

The copyright © of this thesis belongs to its rightful author and/or other copyright owner. Copies can be accessed and downloaded for non-commercial or learning purposes without any charge and permission. The thesis cannot be reproduced or quoted as a whole without the permission from its rightful owner. No alteration or changes in format is allowed without permission from its rightful owner.



**A COMPRESSIVE CONCRETE STRENGTH PREDICTION
MODEL USING ARTIFICIAL NEURAL NETWORKS**



INTELLIGENT SYSTEM, MASTER OF SCIENCE

UNIVERSITI UTARA MALAYSIA

2017

Permission to Use

In presenting this project in partial fulfillment of the requirements for a postgraduate degree from the Universiti Utara Malaysia, I agree that the University Library may make it freely available for inspection. I further agree that permission for copying of this project in any manner in whole or in part, for scholarly purposes may be granted by my supervisor(s) or in their absence by the Dean of Postgraduate Studies and Research. It is understood that any copying or publication or use of this project or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to Universiti Utara Malaysia for any scholarly use which may be made of any material from my project.

Requests for permission to copy or to make other use of materials in this project, in whole or in part, should be addressed to



UUM

Dean of Postgraduate Studies and Research

College of Arts and Sciences

Universiti Utara Malaysia

06010 UUM Sintok

Kedah DarulAman

Malaysia

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.

Acknowledgement

Heartfelt thanks are to my dear supervisor, Prof. Dr. Faudziah Ahamad for patiently navigating and generously sharing her rich source of knowledge with me. She always give me a hand when I cannot progress my dissertation. She is indeed a teacher of "pen hand, open mind and open heart".

Equally, I need to thanks to my parents for all their love, unlimited help and the great support they offered to me.

I also need to say "thank you" to the friends around me for giving me suggestions and sharing their experiences with me. They really help me a lot.

In the end, thanks to Universiti Utara Malaysia for supporting me a good place for studying knowledge and experiences.

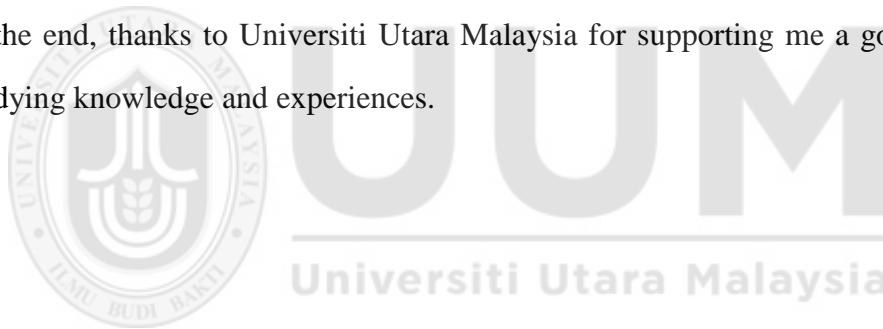


Table of Contents

Permission to Use.....	I
Abstract (English)	II
Abstrak (Bahasa malaysia).....	III
Acknowledgement.....	IV
List of Tables	VII
List of Figures	IX
CHAPTER ONE INTRODUCTION	1
1.1 Background	1
1.2 Problem Statement	4
1.3 Research Questions	5
1.4 Research Objectives	6
1.5 Significance of the study	6
1.6 Scope of this study	7
1.7 Thesis organization	7
CHAPTER TWO LITERATURE REVIEW.....	8
2.1 Theoretical background.....	8
2.1.1 Compressive strength of concrete	8
2.1.2 Attributes	9
2.1.3 Past studies on prediction techniques.....	13
2.2 ANN concepts and architecture.....	22
2.2.1 Construction of Neural Network Model and Parameters.....	23
2.2.2 A simple neural network model	25
2.3 Summary	26
CHAPTER THREE METHODOLOGY	27
3.1 Research Process	27
3.1.1 Phase 1 Data Collection	28
3.1.2 Phase 2 Normalization	36
3.1.3 Phase 3 Determine Parameters.....	37

3.1.4 Phase 4 Construct Prediction Model	42
3.1.5 Phase 5 Evaluation	44
3.1.5.1 Correlation coefficient	44
3.1.5.2 Root mean square error (RMSE).....	45
3.1.5.3 Mean absolute error (MAE)	45
3.2 Summary	46
CHAPTER FOUR RESULTS	47
4.1 Deliverables for objective 1	47
4.2 Deliverables for objective 2	48
4.3 Deliverables for Objective 3	48
4.3.1 Model 1 parameters:.....	49
4.3.2 Model 2 to Model 8 parameters	56
4.4 Deliverables for objective 4	59
4.5 Summary	64
CHAPTER FIVE EVALUATION AND DISCUSSION	65
5.1 Prediction models.....	65
5.2 Evaluation Results and Discussion	66
5.3 Comparison with past work	75
5.3 Summary	76
CHAPTER SIX CONCLUSION	78
6.1 Work summary	78
6.2 Contribution	79
6.3 Future works	80
REFERENCES.....	81

List of Tables

Table 2.1 Attributes used by existing researchers	10
Table 2.2 The occurrences of attributes from previous attributes	12
Table 2.3 Various prediction techniques	14
Table 2.4 RMSE for several modeling methods	20
Table 2.5 Prediction results for three algorithms	21
Table 3.1 Inputs and output attributes	29
Table 3.2 (a) Statistical descriptions for Dataset 1	30
Table 3.2 (b) Statistical descriptions for Dataset 2	30
Table 3.2 (c) Statistical descriptions for Dataset 3	31
Table 3.2 (d) Statistical descriptions for Dataset 4	31
Table 3.2 (e) Statistical descriptions for Dataset 5	32
Table 3.2 (f) Statistical descriptions for Dataset 6	33
Table 3.2 (g) Statistical descriptions for Dataset 7	33
Table 3.2 (h) Statistical descriptions for Dataset 8	34
Table 3.3 Sample of raw data (before) and normalized data (after).....	36
Table 3.4 Testing parameters.....	41
Table 3.5 Models and Attributes	43
Table 4.1 Description of basic attributes	47
Table 4.2 Description of additional attributes	48
Table 4.3 Experiments using 5 attributes	51
Table 4.4 Values used for determining suitable parameter for Models 2 to 8.....	57
Table 4.5 Best parameters for Models 2 to 8	58
Table 5.1 8 prediction models and parameters	65
Table 5.2 Evaluation results	66
Table 5.3 The comparison with past work for 28 days	76
Table 8.1 50 Samples of Dataset 1	88
Table 8.2 50 Samples of Dataset 2	90
Table 8.3 50 Samples of Dataset 3	92

Table 8.4 50 Samples of Dataset 4	94
Table 8.5 50 Samples of Dataset 5	96
Table 8.6 50 Samples of Dataset 6	98
Table 8.7 50 Samples of Dataset 7	100
Table 8.8 50 Samples of Dataset 8	102
Table 8.9 Parameters testing for Model 2	104
Table 8.10 Parameters testing for Model 3	109
Table 8.11 Parameter testing for Model 4.....	114
Table 8.12 Parameters testing for Model 5	119
Table 8.13 Parameters testing for Model 6	124
Table 8.14 Parameters testing for Model 7	129
Table 8.15 Parameters testing for Model 8	134
Table 8.16 Final parameters and evaluation results for each model	139



List of Figures

Figure 2.1: The general diagram of SVM	16
Figure 2.2: Block diagram of an adaptive system.....	18
Figure 2.3: Basic neuron model	24
Figure 2.4: A simple neural network model.....	25
Figure 3.1: The research process diagram.....	28
Figure 3.2: The scatter plot of dataset.	35
Figure 3.3: Eight situations of different combinations of attributes	37
Figure 3.3: The general model for compressive strength of concrete.....	43
Figure 4.1: The combinations of parameters.....	50
Figure 4.2: The main architecture for the study.....	59
Figure 4.3: The ANN architecture for Model 1.....	60
Figure 4.4: The ANN architecture for Model 2.....	61
Figure 4.5: The ANN architecture of Model 3.....	61
Figure 4.6: The ANN architecture of Model 4.....	62
Figure 4.7: The ANN architecture for Model 5.....	62
Figure 4.8: The ANN architecture for Model 6.....	63
Figure 4.9: The ANN architecture for Model 7.....	63
Figure 4.10: The ANN architecture of model 8	64
Figure 5.1: Correlation coefficient of 8 models	67
Figure 5.2: MAE and RMSE of 8 models.....	69
Figure 5.3: Comparison for Model 1.....	70
Figure 5.4: Comparison for Model 2.....	71
Figure 5.5: Comparison for Model 3.....	71
Figure 5.6: Comparison for Model 4.....	72
Figure 5.7: Comparison for Model 5.....	72
Figure 5.8: Comparison for Model 6.....	73
Figure 5.9: Comparison for Model 7.....	73
Figure 5.10: Comparison for Model 8	74

Figure 8.1: Weights and threshold in Model 1	140
Figure 8.2: Weights and threshold in Model 2	141
Figure 8.3: Weights and threshold in Model 3	142
Figure 8.4: Weights and threshold in Model 4	143
Figure 8.5: Weights and threshold in Model 5	144
Figure 8.6: Weights and threshold in Model 6	145
Figure 8.7: Weights and threshold in Model 7	146
Figure 8.8: Weights and threshold in Model 8	147



List of Appendices

Appendix A. Sample of Raw Dataset.....	88
Appendix B. Tables of testing parameters for Model 2	104
Appendix C. Tables of testing parameters for Model 3	109
Appendix D. Tables of testing parameters for Model 4	114
Appendix E. Tables of testing parameters for Model 5.....	119
Appendix F. Tables of testing parameters for Model 6	124
Appendix G. Tables of testing parameters for Model 7	129
Appendix H. Tables of testing parameters for Model 8	134
Appendix I. Table of information for and final results	139
Appendix J. Figures of weights and threshold in each model.....	140



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 July 28, 1976, the city of Tangshan, China

The contents of
the thesis is for
internal user
only

REFERENCES

- Aggarwal, R., Kumar, M., Sharma, R. K., & Sharma, M. K. (2015). Predicting Compressive Strength of Concrete. *International Journal of Applied Science and Engineering*, (April), 171–185.
- Akande, K., Owolabi, T., Twaha, S., & Olatunji, S. (2014). Performance Comparison of SVM and ANN in Predicting Compressive Strength of Concrete. *IOSR Journal of Computer Engineering*, 16(5), 88–94.
<http://doi.org/10.9790/0661-16518894>
- Alilou, V. ., & Teshnehlal, M. (2010). Prediction of 28-day compressive strength of concrete on the third day using artificial neural networks. *International Journal of Engineering (IJE)*, (3), 565–576. Retrieved from
<http://www.cscjournals.org/csc/manuscript/Journals/IJE/volume3/Issue6/IJE-126.pdf>
- Atici, U. (2011). Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network. *Expert Systems With Applications*, 38(8), 9609–9618.
<http://doi.org/10.1016/j.eswa.2011.01.156>
- Betrie, G. D., Sadiq, R., Morin, K. A., & Tesfamariam, S. (2014). *Uncertainty quantification and integration of machine learning techniques for predicting acid rock drainage chemistry : A probability bounds approach*. *Science of the Total Environment* (Vol. 490). Elsevier B.V.
<http://doi.org/10.1016/j.scitotenv.2014.04.125>
- Bilim, C., Atis, C. D., Tanyildizi, H., & Karahan, O. (2009). Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network. *Advances in Engineering Software*, 40, 334–340.
<http://doi.org/10.1016/j.advengsoft.2008.05.005>
- Bray, J. D., Rourke, T. D. O., Cubrinovski, M., Zupan, J. D., Taylor, M., Toprak, S., ... Ballegooy, S. Van. (2013). *Liquefaction Impact on Critical Infrastructure in Christchurch*. Christchurch. Retrieved from

<http://www.cee.cornell.edu/cee/people/profile.cfm?netid=tdo1>

- Celikyilmaz, A., & Turksen, I. B. (2008). Enhanced fuzzy system models with improved fuzzy clustering algorithm. *IEEE Transactions on Fuzzy Systems*, 16(3), 779–794. <http://doi.org/10.1109/TFUZZ.2007.905919>
- Cesa-Bianchi, N., & Lugosi, G. (2006). *Prediction, Learning, and Games*. (N. Cesa-Bianchi & G. Lugosi, Eds.). Barcelona: Cambridge University Press. <http://doi.org/10.1017/CBO9780511546921>
- Chou, J., Chiu, K., Farfoura, M., & Al-Taharwa, I. (2011). Optimizing the prediction accuracy of concrete compressive strength based on a comparison of data mining techniques. *Journal of Computing in Civil Engineering*, 25(3), 242–253.
- De Melo, V. V., & Banzhaf, W. (2016). Predicting high-performance concrete compressive strength using features constructed by kaizen programming. *Proceedings - 2015 Brazilian Conference on Intelligent Systems, BRACIS 2015*, 80–85. <http://doi.org/10.1109/BRACIS.2015.56>
- Deepa, C., Sathiya Kumari, K., & Pream Sudha, V. (2010). Prediction of the Compressive Strength of High Performance Concrete Mix using Tree Based Modeling. *International Journal of Computer Applications*, 6(5), 18–24.
- Doug. (2016). How to choose the number of hidden layers and nodes in a feedforward neural network? Retrieved from <http://stats.stackexchange.com/questions/181/how-to-choose-the-number-of-hidden-layers-and-nodes-in-a-feedforward-neural-netw>
- Fred, F. (2014). What are advantages of Artificial Neural Network over Support Vector Machine. Retrieved from <http://stackoverflow.com/questions/11632516/what-are-advantages-of-artificial-neural-networks-over-support-vector-machines>
- Ghan, Y. N., Peng, G. F., & Anson, M. (1999). Residual strength and pore structure of high-strength concrete and normal strength concrete after exposure to high temperatures, 21, 23–27.
- Gilan, S. S., Ali, A. M., & Ramezani pour, A. A. (2011). Evolutionary fuzzy function with support vector regression for the prediction of concrete

compressive strength. *Proceedings - UKSim 5th European Modelling Symposium on Computer Modelling and Simulation, EMS 2011*, 263–268.
<http://doi.org/10.1109/EMS.2011.28>

Gupta, S. M. (2007). Support Vector Machines based Modelling of Concrete Strength. *World Academy of Science, Engineering and Technology*, 36(1), 305–311.

Huixian, L., Housner, G. W., Lili, X., & Duxin, H. (2002). The Great Tangshan Earthquake of 1976. *Technical Report: Caltech EERL.2002.001*.

Jang, J. S. R. (1993). ANFIS : Adaptive Network Based Fuzzy Inference System. *Systems, Man and Cybernetics, IEEE Transactions on*, 23(3), 665–685.
Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=256541

Jayalakshmi, T., & Santhakumaran, A. (2011). Statistical normalization and back propagation for classification. *International Journal of Computer Theory and Engineering*, 3(1), 89–93. Retrieved from
<http://www.ijcte.org/papers/288-L052.pdf>

Jordans, M., Kohrt, B., & Tol, W. (2015). *Nepal Earthquakes 2015*. Nepal. Retrieved from
https://interagencystandingcommittee.org/system/files/20150622_nepal_earthquakes_mhpss_desk_review_150619.pdf

Kabir, A., Hasan, M., & Miah, K. (2012). Predicting 28 Days Compressive Strength of Concrete from 7 Days Test Result. *Advances in Design and Construction of Structures*, 18–22.

Kasi, K. (2015). What is difference between SVM and Neural Networks? Retrieved from
<https://www.quora.com/What-is-difference-between-SVM-and-Neural-Networks>

Kattan, M. W. (2011). Factors Affecting the Accuracy of Prediction Models Limit the Comparison of Rival Prediction Models When Applied to Separate Data Sets. *European Urology*, 59(4), 566–567.
<http://doi.org/10.1016/j.eururo.2010.11.039>

- Kosko, B. (1992). Neural Networks and Fuzzy Systems. *Journal of Englewood Cliffs*, 449.
- Liu, J. C., Sue, M. L., & Kou, C. H. (2009). Estimating the strength of concrete using surface rebound value and design parameters of concrete material. *Tamkang Journal of Science and Engineering*, 12(1), 1–7.
- MacKay, D. J. C. (1994). Bayesian non-linear modelling for the energy prediction competition. *ASHRAE Transactions*, 100, 1053–1062.
- Makin, J. G. (2006). Backpropagation. *University of California, Berkeley*, 1–8.
- Martinez-Molina, W., Torres-Acosta, A. A., Jauregui, J. C., Chavez-Garcia, H. L., Alonso-Guzman, E. M., Graff, M., & Arteaga-Arcos, J. C. (2014). Predicting concrete compressive strength and modulus of rupture using different NDT techniques. *Advances in Materials Science and Engineering*, 2014, 1–15.
<http://doi.org/10.1155/2014/742129>
- Michele, M., Raucoules, D., Lasserre, C., Pathier, E., Klinger, Y., Van der Woerd, J., ... Xu, X. (2010). The M-w 7.9, 12 May 2008 Sichuan earthquake rupture measured by sub-pixel correlation of ALOS PALSAR amplitude images. *Earth Planets And Space*, 62(11), 875–879. <http://doi.org/10.5047/eps.2009.05.002>
- Moriasi, D. N., Arnold, J. G., Liew, M. W. Van, Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactin of the ASABE*, 50(3), 885–900.
- Musson, R. M. W. (2008). *The seismicity of the British Isles to 1600*. British.
 Retrieved from
<http://www.earthquakes.bgs.ac.uk/historical/data/studies/MUSS008/MUSS008.pdf>
- Muthupriya, P., Subramanian, K., & Vishnuram, B. G. (2011). Prediction of Compressive Strength and Durability of High Performance Concrete By Artificial Neural Networks. *International Journal of Optimization in Civil Engineering*, 189–209.
- Nayak, S. C., Misra, B. B., & Behera, H. S. (2014). Impact of Data Normalization on

Stock Index Forecasting. *International Journal of Computer Information Systems and Industrial Management Applications*, 6, 257–269.

Nikoo, M., Torabian Moghadam, F., & Sadowski, L. (2015). Prediction of concrete compressive strength by evolutionary artificial neural networks. *Advances in Materials Science and Engineering*, 2015, 1–8.

<http://doi.org/10.1155/2015/849126>

Noorzaei, J., Hakim, S. J. S., Jaafar, M. S., & Thanoon, W. A. M. (2007). Development of Artificial Neural Networks for Predicting Concrete Compressive Strength. *International Journal of Engineering and Technology*, 4(2), 141–153.

Oravec, M., Petráš, M., & Pilka, F. (2008). Video Traffic Prediction Using Neural Networks. *Electrical Engineering*, 5(4), 59–78.

Panchal, G., Ganatra, A., Kosta, Y. P., & Panchal, D. (2011). Behaviour Analysis of Multilayer Perceptrons with Multiple Hidden Neurons and Hidden Layers. *International Journal of Computer Theory and Engineering*, 3(2), 332–337.

Plagianakos, V. P., Magoulas, G. D., & Vrahatis, M. N. (2001). Learning rate adaptation in stochastic gradient descent. *In Advances in Convex Analysis and Global optimization*. Springer US, 433–444.

Pradhan, B., & Kundu, D. (2011). Bayes estimation and prediction of the two-parameter gamma distribution. *Journal of Statistical Computation and Simulation*, 81(9), 1187–1198. <http://doi.org/10.1080/00949651003796335>

Preetham, S., Shivaraj, M., Prema kumar, W. P., & Kumar, H. R. (2014). Support Vector Machine Technique in Analysis of Concrete-Critical Review. *International Journal of Emerging Technologies and Engineering*, 1(9), 199–203.

Rasa, E., Ketabchi, H., & Afshar, M. H. (2009). Predicting Density and Compressive Strength of Concrete Cement Paste Containing Silica Fume Using Artificial Neural Networks. *Journal of Civil Engineering*, 16(1), 33–42.

Rashid, M. A., & Mansur, M. A. (2009). Considerations in producing high strength concrete. *Journal of Civil Engineering*, 37(1), 53–63.

- Sakr, G. E., Elhadj, I. H., & Mitri, G. (2011). *Efficient forest fire occurrence prediction for developing countries using two weather parameters. Engineering Applications of Artificial Intelligence* (Vol. 24).
<http://doi.org/10.1016/j.engappai.2011.02.017>
- Suhad, M. A., & Abbas, M. A. (2015). SUPPORT VECTOR MACHINE (SVM) FOR MODELLING THE STRENGTH OF LIGHTWEIGHT FOAMED CONCRETE. *Diyala Journal of Engineering Sciences*, 29–36.
- Thomas, W. K. (2015). What is the difference between a Bayesian network and Bayesian neural network? Retrieved August 18, 2016, from
https://www.researchgate.net/post/What_is_the_difference_between_a_Bayesian_network_and_Bayesian_neural_network
- Turksen, I. B. (2008). Fuzzy functions with LSE. *Applied Soft Computing Journal*, 8(3), 1178–1188. <http://doi.org/10.1016/j.asoc.2007.12.004>
- Uppada, S. R., Balu, A., Gupta, A. K., & Dutta, J. R. (2014). Modeling Lipase Production From Co-cultures of Lactic Acid Bacteria Using Neural Networks and Support Vector Machine with Genetic Algorithm Optimization. *International Journal of Emerging Technologies in Computational and Applied Sciences (IJETCAS)*, 38–43.
- Vakhshouri, B., & Nejadi, S. (2015). Prediction Of Compressive Strength In Light-Weight Self-Compacting Concrete By ANFIS Analytical Model. *Archives of Civil Engineering*, 61(2). <http://doi.org/10.1515/ace-2015-0014>
- Vale, R. (2014). Bayesian Prediction for The Winds of Winter. Retrieved from
<http://arxiv.org/abs/1409.5830>
- Wankhade, M. W., & Kambekar, A. R. (2013). Prediction of compressive strength of concrete using Artificial Neural Network. *International Journal of Scientific Research and Reviews*, 2(2), 11–26.
- Yaqub, M., Taxila, T., Bukhari, I., & Taxila, T. (2006). Development of Mix Design for High Strength Development of Mix Design for High Strength. *Conference on Our World in Concrete & Structures*, 31–35.
- Yeh, I.-C. (1998). Modeling of Strength of High-Performance Concrete Using

Artificial Neural Networks. *Journal of Civil Engineering*, 28(12), 1797–1808.

Retrieved from

<http://www.sciencedirect.com/science/article/pii/S0008884698001653>

Yeh, I.-C. (2003). A Mix Proportioning Methodology for Fly Ash and Slag Concrete Using Artificial Neural Networks. *Chung Hua Journal of Science and Engineering*, 1(1), 77–84.

Yeh, I.-C. (2006). Exploring Concrete Slump Model Using Artificial Neural Networks. *Journal of Computing in Civil Engineering*, 217–221.

<http://doi.org/10.1016/j.neunet.2008.04.002>

Yeh, I. C., & Lien, L. C. (2009). Knowledge discovery of concrete material using Genetic Operation Trees. *Expert Systems with Applications*, 36(3 PART 2), 5807–5812. <http://doi.org/10.1016/j.eswa.2008.07.004>

