard procedure(Michele et al., 2010). Again on July28, 1976, the city of Tangshan, China

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