November-December 2019
ISSN: 0193-4120 Page No. 5841 - 5846

Estimating Arsenic Concentration in Compost Production Using ANN Model

Majeed Safa[1a], Daniel O'Carroll[2b]

[1]Department of Agricultural Management and Property Studies, Lincoln University, New Zealand
[2]Living Earth, Christchurch, New Zealand

[a]Majeed.safa@lincoln.ac.nz, [b]docarroll@livingearth.co.nz

Article Info
Volume 81
Page Number: 5841 - 5846
Publication Issue:
November-December 2019

Article History
Article Received: *5March 2019*
Revised: *18 May 2019*
Accepted: *24 September2019*
Publication: *27 December 2019*

Abstract
Arsenic concentration is one of the most critical concerns in compost production. Measuring arsenic concentration is time consuming and expensive process for compost companies. Also, compost factories need to test the arsenic concentration in their product continuously. Developing a practical model can help compost factory managers to make a faster decision with minimum cost. This study has been designed to predict arsenic concentration in compost, based on input materials and outside temperature, using an Artificial Neural Network model (ANN) in Christchurch, New Zealand. After investigating several ANN model structures a modular ANN model was selected with minimum error margin. The final ANN model developed was based on monthly input of kerbside collections, food wastes, river wastes, and average monthly air temperature for the last eight years. Comparing observed and predicted data indicated that the ANN model could predict arsenic concentration in different conditions, which is accounted for 94% of the variance for training and 97% of the variance for validation data. However, it should be mentioned each model would be unique best on inputs and weather condition in each city or factory.

Keywords: *Arsenic Concentration, Compost, Waste Management*

1. Background

Arsenic is one of the important chemical element in nature, which can occur naturally, or after pollution from human activities[1, 2]. Typically, arsenic is found in a different source, such as nature combined with chlorine, Sulphur, and oxygen, trace quantities from the breakdown of living components, geological creation, and ores containing silver, nickel, gold, cobalt, and antimony [3]. Also, arsenic can be found in food and beverages, groundwater, and soil. Organic arsenic, for example, is mixed with hydrogen and carbon; while inorganic arsenic is mixed with iron, sulfur, and oxygen [2, 4-6]. The inorganic form of arsenic has a significant level of hazard compared with the organic form [5, 7-10].

Arsenic contamination has a significant effect on human health [5, 11]. It is found that arsenic causes some types of cancers [12-16] and also other severe neuro-behavioral and neuropathic disease [17], memory and intellectual function [18, 19], reproductive effects [20], steatosis (fatty liver) [21, 22], the hormonal system, diabetes mellitus type 2 [23, 24] as well as serious diseases, such as cardiovascular disease [25, 26], ischemic heart diseases [27], carotid atherosclerosis [28], and respiratory system diseases [29, 30].

In New Zealand, inorganic arsenic mostly is registered to be used in timber preservatives [1]. Copper-Chrome-Arsenic (CCA) is the most common wood preservatives in New Zealand. They are a combination of different elements; arsenic oxides or salts, copper, and chromium and are mainly used in the vacuum-pressure treatment of timber, which is sold to the general public and commercial consumers. CCA is mainly used to protect the timber from pests and fungi [31]. CCA treatment was created in 1933 and became the most extensively used waterborne preservative globally by the 1960s. [31]. CCA is identified as potentially being hazardous, and it is not allowed to be used in many countries [32, 33]. In New Zealand, CCA preservatives are permitted to be practiced in some hazard classes (H1-H6) in which timber falls under risk of biodegradation. The arsenic portion in treated timber for residential purposes is 0.11-0.22 [31].

ANN models have been developed in many projects for studying the links among dependent and independent input variables [34-38]. Neural networks can discover an association between the dependent (input) and independent (output) variables, as well as the controlled and uncontrolled factors [38, 39]. To develop a practical ANN model, the accuracy of the information and the sample size are vital matters. ANN models can be described as the mathematical equations to categorize or predict information in different conditions. Therefore, it can play a significant role in mimicking nonlinear connections [40, 41].

2. Model

The high concentration of arsenic of compost in winters would be because of the constant arsenic inputs, which were diluted in summer or because of specific contaminated inputs in winter or both. Therefore, the correlation between arsenic concentration and the air temperature was expected. Thus, the average monthly temperature is investigated and

The most common and basic ANN structure is the feed-forward multi-layered perception (MLP) paradigm, which is used in modeling or describing how ANN models are working. The MLP paradigm consists of the independent (input) data, few hidden layers, and an output layer [42-45]. The weighted input variables of each hidden layer, use a transfer function to calculate the output of the hidden layer. Logistic, sine, linear, Gaussian, and hyperbolic-tangent are the most frequently used transfer functions. The calculated results of each layer are sent to the next layer through weighted networks. The transfer functions of the neurons in the hidden layers are used to process the the input data. The predicted output is the final results associated with the last layer [35, 37, 46]. During model training, the weights and biases are optimized to reduce error margin.

The main inputs in compost production can be categorized into four categories: kerbsides, green wastes, food wastes, and river wastes. In the compost production process, a significant volume of water is consumed as well. Therefore, arsenic concentration in the main inputs and water were investigated as well. The monthly data of the mentioned inputs and air temperature for the last eight years were used to develop an ANN model. There was a significant correlation between kerbside collections and green wastes. Therefore, green wastes were removed from the list of input variables. The final ANN model developed based on monthly data for the last eight years (96 months) of four input variables, including kerbside collections, food wastes, river wastes, and average air temperature. Based on data availability the sample size was 96 months. Initially, a sample of 86 months and 11 months selected randomly for training and validation, respectively. The validation data are used to make sure the final model can work in different conditions. It was preferred to develop the model based on weekly data; however, because of the lack of availability of weekly data, the model was developed based on monthly data. To improve the accuracy of model output, the error between the predicted and observed data should be reduced by adjusting the weights in each layer. The mean square error (MSE) is the most common method to calculates the error of ANN prediction models with one dependent variable (output neuron), it can be presented as:

$$MSE = \frac{1}{2N}\sum_{i}^{N}(t_i - z_i)^2 \quad \textbf{(1)}$$

Where t_i and z_i are observed and calculated (predicted) data for the i_{th} training or validation process, N presents the number of samples, [35]. In some studies, the root means square error (RMSE) is used to justify the errors in the units of data. In this study, Quick Prop was used as the learning technique. Quick Prop indirectly applies the second estimation of the error to adjust the weights (Equations 2, 3, and 4). In Quick Prop, the updated weights are calculated after each iteration.

$$w_{m+1} = w_m + \Delta w_m \quad \textbf{(2)}$$

$$\Delta w_m = \frac{d_m}{d_{m-1} - d_m}\Delta w_{m-1} \quad \textbf{(3)}$$

$$d_m = \sum_{n-1}^{N}\left[\frac{\partial E}{\partial w_m}\right]_n \quad \textbf{(4)}$$

Where Δw_m is the weight increase, d_m is the estimation of the error regarding the weight for the existing calculation, m; and $\partial E/\partial wm$ is the existing error incline for a specific input variable [35]. In the first step of ANN model development, a BP structure was developed, however more complex model was investigated as well to find the best results. Several parameters such as network structure and transfer functions were examined to establish the most exceptional model with the lowest reasonable error margin. The genetic algorithm was used in this study to find the optimum number of neuron each hidden layer. After studying several model structures with different transfer function and a varied number of the hidden layer, a modular neural network structure was developed with lowest estimated MSE. In the modular neural network structure, the data are processed in two branches of independent neural networks (Figure 1). These branches trained datasets separately and then outputs data of each branch are joined in the output layer. The modular structure, due to the layer arrangement, can train data with diverse transfer functions at the same time. In the developed model of this study, a linear transfer function was applied in the input and output layers; a hyperbolic tangent and logistic functions were used for the of hidden layers of branches (Figure 1). These transfer functions are:

November-December 2019
ISSN: 0193-4120 Page No. 5841 - 5846

$$tanh(u) = \frac{1+e^{-u}}{1-e^{-u}} \quad \textbf{(5)}$$

$$L(u) = [1+e^{-u}]^{-1} \quad \textbf{(6)}$$

Where *tanh(u)* is the hyperbolic tangent transfer function; *L(u)* is the logistic transfer function; and *u* is the inputs data of the neuron [35].

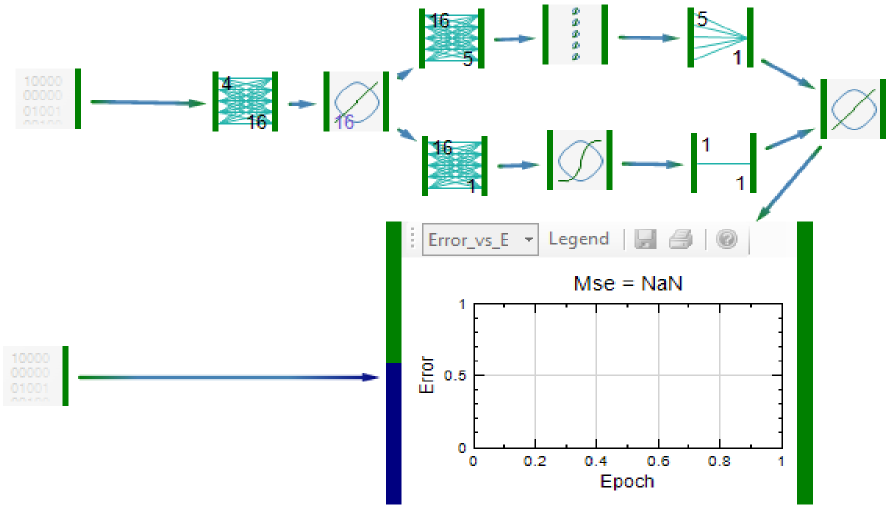

Figure 1: Structure of the ANN model

3. Results

The lowest error was found after 41904 iterations. The MSE of the final ANN model was ,estimated at around 1.7 for the training and 2.0 for the validation data. The RMSE was estimated around 1.32 ppm for the training and 1.43 ppm for the validation data, which was the lowest error between several investigated ANN models. The regression analysis between actual (observed) and predicted data (Figure 2) shows the estimated R^2 (R-squared) was 0.89 for training and 0.95 for validation of the ANN model. It is clear that due to several uncontrolled factors, which could impact arsenic concentration in compost product; nevertheless, the results looked better than the expectation and the final ANN model can find arsenic concentration in with a reasonably small error.

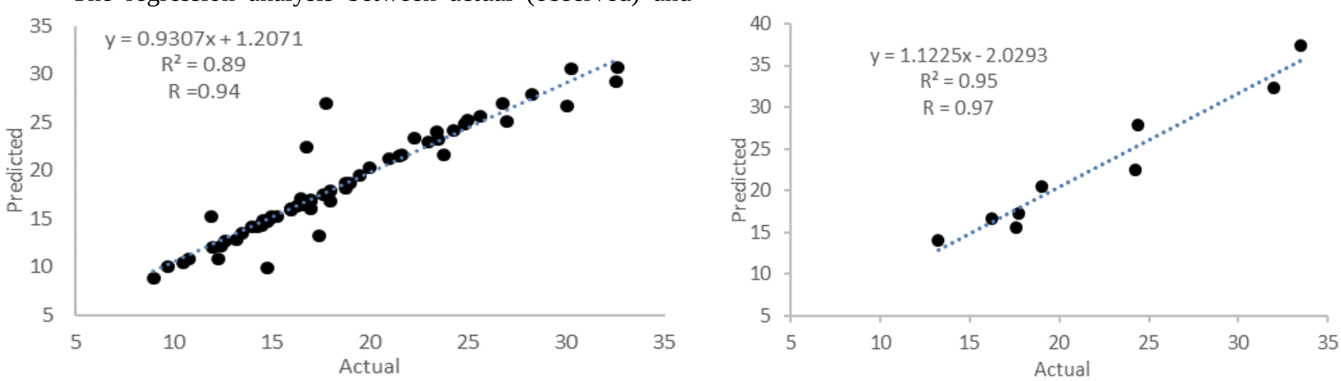

Figure 2: Regression analysis of actual and predicted arsenic concentration (Training and validation)

The final model predicted arsenic concentration with an error margin of around ±0.38 ppm (training data) and ±0.34 ppm (validation data) and this level of error considering the uncertainties involved is remarkable (Figures 3&4). The four lines in figures 3&4 show the predicted output, actual output, and the high and low margins of the 5% confidence intervals. The grey area indicates the estimated result was within the 95% confidence level. For example, this means that there is only a 5% chance in training data that the possible error is more than ±3.8 ppm. It appears the model is capable of predicting arsenic concentration. However, the months with significant differences between predicted and actual data should be investigated.

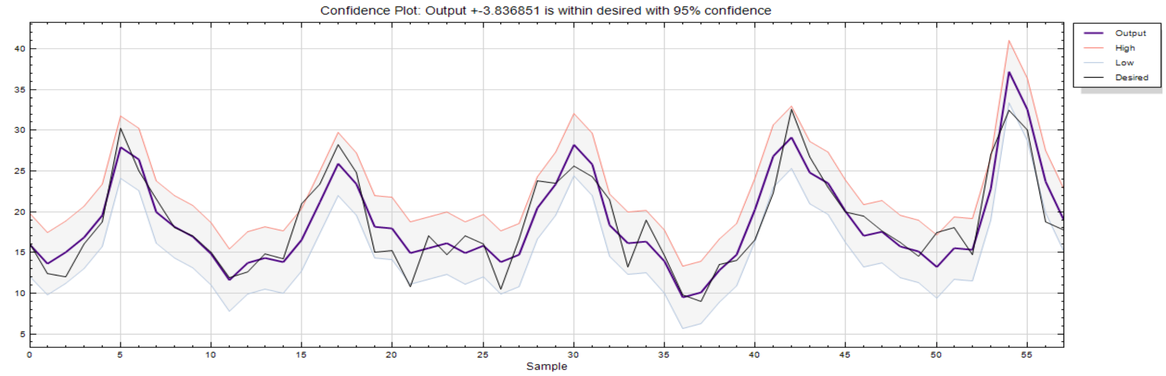

Figure 3: Predicted, actual, and the 95% confidence interval (Training)

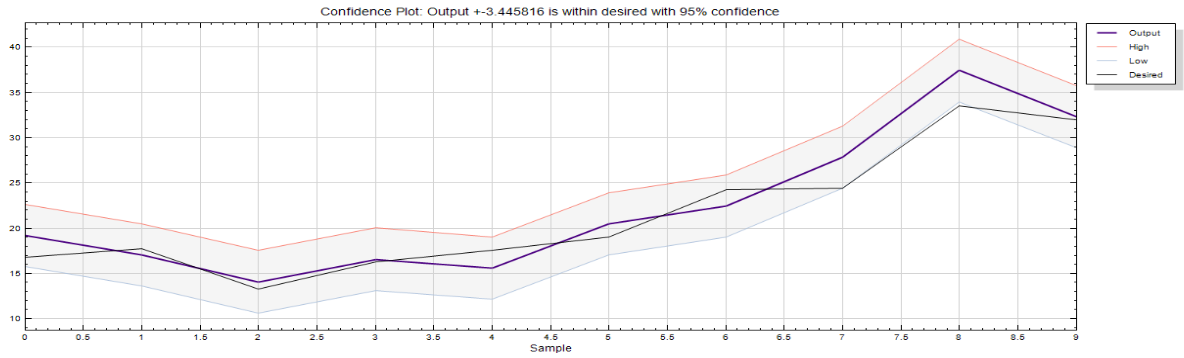

Figure 4: Predicted, actual, and the 95% confidence interval (Validation)

The sensitivity analysis shows the average monthly temperature has the highest effect on the model output with 85% sensitivity. Also, the sensitivity of Kerbsite, food waste, and river weeds are estimated around 19%, 12%, and 3.4% respectively. It appears the component and volume of waste are changed based on the outside temperature. The high rate of arsenic in winter would be because of burning ACC treated timber and wood ashes in log burners.

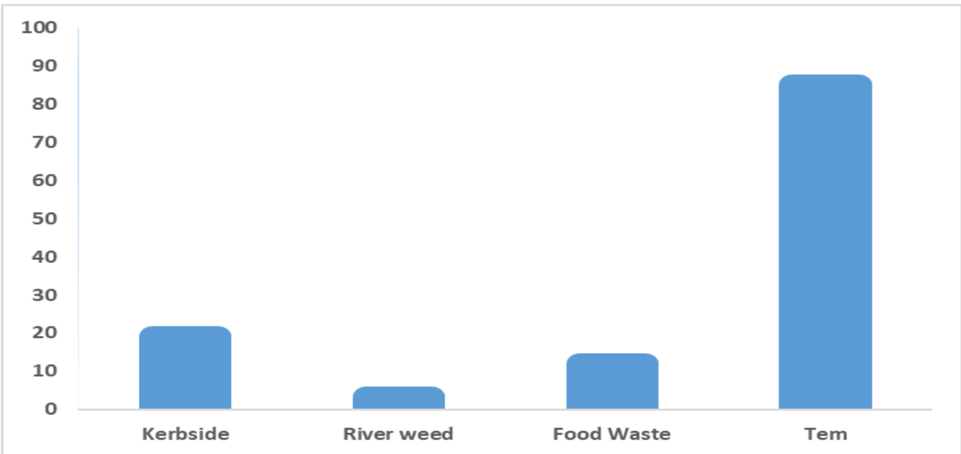

Figure 5:The sensitivity analysis of the final ANN model

4. Conclusion

The result of the study shows after investigating several ANN model, developing an ANN model predict arsenic concentration in compost production with minimum possible error is possible. It was challenging to find similar study using nonlinear models in compost production industry to inspect the results of this study

TEST Engineering & Management

November-December 2019
ISSN: 0193-4120 Page No. 5841 - 5846

The similarity between the results of training and validation data show the model is capable estimating arsenic concentration in different conditions. It appears by temperature change in different months arsenic concentration in compost input change as well. It would be because of components of inputs in different seasons. Also, It was found ashes from log burners contain significant arsenic which increases the arsenic concentration in winter. The models can be used to manage arsenic, and other heavy metals content in compost in a different time of year. The result shows the sample size and accuracy of data is the first step to develop a practical model. Also, developing models based on weekly data can improve the prediction. The method can be used to estimate other heavy metals as well. However, the model for each site is a unique study based on climate, inputs, and other factors. Also, it should be mentioned the final ANN model works based on waste inputs and outside temperature; therefore, the estimation models in different cities or factories would be different.

References

[1] (FSANZ), F.S.A.N.Z., Arsenic, in Chemicals in food 2019: FSANZ.

[2] Sodhi, K.K., et al., Perspectives on arsenic toxicity, carcinogenicity and its systemic remediation strategies. Environmental Technology & Innovation, 2019: p. 100462.

[3] Lederer, W.H. and R.J. Fensterheim, Arsenic--industrial, biomedical, environmental perspectives. 1983: Van Nostrand Reinhold Company.

[4] ATSDR. Safe Gardening, Safe Play, and a Safe Home. 2004 [cited 2017 08/10/2017]; Available from: https://www.atsdr.cdc.gov/sites/springvalley/svgardening.html.

[5] Upadhyay, M.K., et al., A review of arsenic in crops, vegetables, animals and food products. Food Chemistry, 2019. 276: p. 608-618.

[6] Asere, T.G., C.V. Stevens, and G. Du Laing, Use of (modified) natural adsorbents for arsenic remediation: A review. Science of The Total Environment, 2019. 676: p. 706-720.

[7] Ampiah-Bonney, R.J., J.F. Tyson, and G.R. Lanza, Phytoextraction of Arsenic from Soil by Leersia Oryzoides. International Journal of Phytoremediation, 2007. 9(1): p. 31-40.

[8] Chutia, P., et al., Arsenic adsorption from aqueous solution on synthetic zeolites. Journal of Hazardous Materials, 2009. 162(1): p. 440-447.

[9] Tangahu, B.V., et al., A Review on heavy metals (As, Pb, and Hg) uptake by plants through phytoremediation. International Journal of Chemical Engineering, 2011. 2011.

[10] Vaclavikova, M., et al., Removal of arsenic from water streams: an overview of available techniques. Clean Technologies and Environmental Policy, 2008. 10(1): p. 89-95.

[11] Saha, J.C., et al., A Review of Arsenic Poisoning and its Effects on Human Health. Critical Reviews in Environmental Science and Technology, 1999. 29(3): p. 281-313.

[12] Rossman, T.G., A.N. Uddin, and F.J. Burns, Evidence that arsenite acts as a cocarcinogen in skin cancer. Toxicology and Applied Pharmacology, 2004. 198(3): p. 394-404.

[13] Steinmaus, C., et al., Case-Control Study of Bladder Cancer and Drinking Water Arsenic in the Western United States. American Journal of Epidemiology, 2003. 158(12): p. 1193-1201.

[14] Hopenhayn-Rich, C., M.L. Biggs, and A.H. Smith, Lung and kidney cancer mortality associated with arsenic in drinking water in Cordoba, Argentina. International Journal of Epidemiology, 1998. 27(4): p. 561-569.

[15] Paul, D.S., et al., Examination of the effects of arsenic on glucose homeostasis in cell culture and animal studies: Development of a mouse model for arsenic-induced diabetes. Toxicology and Applied Pharmacology, 2007. 222(3): p. 305-314.

[16] Jovanovic, D. and Z. Rasic-Milutinovic, Public health effects of arsenic exposure. Best Practice Guide on the Control of Arsenic in Drinking Water, 2017: p. 25-32.

[17] Tsai, S.-Y., et al., The Effects of Chronic Arsenic Exposure from Drinking Water on the Neurobehavioral Development in Adolescence. NeuroToxicology, 2003. 24(4): p. 747-753.

[18] Wasserman, G.A., et al., Water arsenic exposure and children’s intellectual function in Araihazar, Bangladesh. Environmental health perspectives, 2004. 112(13): p. 1329.

[19] Mónaco, N.M., et al., Low arsenic concentrations impair memory in rat offpring exposed during pregnancy and lactation: Role of α7 nicotinic receptor, glutamate and oxidative stress. NeuroToxicology, 2018. 67: p. 37-45.

[20] Chakraborti, D., et al., Arsenic groundwater contamination in Middle Ganga Plain, Bihar, India: a future danger? Environmental Health Perspectives, 2003. 111(9): p. 1194.

[21] Chen, H., et al., Chronic inorganic arsenic exposure induces hepatic global and individual gene hypomethylation: implications for arsenic hepatocarcinogenesis. Carcinogenesis, 2004. 25(9): p. 1779-1786.

[22] Li, W., et al., Quantitative proteomic study of arsenic treated mouse liver sinusoidal endothelial cells using a reverse super-SILAC method. Biochemical and Biophysical Research Communications, 2019. 514(2): p. 475-481.

[23] Bodwell, J.E., L.A. Kingsley, and J.W. Hamilton, Arsenic at Very Low Concentrations

Alters Glucocorticoid Receptor (GR)-Mediated Gene Activation but Not GR-Mediated Gene Repression: Complex Dose−Response Effects Are Closely Correlated with Levels of Activated GR and Require a Functional GR DNA Binding Domain. Chemical Research in Toxicology, 2004. 17(8): p. 1064-1076.
[24] Riz et arsenic au Bangladesh. Revue Française des Laboratoires, 2003. 2003(351): p. 16.
[25] Lee, M.-Y., et al., Enhancement of Platelet Aggregation and Thrombus Formation by Arsenic in Drinking Water: A Contributing Factor to Cardiovascular Disease. Toxicology and Applied Pharmacology, 2002. 179(2): p. 83-88.
[26] Ohgami, N., et al., Carcinogenic risk of chromium, copper and arsenic in CCA-treated wood. Environmental Pollution, 2015. 206: p. 456-460.
[27] Tseng, C.-H., et al., Long-term arsenic exposure and ischemic heart disease in arseniasis-hyperendemic villages in Taiwan. Toxicology Letters, 2003. 137(1): p. 15-21.
[28] Wang, C.-H., et al., Biological gradient between long-term arsenic exposure and carotid atherosclerosis. Circulation, 2002. 105(15): p. 1804-1809.
[29] Milton, A.H., et al., Non-cancer Effects of Chronic Arsenicosis in Bangladesh: Preliminary Results. Journal of Environmental Science and Health, Part A, 2003. 38(1): p. 301-305.
[30] Milton, A.H. and M. Rahman, Respiratory effects and arsenic contaminated well water in Bangladesh. International Journal of Environmental Health Research, 2002. 12(2): p. 175-179.
[31] Read, D., Report on copper, chromium and arsenic (CCA) treated timber. 2003: ERMA New Zealand.
[32] Love, S. Extended producer responsibility of treated timber waste. in Scion. SB07 Sustainable Building Conference, New Zealand (Building Research). 2007.
[33] Jones, A.S., et al., Arsenic, copper, and chromium from treated wood products in the U.S. disposal sector. Waste Management, 2019. 87: p. 731-740.
[34] Parten, C., C. Hartson, and A. Maren, Handbook of neural computing applications. 1990: San Diego, CA (USA); Academic Press Inc.
[35] Samarasinghe, S., Neural networks for applied sciences and engineering : from fundamentals to complex pattern recognition. 2007, Boca Raton, FL: Auerbach. xx, 570 p.
[36] Safa, M. and S. Samarasinghe, CO2 emissions from farm inputs "Case study of wheat production in Canterbury, New Zealand". Environmental Pollution, 2012. 171(0): p. 126-132.
[37] Safa, M., S. Samarasinghe, and M. Nejat, Prediction of Wheat Production Using Artificial Neural Networks and Investigating Indirect Factors Affecting It: Case Study in Canterbury Province, New Zealand. Journal of Agricultural Science and Technology, 2015.
Safa, M., et al., Modelling nitrogen content of pasture herbage using thermal images and artificial neural networks. Thermal Science and Engineering Progress, 2019. 11: p. 283-288.
[38] Kalogirou, S.A., Applications of artificial neural-networks for energy systems. Applied Energy, 2000. 67(1-2): p. 17-35.
[39] Hagan, M., H. Demuth, and M. Beale, Neural network design. 2002: Boston, USA: PWS Publishing Company.
[40] Safa, M. and T. Maxwell, Predicting Pasture Nitrogen Content using ANN Models and Thermal Images in 21st International Congress on Modelling and Simulation. 2015: Gold Coast, Australia. p. 469-475.
[41] Hornik, K., M. Stinchocombe, and H. White, Multilayer feedforward networks are universal approximators. Elsevier Science Ltd. Oxford, UK, UK 1989. 2(5).
[42] Heinzow, T. and R.S.J. Tol Prediction of crop yields across four climate zones in Germany: an artificial neural network approach. Centre for Marine and Climate Research, Hamburg University, Hamburg., 2003.
[43] Jebaraj, S. and S. Iniyan, A review of energy models. Renewable and Sustainable Energy Reviews, 2006. 10(4): p. 281-311.
[44] Safa, M. and S. Samarasinghe, Determination and modelling of energy consumption in wheat production using neural networks: "A case study in Canterbury province, New Zealand". Energy, 2011. 36(8): p. 5140-5147.
[45] Safa, M., et al., Predicting CO_2 emissions from farm inputs in wheat production using artificial neural networks and linear regression models- Case study in Canterbury, New Zealand. International Journal of Advanced Computer Science and Applications, 2016. 7.