Application of artificial neural network and multiple linear regression in modeling nutrient recovery in vermicompost under different conditions

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Abstract

The recovery of nutrients from solid waste is of global significance. Vermicomposting is one of the best technologies for nutrient recovery from solid waste. This study aims to assess the efficiency of Artificial Neural Network (ANN) and Multiple Linear Regression (MLR) models in predicting nutrient recovery from solid waste under different vermicompost treatments. Seven chemical and biological indices were studied as input variables to predict total nitrogen (TN) and total phosphorus (TP) recovery. The developed ANN and MLR models were compared by statistical analysis including R-squared (R^2), Adjusted-R^2, Root Mean Square Error and Absolute Average Deviation. The results showed that vermicomposting increased TN and TP proportions in final products by 1.5 and 16 times. The ANN models provided better prediction for TN and TP with R^2 of 0.9983 and 0.9991 respectively, compared with MLR models with R^2 of 0.834 and 0.729. TN and carbon nitrogen ratio were the most important factors for TP and TN prediction by ANN with percentages of 17.76 and 18.33.

Keywords: Nutrient recovery; Vermicompost; Nitrogen; Phosphorus; Municipal solid waste; Modeling

1. Introduction

Nutrients such as nitrogen (N) and phosphorus (P) are essential for life, and their recovery from waste is a globally significant issue. At the current rate of mining, phosphorus extraction will result in the depletion of the phosphorus reserves in the next 50-300 years (Van Vuuren et al., 2010; Ye et al., 2019; Ye et al., 2017; Zabaleta and Rodic, 2015). According to the reports (Tao et al., 2019; Zabaleta and Rodic, 2015), 90% of this phosphorous is applied for the production of chemical fertilizers. Besides, artificial and nonorganic fertilizers provide 50% of the required nitrogen for agricultural purposes. The excessive input of anthropogenic nitrogen has increased global nitrogen burden, which in turn has disrupted the global nitrogen cycle, causing environmental problems such as global acidification, increased emission of the greenhouse gas N_2O, and eutrophication in aquatic systems (Zheng et al., 2013). In addition, these synthetic phosphorus and nitrogen fertilizers adversely affect the quality of the human food chain and health (Asif et al., 2018; Kakar et al., 2019; Sazvar et al., 2018, Zhai et al., 2017), as these chemical fertilizers are regarded as one of the most important causes of human cancers (Stokes and Brace, 1988). In addition, it is estimated that 1% of the world energy supply is consumed to synthesize these chemical fertilizers (Smith, 2002; Zabaleta and Rodic, 2015). Whilst such nutrients are provided from energy intensive, unhealthy and non-renewable resources, renewable resources such as municipal solid wastes (MSW) are often neglected. Thus, nitrogen and phosphorus recoveries from wastes are recently receiving increasing attention as a promising option instead of abstracting phosphorus fertilizer from phosphate rocks and synthesizing nitrogen fertilizers by the Haber Bosch process (Alidadi et al., 2016; Tao et al., 2019; Zabaleta and Rodic, 2015).

The production of MSW is increasing considerably with different characteristics by virtue of ever-growing human population and related activities (Chang et al., 2020). MSW management is often performed unscientifically and non-systematically in many societies like MSW dumping in the countryside. Currently, the two most extensively applied technologies for MSW management are landfill and incineration, although agricultural use of sewage sludge is a major route in Australia, the US, China, Norway, France, Spain and the UK (Chang et al., 2020). Although highly developed, landfill and incineration have their limitations such as leachate production from landfill sites hence causing soil and groundwater pollution, emission of toxic gases and particles from combustion causing air pollution, and very little nutrient recovery. In comparison, biological stabilization like composting and vermicomposting convert solid waste such as MSW to organic soil fertilizers efficiently, as bioconversion of organic matter to fertilizers is regarded as one of the best recycling technologies (Biruntha et al., 2019; Boruah et al., 2019). However, there are some disadvantages for MSW compost such as fewer micro and macronutrients and having more electrical conductivity than agricultural soils, which can prevent seed germination (Hargreaves et al., 2008; Iqbal et al., 2010). As MSW compost through different composting process cannot meet the quality requirement for improving the fertility and amendment of agricultural soils based on the guidelines, MSW compost is more widely used as a soil conditioner rather than soil fertilizer, and even known as a secondary waste by some researchers (Gomez, 1998; Hargreaves et al., 2008; Stonehouse, 2013; Alidadi et al., 2016). Vermicomposting, compared with composting, can increase the nutrients and other significant properties of the fertilizers produced, and appropriately improve the microbial diversity of the soils which is a key factor for the health of the soils and consequently the food produced (Alidadi et al., 2016). Because the more the soil microbial species, the greater amendment of soil will happen through higher nutrient recovery. Thus, enhancement of soil microbial community structure is essential to maintain soil fertility and healthiness (Wang et al. 2014). With respect to the fact that the fertilizers produced should provide essential needs of the agricultural soils, and total nitrogen (TN) and total phosphorus (TP) are two of the most vital elements which can enhance the growth and metabolic reactions of plants; therefore, optimization and augmentation of these elements in organic fertilizers should be carefully considered (Davidson and Howarth, 2007; Alidadi et al., 2016; Zhang et al., 2018b).

Regarding the fact that the nature of biological processes like composting and vermicomposting is so complex, there is a lack of sufficient understanding regarding such processes. Therefore, mathematical models can provide insights into the process operation, performance prediction as well as its optimization (Petric and Mustafić, 2015). Different studies have been performed regarding the process modeling of wastes bioconversion. In studying the changes of N, temperature and carbon in sewage sludge during composting process, Kabbashi (2011) reported that there were some simple patterns which can be used for the modeling of composting process of sewage sludge. In another study (Gutiérrez et al., 2017) to model the odor emissions and oxygen demand of various substrates in composting process, a nonlinear exponential model along with a four-parameter Gaussian model was successfully fitted to the variations of oxygen demand and odor emissions with time. The obtained R^2 for these two models were 0.93 and 0.90 (P-value < 0.05) correspondingly. Petric and Mustafić (2015) used a mathematical model to study the composting process of the mixture wheat straw and poultry manure using the initial values of the five state variables including moisture content, temperature, concentrations of CO_2 and O_2, and organic matter conversion along with some stoichiometric and kinetic coefficients. Based on the results obtained, the developed model predicted very good performance of the composting process. Besides, different studies have been conducted to improve the proportions of TN and TP in organic fertilizers including mixing MSW with wastewater sludge and adding some additives to the raw material of fertilizers (Petric et al., 2015; Zhang et al., 2018a; Iqbal et al., 2010). However, the investigation of different MSW treatments is expensive and time consuming. In comparison, simulating and modeling the effects of various conditions on nutrient recovery can be more cost effective, reduce the operation times and lead to better outcomes more quickly (Xue et al., 2019). Up to now, various models have been developed to study the composting and other biological processes for environmental remediation such as biological wastewater treatment (Giwa et al., 2016; Kaiser, 1996; Loan et al., 2019; Nadiri et al., 2018; Najafi and Ardabili, 2018). However, most of such models are too complex and need extensive set of input data. In addition, based on the bibliographic research, there is a paucity of study and information regarding vermicomposting process modeling especially in relation to nutrient recovery by this process.

Multiple Linear Regression (MLR) is a statistical method that uses several independent variables to predict the outcome of a dependent variable. MLR can formulate the effects of different independent variables on dependent ones. Although there are some restrictions associated with MLR such as the presence of genotype-environment interaction, significant non-linear relationships and multiple collinearity among independent parameters, and observing regression assumptions necessity, the results of different studies indicated that the output of this model was highly dependent on the application (Astuti et al., 2015; Du et al., 2020; Zaefizadeh et al., 2011). In addition, Artificial Neural Network (ANN) is regarded as an influential, flexible, fast and accurate modeling procedure, which is advantageous than traditional ones. Not only can ANN model processes without considering the nature and mathematical background of phenomenological mechanisms, but also may master nonlinear and linear relationships amongst various parameters from a number of cases (Hosseinzadeh et al., 2018). There are some studies comparing these two models in various applications (Hoang, 2019; Kim et al., 2018; Park et al., 2018; Xu et al., 2014). However, there is a lack of information regarding the relative effects of different operating parameters on nutrient recovery from wastes by vermicomposting, yet the application of mathematical models can aid in the experimental design and modelling. Therefore, this study aims to develop both MLR and ANN models to simulate and predict TN and TP recovery in vermicomposting process. The most important indices of vermicomposting process including dehydrogenase

(DEH) enzyme, water soluble carbon (WSC), NH_4/NO_3 ratio, pH, electrical conductivity (EC), carbon/nitrogen (C/N) ratio, TN and TP are fully considered.

2. Materials and methods

2.1. Experimental design and analytical methods

In this study, four treatments with three replicates were prepared from different ratios of MSW compost to carbonaceous organic materials (COMs) including cardboard, boxwood leaves and sawdust. The ratios of MSW compost and COMs used were 1) 50%/50%, 2) 70%/30%, 85%/15%, and 100%/0% respectively. Then the wastes were processed over 100 days during which the proportions of different chemical and biological indices were measured on day 0, 25, 50, 75 and 100. More details were described in a previous study (Alidadi et al., 2016).

2.2. Data processing and model performance assessment

Before the development of ANN models, the obtained experimental results from all of the treatments were randomly divided into 3 sub-groups of training, validation and testing datasets with the ratios of 70%, 15% and 15% respectively. Then they were normalized in the range of 0.2 to 0.8 according to equation 1 (Hosseinzadeh et al., 2018):

$$\text{Normalized value of } x_i = \frac{x_i - \text{minimum value of data}}{\text{maximum value of data} - \text{minimum value of data}} \times (0.8 - 0.2) + 0.2 \qquad (1)$$

The segmentation of data into 3 sub-groups was carried out in order to hinder over-training problem during the model development. Furthermore, the data was normalized due to the reduction of the computational issues in the process of ANN model training.

2.3. Artificial neural network approach

ANN, as one of the computational methods in artificial intelligence, is a new computing system and technique, which is inspired by the human nervous system and process data or information. The key part of this computing system is its information processors which are called neurons. The ANN system is made up of a large number of interconnected neurons that work together to solve a problem. It is set up to perform specific tasks with learning from a given example (Elmolla et al., 2010) such as prediction of TN and TP in this study.

In this work, the Toolbox of Neural Network which is included in MATLAB R2015b was applied to predict the TN and TP concentrations for the produced vermicomposts. For this, a large number of 3 layered ANN models were built to select the best predictive model. The applied transfer functions for hidden and output layers of developed ANN models were tangent sigmoid functions. The training of ANN models was carried out by the algorithm of Levenberg–Marquardt. The algorithm iteratively modifies the weights (input and output layer weights) and biases of an ANN model to the extent that the ANN outputs are close to the actual values (Hagan and Menhaj, 1994).

2.4. Multiple linear regression analysis

MLR refers to the regression models with a dependent variable and two or more independent variables. In this case, the values of a dependent variable (e.g. TN) are obtained from the values of independent variables (pH, EC, C/N, NH_4/NO_3, WSC, DEH enzyme and TP), by constructing a general linear relationship as shown in equation 2 (Ghaedi et al., 2015):

$$y = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + \beta_3\chi_3 \cdots \beta_n\chi_n \qquad (2)$$

where y is a dependent variable describing the predicted values of TN; χ_1, χ_2, χ_3, and χ_n are independent variables; β_0 to β_n are the linear regression coefficients.

2.5. Comparison of MLR and ANN models

The TN and TP values were predicted, together with R-squared (R^2), Adjusted-R^2, Root Mean Square Error (RMSE) and Absolute Average Deviation (AAD), which were compared with the actual values of TN and TP in order to assess, validate and test the goodness of fit and the prediction accuracy of the models. In general, a model that contains the lowest error values (RMSE, AAD) and the highest values of correlation coefficients (R^2, adjusted R^2) is considered as the best model. The required formulae for the calculation of relevant statistical indices are presented in Table 1 (Hosseinzadeh et al., 2018).

Table 1. The statistical indices used for assessment of developed models

Index	Equation
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{prd,i} - y_{Act,i}\right)^2}$
Determination coefficient	$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_{prd,i} - y_{Act,i})}{\sum_{i=1}^{N}(y_{prd,i} - y_m)}$
Absolute Average Deviation (AAD)	$AAD = \left(\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_{prd,i} - y_{Act,i}}{y_{Act,i}}\right)\right) \times 100$
Adjusted determination coefficient	$R^2 adjusted = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1}$

N is the total number of data points; $y_{Act,i}$ is the actual value of TN or TP; $y_{prd,i}$ is the predicted value of TN or TP; and y_m is the mean of actual values of TN or TP.

3. Results and discussion

3.1. TN modeling by ANN

To develop a robust model of ANN which is able to capture the behavior of TN, several ANN models were designed using pH, EC, C/N, NH_4/NO_3, WSC, DEH enzyme and TP as inputs and TN as output of ANN models. First, these different neurons of ANN hidden layer were studied from 1 to 20. Judgment on the best structure of ANN model was based on the highest value of correlation coefficient (R) and the least amount of Mean Square Error (MSE) for testing, validation and training datasets. The results demonstrated that a network with seven neurons of hidden layer provides the greatest performance. Therefore, a 7-7-1 topology was selected for the developed ANN model for TN (Fig. 1). Fig. 2 shows the scatter plots of forecasted TN values (ANN output) versus the actual TN values in the training, validation, testing and all datasets. As observed in Fig. 2, the R values of training, validation and testing datasets in the developed ANN models for TN were 0.9993, 0.9999 and 0.9993 respectively, and the obtained proportions of MSE (for normalized data) were in order 0.000066, 0.000009 and 0.000197 correspondingly. In this topology, the first and last numbers represent the number of input and output variables of ANN model respectively, and the middle number represents the number of hidden layer neurons.

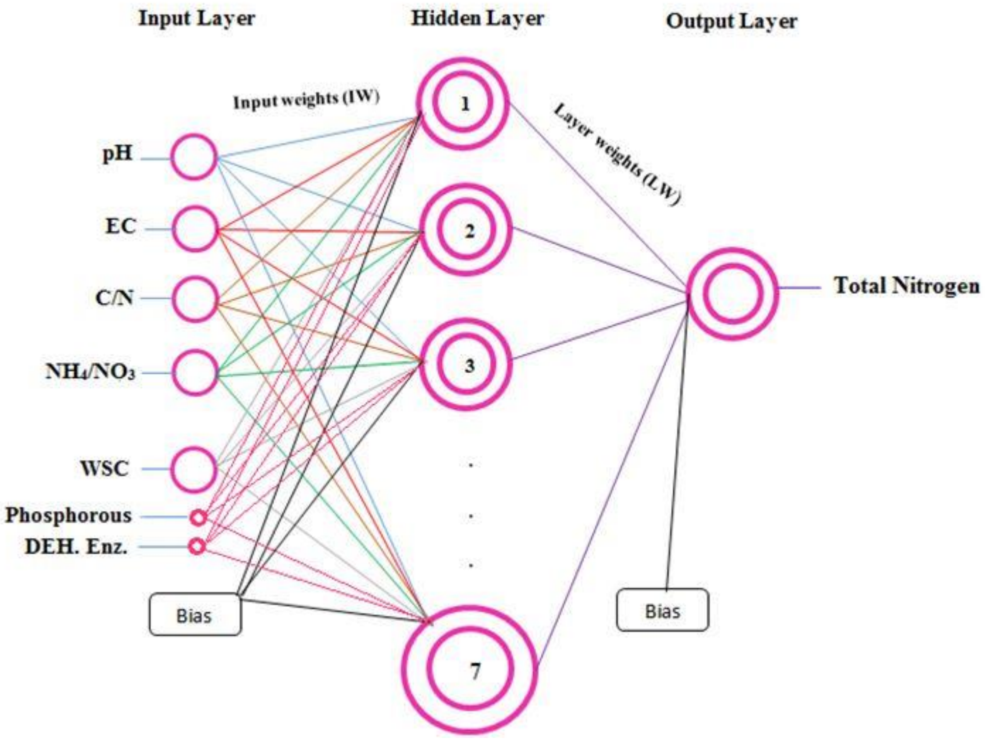

Fig. 1. Topology of developed ANN model for TN prediction.

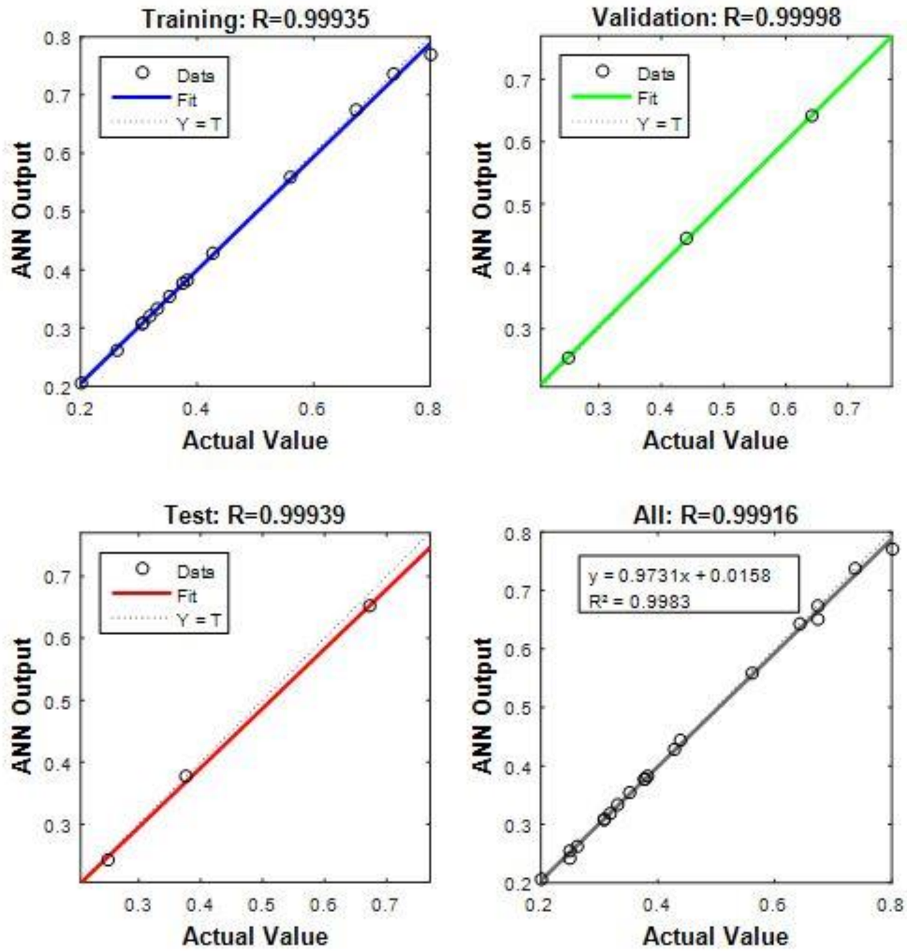

Fig. 2. Scatter plots of forecasted TN values versus the actual values in the training, validation, testing and overall datasets.

The best linear fit, determination coefficient (R^2) and equation related to the developed ANN model for all data are shown in equations 3-5 respectively:

$$y = 0.9731x + 0.0158 \qquad (3)$$

$$R^2 = 0.9983 \qquad (4)$$

$$ANN\ equation = Purelin(LW \times tansig\left(IW \times \left[DEH; WSC; \frac{NH4}{NO3}; pH;\ EC; \frac{C}{N}; TP\right] + b_1) + b_2\right) \qquad (5)$$

The R^2 value of 0.9983 confirms that the developed ANN model with topology of 7-7-1 can explain 99.83% variability between the real and predicted values of TN. Fig. 3 shows the residual errors between real and predicted value for all datasets, which varied between the two models. The residual errors were very low and close to zero for ANN model, while in comparison, the residual errors fluctuated and were significantly larger for MLR model. The results demonstrate an excellent compatibility among the ANN outputs and actual values. Also, (George et al. 2018) developed an ANN model to simulate the gasification process of biomass according to the gained experimental results. Their developed model with topology of 7-1-4 could satisfactorily model the process with a regression coefficient (R) of 0.987 and MSE of 0.71. Furthermore, in another study the transmembrane pressure in an anoxic-aerobic membrane bioreactor was simulated using ANN model. The developed model could well mimic this response variable behavior in process with $R^2 = 0.850$ (Schmitt et al., 2018). Therefore, the developed models in the present study benefit from higher accuracies.

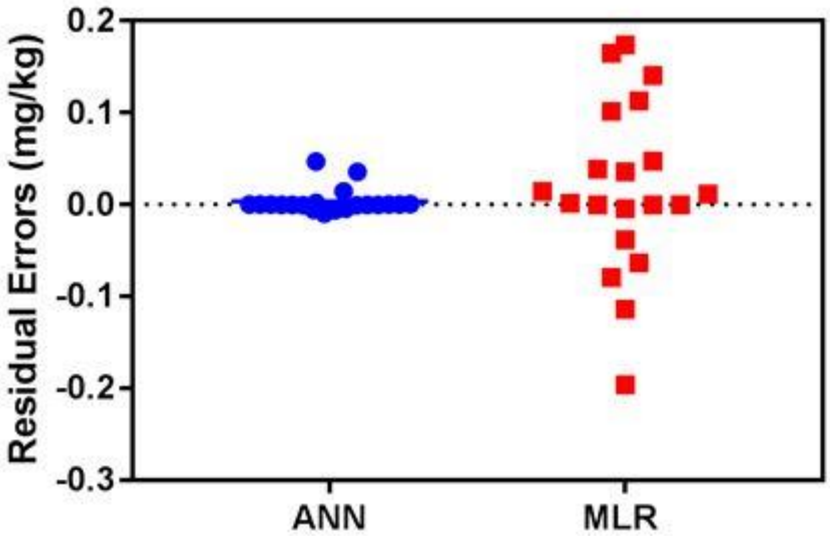

Fig. 3. Distribution of residual errors in prediction of total nitrogen (real scale) by ANN and MLR approaches.

3.2. Total phosphorus modeling by ANN

To model TP by ANN method, various topologies (hidden layer neuron from 1-20) were investigated. ANN model was developed using pH, EC, C/N, NH_4/NO_3, WSC, DEH enzyme and TN as inputs and TP as output (equation 6). The decision on the best structure of ANN model was based on the approach as for TN modeling. The results show that an ANN model with 7 hidden layer neurons provides the best performance. Fig. 4 shows the scatter plots of forecasted TP values versus the actual values, where the R values of training, validation and testing datasets in the developed ANN model were 0.9999, 0.9998 and 0.9992 respectively and the obtained amounts of MSE (for normalized data) were 4.2×10^{-6}, 1.6×10^{-5} and 1.7×10^{-4}. Therefore, the topology of developed ANN model for TP is also 7-7-1. The best linear fit and R^2 of developed ANN model for all data are presented in Fig. 4. The R^2 value of 0.9991 in prediction of TP confirms that the developed ANN model can explain 99.91% variations between the real and predicted values of TP.

$$ANN\ equation = Purelin(LW \times tansig\left(IW \times \left[DEH; WSC; \frac{NH4}{NO3}; pH;\ EC; \frac{C}{N}; TN\right] + b_1) + b_2\right) \quad (6)$$

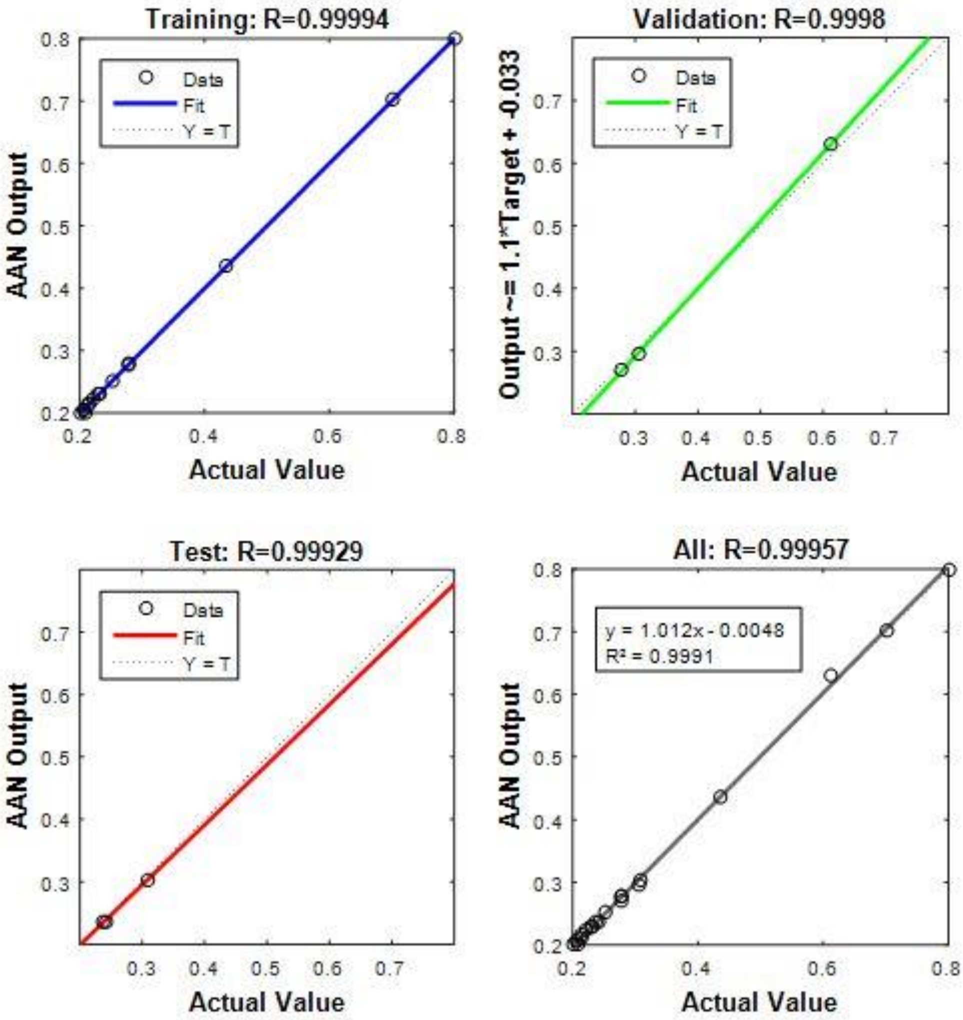

Fig. 4. Scatter plots of forecasted total phosphorus values versus the actual values.

Fig. 5 shows the distribution of residual errors in prediction of TP, where the residual error distribution was close to the zero error. Therefore, it can be concluded that the developed ANN model can well mimic the behavior of TP in the vermicompost system.

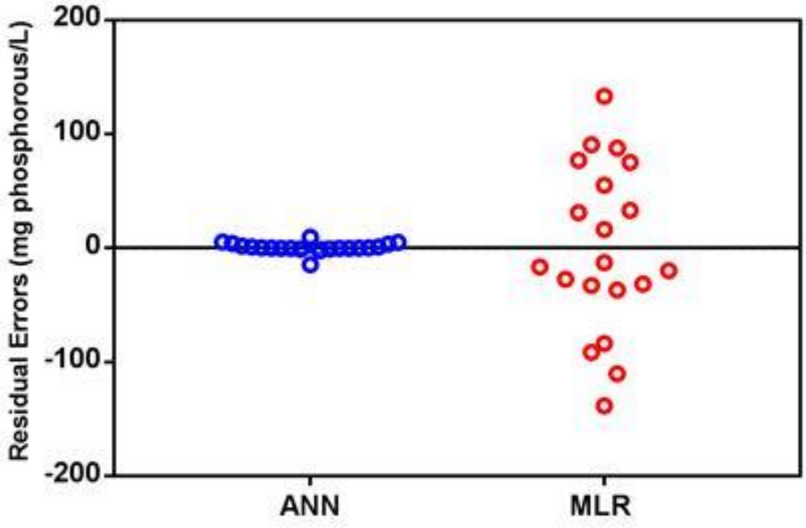

Fig. 5. Distribution of residual errors in prediction of total phosphorus (real scale) by ANN and MLR models.

In another study, Uzun et al. (2017) developed and applied an ANN model to predict the high heating value of solid biomass fuel, and demonstrated that the model was able to successfully predict the response variable with correlation coefficient of 0.963 and RMSE of 0.375. However, the developed ANN model by Xu et al. (2014) did not satisfactorily predict the methane yield of different biomasses with R^2 of 0.528. They attributed the unsatisfactory prediction to the existence of possible overfitting owing to use of too many parameters associated with various observations.

3.3. MLR modeling

At this step of the study, an MLR code was written in the MATLAB R2015b software to model the TN and TP. It is noted that the data used in MLR approach were same as the data used for ANN models. Equations 5 and 6 were proposed by the software as the result of MLR modeling for TN and TP respectively. The *P*-values of the developed model for TP and TN were 0.0102 and 0.0007 respectively. These results confirm that the developed models are statistically significant (*p*-value < 0.05). Also, Huang et al. (2011) used MLR to model some nutrients in composting of chicken manure and concluded that the developed MLR models have good performance, which is same with the present study.

$$\boldsymbol{Total\ Nitrogen} = -\mathbf{0.0226}\,(pH) - \mathbf{0.1189}\,(EC) - \mathbf{1.7409}\left(\frac{C}{N}\right) + \mathbf{1.6137}\left(\frac{NH_4}{NO_3}\right) - \mathbf{0.4996}\,(WSC) + \mathbf{0.2625}\,(Phosphorus) + \mathbf{0.1553}\,(DEH.Enz) + \mathbf{0.6982} \quad (5)$$

$$\boldsymbol{Phosphorous} = -\mathbf{0.2118}\,(pH) - \mathbf{0.3181}\,(EC) - \mathbf{0.0082}\left(\frac{C}{N}\right) + -\mathbf{0.1605}\left(\frac{NH_4}{NO_3}\right) - \mathbf{0.6559}\,(WSC) + -\mathbf{0.2942}(DEH.Enz) + \mathbf{0.4031}\,(Total\ nitrogen) + \mathbf{0.9042} \quad (6)$$

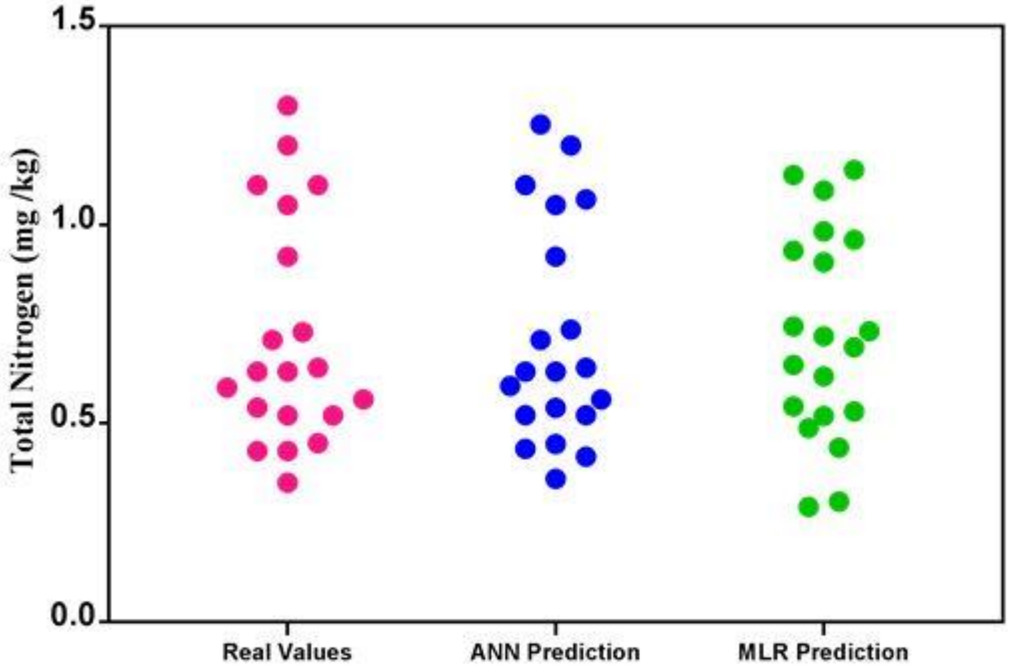

Fig. 6. Trend of actual total nitrogen and its mimic by ANN and MLR methods.

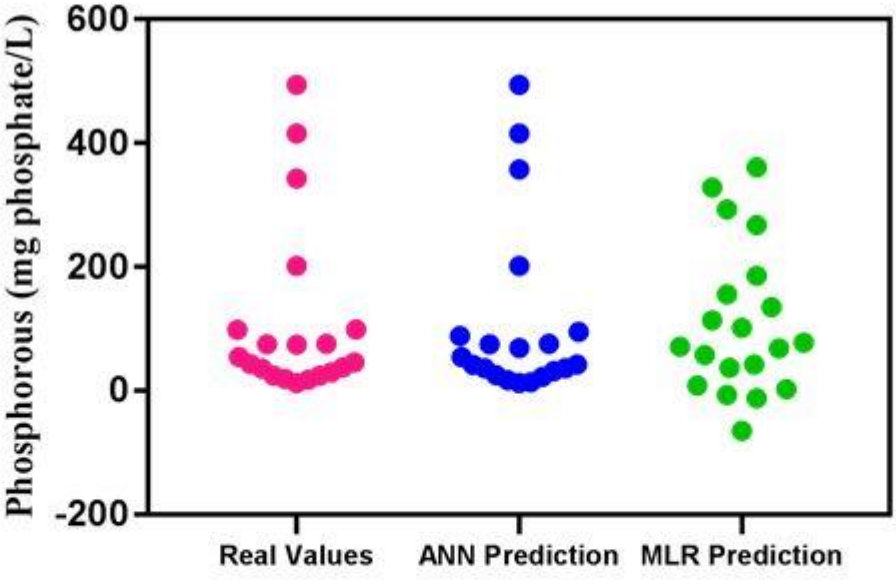

Fig. 7. Trend of actual total phosphorus and its mimic by ANN and MLR methods.

In another study (Zhu et al. 2010) applied MLR to predict the digestibility of some different biomasses. They concluded that MLR could be applied to predict digestibility. However, the R^2 obtained was lower than the R^2 of the present study. Also, Sharon Mano Pappu et al. (2013) studied the application of MLR in prediction of *Spirulina platensis* growth in outdoor cultures. This can grow under heterotrophic, autotrophic and mixotrophic conditions under subtropical and tropical conditions, and has different applications in the environment. Light intensity, temperature, pH, time, dissolved oxygen, nitrate, phosphate, bicarbonate and biomass concentrations were taken into account as the input variables. Finally, the developed MLR models had various correlation coefficients (R^2) ranging from 0.87 to 0.97 which are higher than the obtained ones in the present study.

3.4. Comparison of ANN and MLR models in TN and TP prediction

The prediction strength of ANN and MLR models was investigated to predict the 20 data points of TN and TP which were obtained from the experiments. The predicted TN and TP values were then compared with the real results. The R^2 value, RMSE and AAD as statistical indices were employed to determine and compare the performance of ANN and MLR models. The trend of actual and forecasted data points of TN and TP nutrients by ANN and MLR methods shows that ANN models mimic the trend of TN and TP better than MLR models (Figs 6 and 7). The details of prediction, the input variables along with their values for TN and TP are presented in Tables 1 and 2 respectively**.** Table 3 presents the obtained values of statistical indices (R^2, adjusted- R^2, RMSE, AAD) in this work. The R^2 value for the ANN and MLR in prediction of TN is 0.9983 and 0.8340, the adjusted-R^2 is 0.9982 and 0.7371, the RMSE is 0.013 and 0.092, and the AAD is 0.241 and 1.533 correspondingly. Also, the R^2 value for the ANN and MLR in prediction of TP is 0.9991 and 0.729, the adjusted-R^2 is 0.9991 and 0.571, the RMSE is 4.3 and 71.49, and the AAD is 2.85 and 22.8. (Boniecki et al., 2012) constructed various models of ANN to predict and model the emissions of ammonia released from composting process of sewage sludge. For the best-developed model, the R^2 value was 0.981 demonstrating that the developed models in the present study benefits from higher accuracy. In another study (Qdais et al., 2010), different ANNs were designed to model and control the methane production from anaerobic process operated under various (Organic Loading Rates) OLRs. The obtained R^2 value for the best model was 0.8703, which was close to the value obtained in this study.

Table 2. Input variables of ANN and MLR models and their corresponding prediction of total nitrogen

pH	EC (µS/cm)	C/N	NH_4/NO_3^-	WSC (mg/l)	TP (mg/l)	DEH enzyme (µg/g 24 h)	TN (mg/kg)		
							Real	ANN	MLR
7.32	712.80	102.57	15.03	319	12.46	29.54	0.35	0.36	0.30
8.56	468.00	87.11	6.50	256	24.34	159.59	0.43	0.44	0.29
8.85	655.20	36.19	1.94	197	75.26	261.72	0.52	0.52	0.73
8.11	1569.60	25.31	1.00	180	99.18	320.28	0.71	0.71	0.91
8.01	720.00	14.01	0.48	151	201.65	298.35	1.20	1.12	1.08
7.27	748.80	80.51	16.06	286	18.86	22.16	0.43	0.42	0.53
8.58	655.20	68.86	7.39	231	37.81	86.84	0.54	0.54	0.44
8.69	1044.00	36.18	3.44	209	42.72	276.34	0.63	0.64	0.74
8.24	1404.00	19.35	1.74	162	98.22	305.66	1.10	1.06	0.96
7.93	1368.00	12.93	1.03	149	342.96	211.06	1.30	1.25	1.13
7.56	871.15	71.63	9.99	267	24.32	11.07	0.45	0.45	0.49
8.5	886.45	53.57	6.50	227	35.46	50.58	0.59	0.59	0.54
8.61	900.00	34.73	2.30	223	54.56	152.27	0.73	0.74	0.69
8.26	1296.70	19.54	1.83	151	75.34	261.72	1.10	1.10	0.94
8.01	864.00	16.61	0.95	128	494.17	108.70	1.05	1.05	1.14
7.5	1140.00	56.65	9.11	228	29.93	0	0.63	0.63	0.62
8.22	994.73	55.51	5.28	228	45.82	14.40	0.52	0.52	0.52
7.96	828.00	48.57	3.24	180	17.62	145.04	0.56	0.56	0.65
8.21	1296.00	42.93	2.84	159	74.35	203.30	0.64	0.64	0.72
8.12	936.00	28.16	1.27	124	415.82	94.15	0.92	0.92	0.98

Table 3. Input variables of ANN and MLR models and their corresponding prediction of total phosphorus

pH	EC (µS/cm)	C/N	NH_4/NO_3^-	WSC (mg/l)	DEH enzyme (µg/g 24 h)	TN (mg/kg)	TP (mg/l)		
							Real	ANN	MLR
7.32	712.80	102.57	15.03	319	29.54	0.35	12.46	12.51	-64.68
8.56	468.00	87.11	6.50	256	159.59	0.43	24.34	24.88	-6.81
8.85	655.20	36.19	1.94	197	261.72	0.52	75.26	75.43	42.10
8.11	1569.60	25.31	1.00	180	320.28	0.71	99.18	94.94	8.33
8.01	720.00	14.01	0.48	151	298.35	1.20	201.65	201.79	292.92
7.27	748.80	80.51	16.06	286	22.16	0.43	18.86	13.49	2.50
8.58	655.20	68.86	7.39	231	86.84	0.54	37.81	36.66	57.43
8.69	1044.00	36.18	3.44	209	276.34	0.63	42.72	41.56	-12.52
8.24	1404.00	19.35	1.74	162	305.66	1.10	98.22	88.58	134.92
7.93	1368.00	12.93	1.03	149	211.06	1.30	342.96	357.36	267.60
7.56	871.15	71.63	9.99	267	11.07	0.45	24.32	22.56	37.05
8.50	886.45	53.57	6.50	227	50.58	0.59	35.46	36.21	68.28
8.61	900.00	34.73	2.30	223	152.27	0.73	54.56	54.45	71.06
8.26	1296.70	19.54	1.83	151	261.72	1.10	75.34	74.95	185.37
8.01	864.00	16.61	0.95	128	108.70	1.05	494.17	494.12	360.97
7.50	1140.00	56.65	9.11	228	0	0.63	29.93	31.94	113.45
8.22	994.73	55.51	5.28	228	14.40	0.52	45.82	42.24	77.35
7.96	828.00	48.57	3.24	180	145.04	0.56	17.62	17.28	155.91
8.21	1296.00	42.93	2.84	159	203.30	0.64	74.35	69.12	101.50
8.12	936.00	28.16	1.27	124	94.15	0.92	415.82	415.89	328.10

Table 3. Statistical comparison of ANN and MLR models

	Total nitrogen		Total phosphorus	
Index	ANN	MLR	ANN	MLR
R^2	0.9983	0.834	0.9991	0.729
Adjusted-R^2	0.9982	0.7371	0.9991	0.571
RMSE	0.013	0.0928	4.3	71.49
AAD (%)	0.241	1.533	2.85	22.8

3.5. Sensitivity analysis

To assess the importance (%) of pH, EC, C/N, NH_4/NO_3, WSC, DEH enzyme and TP on ANN model output (prediction of TN), a sensitivity analysis approach which partitions the connection weights of the developed ANN model was employed. This approach is an equation based technique (equation 7) that was first introduced by Garson (Baziar et al., 2017), and was also used to determine the importance of input variables in developed ANN model for TN and TP. Table 5 shows the obtained ANN weights matrix in this work. Fig. 8 presents the importance of each input parameter on the prediction of TN and TP.

$$Ij = \frac{\sum_{m=1}^{m=Nh}\left(\left(\frac{\left|W_{jm}^{ih}\right|}{\sum_{k=1}^{Ni}\left|W_{km}^{ih}\right|}\right) \times \left|W_{mn}^{ho}\right|\right)}{\sum_{k=1}^{k=Ni}\left\{\sum_{m=1}^{m=Nh}\left(\frac{\left|W_{km}^{ih}\right|}{\sum_{k=1}^{Ni}\left|W_{km}^{ih}\right|}\right) \times \left|W_{mn}^{ho}\right|\right\}} \times 100 \qquad (7)$$

where Ij is the percentage of variable importance, *W* is ANN weight, N_h is ANN hidden layer neurons, N_i is the number of input variables (neurons), the letters of *i*, *h* and *o* are respectively related to the input, hidden, and output layer of ANN model, *n* is the number of output variable, *k* is the number of input variables, and *m* is the number of hidden neurons (Baziar et al., 2017).

Table 4. ANN model weights and biases for (a) total nitrogen, and (b) total phosphorus

(a)	IW							LW	b1	b2
	-0.785	-0.736	0.539	-0.664	0.832	-0.629	0.413	-0.485	1.917	-0.142
	0.936	-0.573	-0.867	-0.285	0.912	-0.602	-1.076	0.499	-1.019	
	-0.594	1.080	1.540	-0.929	-0.042	-0.658	-0.161	-1.083	-0.952	
TN (mg/kg)	0.473	0.380	0.366	-0.572	0.439	0.711	-0.900	0.504	0.545	
	-1.437	1.233	-0.551	-0.404	-0.156	-0.269	0.508	1.156	-0.244	
	0.135	-0.292	-0.475	0.694	-0.427	-1.407	0.740	0.528	1.412	
	0.630	0.124	0.967	-0.030	1.438	-0.032	-0.631	-0.875	2.468	

(b)	IW							LW	b1	b2
	-0.408	-1.138	1.645	0.942	0.295	-0.733	-0.342	-0.845	1.702	0.698
	0.204	-0.624	0.265	-0.812	-1.337	-1.550	-1.286	0.930	-0.906	
	-0.863	-2.009	-1.195	1.116	-0.242	-1.707	2.550	2.854	-1.946	
TP (mg/l)	1.676	0.751	-0.672	-0.354	0.775	-1.217	-0.260	2.153	0.596	
	-0.281	0.093	-0.297	0.220	0.113	1.129	-2.008	0.422	-0.053	
	0.968	0.088	1.429	1.135	-0.961	-0.300	-0.951	-1.259	1.764	
	0.716	0.443	-0.676	0.523	0.975	0.472	-0.661	-0.205	2.163	

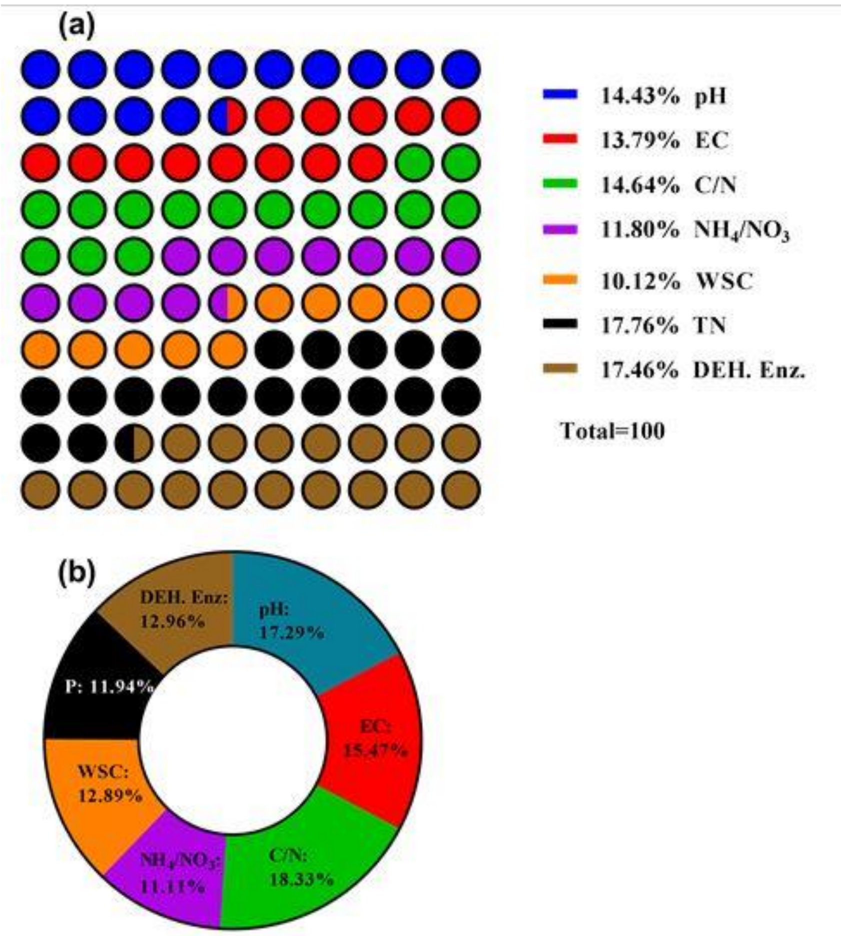

Fig. 8. The percentage of variable importance in (a) total phosphorus, (b) total nitrogen from the ANN model.

As observed in Fig. 8, all input layer variables had significant effect on ANN outputs. However, the highest degree of importance was attributed to TN (17.76%) and C/N ratio (18.33%) as shown in Fig. 8(a) and 8(b), respectively. In addition, in a sewage sludge composting process study (Boniecki et al., 2012), four different ANN models were developed to predict the ammonia emissions. Their sensitivity analysis of the process demonstrated that C/N ratio and pH were two of the most efficient variables affecting the process performance

4. Conclusions

Nutrient recovery from waste is a challenging task and is receiving global interest to support UN sustainable development goals. This study focused on TN and TP recovery from vermicompost treatment of MSW, with the dual purposes of solid waste treatment and resource recovery. Four different treatments with various ratios of MSW to COMs were conducted, and the experimental results were used to build ANN and MLR models which were capable of predicting TN and TP changes during vermicompost. The models were compared by statistical analysis including R^2, adjusted-R^2, RMSE and AAD, demonstrating that ANN model provided better prediction than MLR.

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