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Modelling and optimization of sewage sludge composting using biomass ash via deep neural network and genetic algorithm

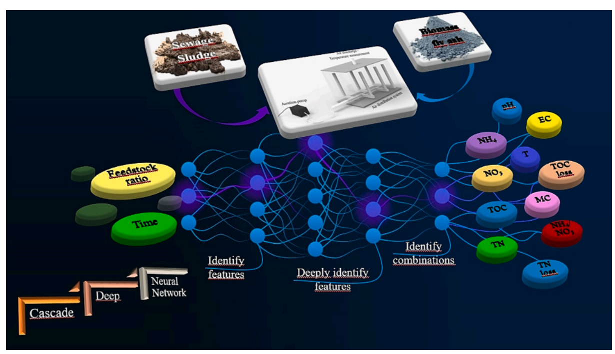
Hale Dogan [a], Fulya Aydın Temel [b,*], Ozge Cagcag Yolcu [c], Nurdan Gamze Turan [a]

[a] Department of Environmental Engineering, Faculty of Engineering, Ondokuz Mayıs University, Samsun 55200, Turkey
[b] Department of Environmental Engineering, Faculty of Engineering, Giresun University, Giresun 28200, Turkey
[c] Department of Statistics, Faculty of Sciences and Arts, Marmara University, İstanbul 34722, Turkey

HIGHLIGHTS

- Interactions of physicochemical factors were evaluated in co-composting.
- Biomass fly ash decreased carbon and nitrogen losses during composting.
- Adding biomass fly ash to dewatered sewage sludge improved the compost quality.
- Composting process parameters was predicted by Deep Cascade Forward Neural Network.
- The optimal conditions for composting were determined by Genetic Algorithm.

GRAPHICAL ABSTRACT



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ABSTRACT

In this study, the use of Deep Cascade Forward Neural Network (DCFNN) was investigated to model both linear and non-linear chaotic relationships in co-composting of dewatered sewage sludge and biomass fly ash (BFA). Model results were evaluated in comparison with RSM, Feed Forward Neural Network (FFNN) and Feed Back Neural Network (FBNN), and Cascade Forward Neural Network (CFNN). DCFNN produced predictive results with MAPE values less than 1% for all datasets in all experimental designs except one with 1.99%. Furthermore, the decision variables were optimized by Genetic Algorithm (GA). The desirability level obtained from the optimization results was found to be 100% in a few designs and above 95% in all other designs. The results showed that DCFNN is a reliable and consistent tool for modeling composting process parameters, also GA is a satisfactory tool for determining which outputs the input parameters will produce in an experimental setup.

1. Introduction

In integrated solid waste management, there is an increasing interest in re-managing infrastructures related to waste generated in urban environments. While wastewater treatment plants make a significant contribution to environmental services, there is a need for technological and economic decisions regarding the disposal of sewage sludge (Tsui et al., 2022). In raw form, both sewage sludges contain high concentrations of organic matter, various pathogens, and heavy metals. Therefore, direct disposal of the sewage sludge or its application to the

* Corresponding author.

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Table 1
Properties of the composting materials.

Parameters	DSS	SSS	BFA
pH	5.86 ± 0.03	6.22 ± 0.04	5.14 ± 0.02
EC (mS/cm)	2.74 ± 0.02	2.48 ± 0.03	2.47 ± 0.04
MC (%)	65.12 ± 1.13	60.61 ± 1.08	6.13 ± 0.98
TOC (%)	37.14 ± 1.21	34.24 ± 1.44	6.29 ± 0.91
TN (%)	2.14 ± 0.04	1.89 ± 0.03	0.11 ± 0.02
C/N	17.36 ± 0.57	18.12 ± 0.68	57.18 ± 0.42
NH_4^+-N (mg/L)	387.84 ± 10.14	262.13 ± 8.76	nd
NO_3^--N (mg/L)	57.87 ± 2.31	44.13 ± 1.12	nd

*nd: non-detected

soil can cause serious problems such as groundwater pollution, deterioration of soil structure, and odor (Al-Gheethi et al., 2018). Sludge disposal methods consisted of thermal treatment, chemical treatment, and biological treatment are used for volume reduction, carbon, and nitrogen recovery, pathogen elimination, and heavy metal stabilization. Thermal methods that have the advantages such as weight reduction and biofuel, and biological methods that have the advantages such as working with less energy and the ability to hold nitrogen are preferred more than chemical methods (Liew et al., 2021). However, thermal and biological methods are still in the background in developing countries due to their high investment cost (Liew et al., 2022). It should be focused on researching low-cost sludge disposal methods for sustainable sludge disposal. Currently, composting stands out as a low-cost method that can be solved the sludge management problem.

Composting is a stabilization method that destroys pathogens with biologically produced heat, and biodegrades organic components to form a final compost that can be applied to the soil (Kabak et al., 2022). The composting process is affected by factors related to the material mixture formula (nutrient content, pH and moisture, etc.), and process management (oxygen content, temperature, and water content, etc.). In the composting process, it is possible to reduce the heavy metal content, increase the microbial activity, facilitate the process and improve the quality of the final product by using additives such as fly ash (Wong et al., 2009), zeolites (Turan and Ergun, 2008), bentonite (Li et al., 2012), pumice (Aycan Dümenci et al., 2021), hazelnut kernel (Aycan et al., 2014), etc.

Biomass power plants have been of great importance in recent years due to the energy crisis and the increasing interest in renewable energy sources. It is expected that its use as an energy source will increase greatly according to world energy scenarios. Biomass fly ash (BFA) is an important waste from biomass power plants. BFA is usually deposited, used for the cement and concrete industries, and building materials. Since it is generally rich in elements such as P, C, K, Si, Ca, and Mg, it can be used as an additive material in the composting process to recovery essential plant nutrients and apply to the agricultural or forest soil (Zhai et al., 2021). Although research shows that biomass ashes have a general potential to increase plant growth and nutrient uptake, there are limited studies on the interactions of different types of BFA and crops.

Recently, many research areas, including environmental science, have focused on data processing, induction, and deduction (Xu et al., 2021). Although statistics-based methods such as Response Surface Methodology (RSM) are widely used for the prediction of the parameters of the composting process, machine-learning methods are quite successful. There are a limited number of studies using ANNs for the modeling of the composting process, the prediction of missing data, and the optimization of physicochemical parameters and processes (Ding et al., 2022; Hosseinzadeh et al., 2020; Kabak et al., 2022; Sharma et al., 2021; Shi et al., 2022). However, models working in a way of the deep learning principle in the modeling of composting processes have been encountered in only one work (Kujawa et al., 2020).

Deep Neural Networks (DNNs) are much more successful than classical ANNs in identifying non-linear relationships between multivariate inputs and process parameters and extracting certain features (Kirisci and Cagcag Yolcu, 2022). In a composting process, it is inevitable that the chaotic relationships between multivariate model inputs and process parameters contain both linear and non-linear structures. In the literature, statistical-based methods focus on modeling only linear relationships, while classical and deep neural network-based prediction methods only model non-linear relationships. The Deep Cascade Forward Neural Network (DCFNN) has the capability to model both non-linear and linear relationships together with its architecture. There are deficiencies in the research on the use of mathematical modeling tools and classical ANNs in modeling the composting process parameters. While traditional mathematical modeling tools can only model linear structures, traditional ANN and deep ANN-based tools can only model non-linear structures. Classical ANNs cannot capture deep complex multivariate structures. However, the proposed DCFNN can model both non-linear and linear structures together. DCFNN-based predictor is much more successful than classical ANNs in capturing complex relationships between multivariate inputs and process parameters by its deep architecture.

In the present study, the co-composting of two different sewage sludge, dewatered by a decanter and separator, and BFA was examined in the pilot-scale in-vessel reactor. From a holistic perspective, some of the main purposes of the study were: (*i*) to evaluate with an inquiring point of view physicochemical parameters, (*ii*) to compare examine the efficiency of mixture ratios of BFA and sewage sludges, (*iii*) to extract certain features hidden in multivariate inputs of the composting process by using a deep neural network, (*iv*) to more rationally predict the composting process parameters using a Deep Cascade Forward Neural Network that allows non-linear and linear relationships to be modeled together, (*v*) to determine the best predictor one among the RSM, some classical neural networks, and DCFNN by addressing Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) criteria, (*vi*) to detect the statistical effects of the contents of the trials ratio on the composting process, (*vii*) to identify the best parameter values via GA in a way to optimize the output parameters.

2. Materials and methods

2.1. Composting materials

The sewage sludges were obtained from the advanced biological treatment plant in Samsun, Turkey. Two different sewage sludges dewatered by decanter and separator were used in the treatments. BFA samples were taken from a biomass power plant in Samsun, Turkey. The biomass power plant, which has an electricity generation capacity of 27 MW/h, uses the circulating fluidized bed combustion method. The main raw materials used as biomass in the plant are forestry waste, agricultural waste, bark, straw, and branches. The biomass in a fluidized bed is combusted with air by mixing at 750 °C. The unburned fuel particles pass through and are separated by a cyclone separator. BFA is produced from the cyclone separator and dust collector. The physicochemical properties of the composting feedstocks were given in Table 1.

2.2. Process and experimental design

The composting process of waste was performed by aerated in-vessel reactors (depth × width × length = 25 × 40 × 30 cm). The reactors were designed from translucent plastic for the gradual monitoring of compost production. Aeration was done with a pump with a capacity of 10 L/min. Airflow was provided by the air distribution pipes mounted on the in-vessel of the reactor in vertical and horizontal positions. The main pipe was mounted to the reactor at a height of 5 cm from the bottom of the reactor. Perforated pipes made of PVC with a diameter of 2 cm were used as air distribution pipes. The holes were 3 mm and formed crosswise. A thermometer probe was set in the upper middle part of the reactor and the temperature was daily measured with a digital thermometer (Loyka-9263).

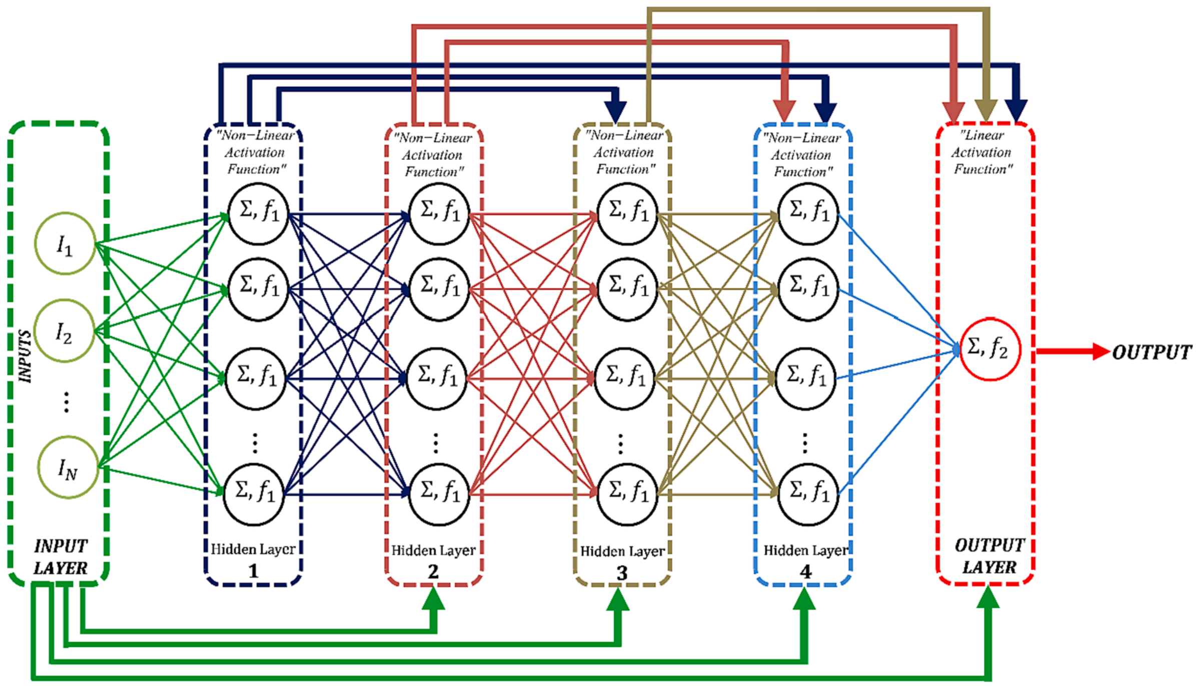

Fig. 1. A prototype of DCFNN – with four hidden layers.

BFA was added to sewage sludge at 10, 25, and 50 % as weight, and the materials were thoroughly mixed manually. Approximately 20 kg of mixture was composted in in-vessel composting reactors for 105 days. Approximately 100 g of composting material was collected from each composting reactor once a week to determine physicochemical parameters (pH, electrical conductivity (EC), moisture content (MC), total organic carbon (TOC), total nitrogen (TN), ammonium nitrogen (NH_4^+-N) and nitrate nitrogen (NO_3^--N)). Temperature was monitored by a digital thermometer (Loyka-9263) in the middle of the reactor. All parameters were analyzed according to standard test methods (Baird et al., 2017). EC and pH were determined in aqueous supernatant (1:10 (w/v) by a pH-EC meter (Orion Star^{TM} A325). MC was determined by using an oven-drying (Nüve-FN400). TN and TOC contents were analyzed in the dried samples. The NO_3^--N and NH_4^+-N concentrations were analyzed after extracting with 2 M KCl at a 1:10(w/v) ratio.

2.2.1. Deep cascaded forward neural network

ANNs are biologically inspired computational models widely used for several problems. ANNs are based on a supervised procedure as a machine learning tool. ANNs, which are very simple simulations of the human brain, solve the problems in the field of Artificial Intelligence (AI) by producing new information through learning like a human (Kabak et al., 2022). The Feed-forward neural network (FFNN) is a type of multilayer perceptron (Rumelhart et al., 1986; Werbos, 1974). FFNN is commonly applied for modeling of the composting. FFNN, unlike statistical-based RSM, handles the relations between inputs and outputs in a non-linear manner. In particular, modeling the relationships between the inputs and outputs with both non-linear and linear structures develops performance of the model. As a prediction tool, the Cascaded Forward Neural Network (CFNN) has superior capabilities with the architecture where each layer is fed from all previous layers (Demuth and Beale, 2009; Fahlman and Lebiere, 1990). However, the use of a DCFNN further increases modeling success, as DNNs are much more successful in extracting certain features than classical ANNs and identifying nonlinear relationships between multivariate inputs and process parameters. DNN's use multiple hidden layers in its structure as opposed to traditional neural networks. It provides an important advantage to learn with layers that make it easy to transition from a simple concept to a complex concept with this feature. The features require to be defined correctly in classical ML approach, while deep learning models have the ability to create new features. A prototype of DCFNN with four hidden layers was presented in Fig. 1.

3. Results and discussions

3.1. Effects of BFA on temperature, pH, EC and moisture content

Temperature is a crucial factor for compost stability and quality in composting (Zhao et al., 2020). In the composting process, the temperature goes through the stages of mesophilic, thermophilic, and mesophilic, respectively. The change of temperature was presented in Fig. 2(a). The temperature rapidly increased up to the second week in all treatments. Similar results were found by other researches (Mahapatra et al., 2022; Oviedo-Ocaña et al., 2015). Then, mesophilic phase finished and thermophilic phase started. The maximum temperature reached to 55.5 °C and 56.6 °C for DSS and SSS treatments, respectively. In addition, lower and shorter-term thermophilic temperatures were observed compared to the control groups without BFA. The temperature differences between all treatments were primarily due to increase the activities of microorganisms and decomposition of organic matter as a result of the high moisture content and low carbon content of the sewage sludge. The temperatures in all treatments dropped below 40 °C in approximately 6 weeks. It was observed that BFA had no remarkable effect on composting time. However, BFA allowed the temperature of the compost to reach the high temperatures (>55 °C) necessary for the destruction of weed seeds and many pathogenic microorganisms.

pH is a significant factor affecting the composting process and the maturity of the final compost. The changes of pH for all feedstocks' mixtures in the composting were presented in Fig. 2(b). At the beginning of the composting processes, pH values were found as 5.86 and 6.22 for DSS and SSS treatments, respectively. Since the pH value of BFA (5.14) was lower than the initial values of control treatments of DSS and SSS treatments, a decrease was observed by increasing BFA ratio in the feedstocks' mixtures. The pH values of all trials reduced over the two weeks due to the intensive organic matter degradation and the numerous organic acid accumulation (Wei et al., 2016). Afterward, the

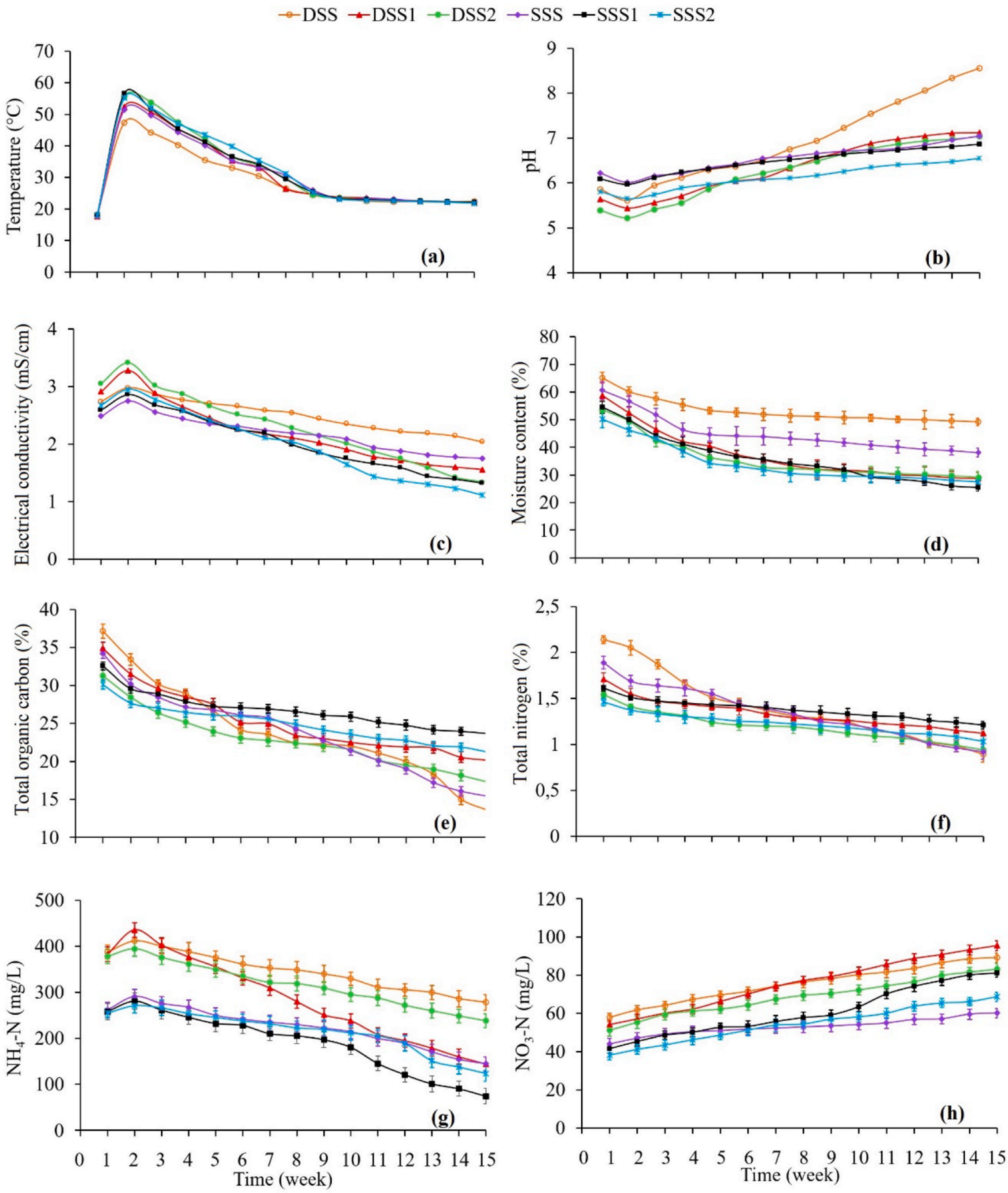

Fig. 2. Changes in temperature (a), pH (b), electrical conductivity (c), moisture content (d), total organic carbon (e), total nitrogen (f), NH_4^+-N (g), and NO_3^--N (h) during the composting process.

pH values slowly increased up to the end of the composting process. The optimal pH of the final compost is 6.5–7.2 (Singh et al., 2012). The final pH values of the DSS and SSS treatments were found as 8.56 and 7.05, respectively. The pH values of the treatments with BFA decreased at the end of the process. The pH value of the composts obtained from all trials except DSS was found in the optimal range.

EC is a significant parameter which can cause inhibit plant growth or phytotoxicity (Chen et al., 2020). The dynamic variations of EC values in the composting processes were presented in Fig. 2(c). Each reactor showed a similar trend. EC rapidly increased at the beginning of the composting in all treatments due to the micromolecular organic acid and various ions (NH_4^+, H^+ and HCO_3^-) produced as a result of increased microbiological activity with the rapid decomposition of organic matter (Ma et al., 2022). Then, a sharp decrease in EC was observed with the conversion of small molecular organic acids and a few salt ions to macromolecular HS^- (such as humic acid) (Yuan et al., 2016). Similar trends was observed by other studies (Chung et al., 2021; Qu et al., 2020). At the end of the composting process, the EC value ranged from 1.11 to 1.56 mS/cm in the treatments containing BFA, while it ranged from 1.75 to 2.04 mS/cm in the control treatments without BFA. The optimal EC value of final compost should be less than 4 mS/cm (Dhanker et al., 2021). Accordingly, all of the composts obtained from the

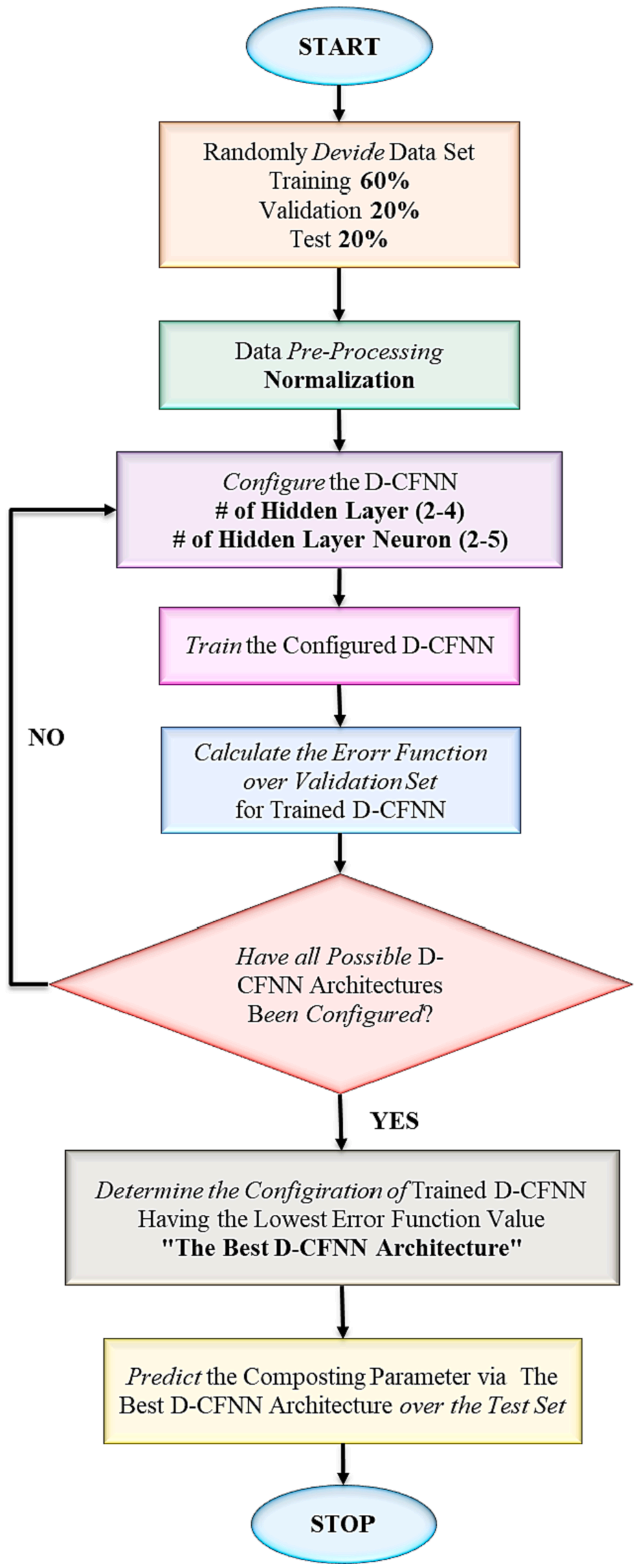

Fig. 3. A flowchart of the proposed prediction tool based on D-CFNM.

treatments met the requirement EC value.

MC is also a critical parameter for composting process. High MC values influences thermophilic temperatures, oxygen transfer, free air space, microbial activity and process efficiency. At the beginning of the process, the MC values of the material to be composted should be between 50 and 60 %. The MC values of DSS and SSS were above 60 % at the beginning of the process. The initial moisture content reached the optimum range with the addition of BFA to both sewage sludges. The changes in moisture content during the composting process were given in Fig. 2(d). As it is seen in Fig. 2(d), MC values for all treatments decreased during the composting process. In the composting process, MC loss is accepted as a factor of the decomposition ratio, as it triggers the heat generated by the biodegradation of organic matter. At the end of the process, the lowest moisture losses were observed in DSS and SSS treatments, while MC losses below 30 % were achieved in all treatments with BFA addition.

3.2. Effects of BFA on carbon and nitrogen dynamics

Carbon and nitrogen are essential nutrients for microorganisms in composting process. Organic waste provides the necessary carbon and nitrogen for microorganisms, but the suitable balance of these nutrients must be present for process efficiency in composting. Therefore, the C/N ratio plays an important role in composting process. While an initial C/N ratio in the composting process is acceptable between 20 and 40, the optimal value for microbial growth is between 25 and 30 (Yılmaz et al., 2022). The rate of decomposition is slow due to the small amount of N available to microorganisms at the ratio of C/N > 30. However, when C/N < 20, excess N is released as NH_3, producing nutrient loss and potential malodor (Reyes-Torres et al., 2018). The initial C/N ratios of DSS and SSS were 17.36 and 18.12, respectively. Both of the sewage sludge had an initial C/N ratio below the acceptable range. With the addition of BFA to sewage sludges, the initial C/N values increased, and provided the acceptable range. In all treatments, the C/N ratio slightly decreased during the composting process. The C/N value of the final compost should be below 20 for mature compost. Accordingly, the final C/N ratio values of the composts obtained from all treatments met the limit given for mature compost.

The TOC content of the final compost showed a decrease during the composting in all treatments with the decomposition of organic materials by microbial activity and the release of organic carbon compounds into the atmosphere by converting to CO_2. TOC losses were 63.62 % and 55.11 % in DSS and SSS treatments, respectively (Fig. 2(e)). The TOC losses decreased with the addition of BFA to sewage sludges. The highest TOC losses were obtained by adding of 5 % BFA for both sewage sludges. TOC losses decreased to 42.19 % in DSS and 27.33 % in SSS using 5 % of BFA. Carbon loss during composting is between 34 % and 77 % of the initial total carbon (Guo et al., 2012). It was seen that BFA was an effective additive to reduce carbon losses.

The changes of TN in the composting processes were presented in Fig. 2(f). In the composting process, N losses occur in three ways: volatilization of ammonia (under high temperature and pH values), NO_x volatilization (due to nitrification and denitrification), and loss of water-soluble nitrogen (through leachate) (Yang et al., 2015). The TN loss leads to odor, acid rain, atmospheric nitrogen deposition, and equipment corrosion. It also reduces the quality of final product for agricultural applications.

Cumulative N losses for DSS and SSS treatments at the end of composting were calculated as 58.41 and 51.32 %, respectively, based on the initial TN values. TN losses decreased in both treatments when BFA was added. The lowest TN losses were obtained by 5 % BFA for both sewage sludges. TN loss decreased 40.93 % in DSS treatment containing 5 % BFA and 51.60 % in SSS treatment containing 5 % BFA compared to control treatments without BFA. As a result, when 5 % BFA was used, TN loss was found as 34.50 % and 24.84 % for DSS and SSS treatments, respectively. It was reported that N losses were between 21 % and 77 % of the initial TN (Chan et al., 2016). Clearly, BFA had obvious effect on reducing TN loss during composting process.

The changes in NH_4^+-N concentrations were illustrated in Fig. 2(g). The NH_4^+-N concentrations of all the treatments increased during two weeks due to the decomposition of organic matter and ammonification

Table 2
The main features of the different experimental designs created with these explanatory variables and response variables.

Design	Material	Explanatory Variables	Response Variable	# of		
				Experiment	Validation Set	Test Set
1	DSS	The ratio of DSS (%) (100, 95, 90)Time (day) (0–105)	T (°C)	45	9	9
2			EC (mS/cm)			
3			pH			
4			TOC loss (%)			
5			TN loss (%)			
6			MC loss (%)			
7			NH_4^+-N/NO_3^--N			
8	SSS	The ratio of SSS (%) (100, 95, 90)Time (day) (0–105)	T (°C)	45	9	9
9			EC (mS/cm)			
10			pH			
11			TOC loss (%)			
12			TN loss (%)			
13			MC loss (%)			
14			NH_4^+-N/NO_3^--N			

of a large part of organic nitrogen compounds (Meng et al., 2017; Zhao et al., 2020). The high temperature (>40 °C) inhibited the activity of nitrifying bacteria and prevented the conversion of NH_4^+-N to NO_3^--N (Li et al., 2021). Subsequently, the NH_4^+-N concentrations gradually decreased in all the treatments until the end of composting process, caused by volatilization and nitrification process (Chung et al., 2021; Pan et al., 2018). The NH_4^+-N concentration was higher in control treatments as compared to treatments containing BFA. The lower NH_4^+-N concentrations were obtained from treatments containing 5 % BFA (DSS1 and DSS2).

The initial NO_3^--N contents of DSS and SSS control treatments were 57.87 mg/L and 44.13 mg/L, respectively. The NO_3^--N contents in all treatments gradually increased during the composting process (Fig. 2 (h)). Similar results was observed in other studies (Yu et al., 2019; Zhao et al., 2020). At the end of the process, NO_3^--N concentrations of DSS and SSS treatments increased by 54.09 % and 36.23 %, respectively, according to the initial values of NO_3^--N. NO_3^--N contents increased in DSS and SSS treatments containing 5 % BFA compared to control treatments. In the final composts, NO_3^--N contents showed a trend like DSS1 > DSS > DSS2 for sewage sludge dewatered by decantor and SSS1 > SSS2 > SSS for sewage sludge dewatered by separator.

The NH_4^+-N/NO_3^--N ratio, known as the nitrification index, is used to determine the maturity of the compost. The highest NH_4^+-N/NO_3^--N ratios were recorded for DSS (3.12) and SSS (2.41) control treatments, which had the highest amounts NH_4^+-N as well as the lowest amounts NO_3^--N. The initial values of the NH_4^+-N/NO_3^--N ratios in composts obtained from all treatments ranged from 5.94 to 7.40, and decreased during the composting process. A similar trend was observed in other studies (Bernal et al., 1998; Gómez-Brandón et al., 2008) The lowest NH_4^+-N/NO_3^--N ratios were achieved with the addition of 5 % BFA to both sewage sludges. A ratio above 3 indicates that the compost is immature. The NH_4^+-N/NO_3^--N ratio of 0.16 is accepted as very mature compost, indicating that the nitrification was completed (Bernal et al., 1998).

3.3. Modelling the composting process

In the present study, the co-composting of two sewage sludges, dewatered by a decanter and separator, and BFA was investigated and modelled. Modelling the co-composting processes is basically a regression problem and involves estimating functions that will produce predictions of the relevant parameters. This study focused on the use of a DCFNN to model and predict parameters in co-composting processes. The composting processes included two main explanatory variables, the content of the trials and the composting duration. Also, the problem-specific response variable consisted of the parameters of the processes. In the analyses, the data sets of the experimental designs were split into three sub-data. The first was the training set reserved for the learning process of the network. The second was the validity set used to detect the optimum conditions for the model hyperparameters, such as # of hidden layers and units of hidden layers. Finally, the test set was used to evaluate the performance of the predictor.

The test dataset remained hidden during model training and model performance evaluation. The split ratio can be taken as 80 %-10 %-10 %, 70 %-15 %-15 %, or 60 %-20 %-20 %. Especially in data sets where the number of data points is not high enough, the split ratio can be taken as 60 %-20 %-20 %. Accordingly, the split ratio used in this study was chosen as 60 %-20 %-20 % (test set with 9 experiments). In this study, DCFNN were trained based on the training set, which constituted 60 % (24 experiments) of the data set. The determination of the optimal values of hyperparameters such as hidden layer and hidden layer unit number, that was, the evaluation of the performance of alternative models, was carried out over the validation set, which consisted of 20 % (9 experiments) of the data set. Finally, the model generalization performance was tested using the test dataset for the optimal values of the hyperparameters. The depth of CFNN is achieved by using more than one hidden layer, and the number of hidden layers is varied between 2 and 4 in deep models. In addition, different numbers of units can be used in each hidden layer. In this study, the number of the hidden layer was determined by changing between 2 and 5 to be specified via the validation set. Thus, hyperparameter tuning was performed based on the validation set obtained for the different trained prediction models. The working principle and some rules of the proposed prediction tool based on DCFNM were given by a flowchart in Fig. 3. The main features of the different experimental designs created with these explanatory variables and response variables were listed in Table 2.

3.3.1. Evaluation perspectives

The performance of DCFNN-based prediction models was compared with a statistically-based RSM with a linear structure, a forward and feedback neural network with a non-linear structure, and a CFNN with linear and non-linear structures. The error metrics of RMSE were used to evaluate modeling performances (Eq. (1)) and MAPE (Eq. (2)). The model fit capability of the DCFNN was investigated by using certain characteristic features of a linear regression (LR) model (Eq. (3)) with no cut-off parameter. For a successful predictor, it is expected that the coefficient of determination (R^2) and the regression coefficient ($\widehat{\beta}$) of the LRM represented by Eq. (3) are equal to one or very close to one. The compatibilities between obtained predictions and experimental results were demonstrated with visual presentations. Moreover, the models with the optimal hyperparameters were run 30 times to evaluate the reliability and validity of DCFNN.

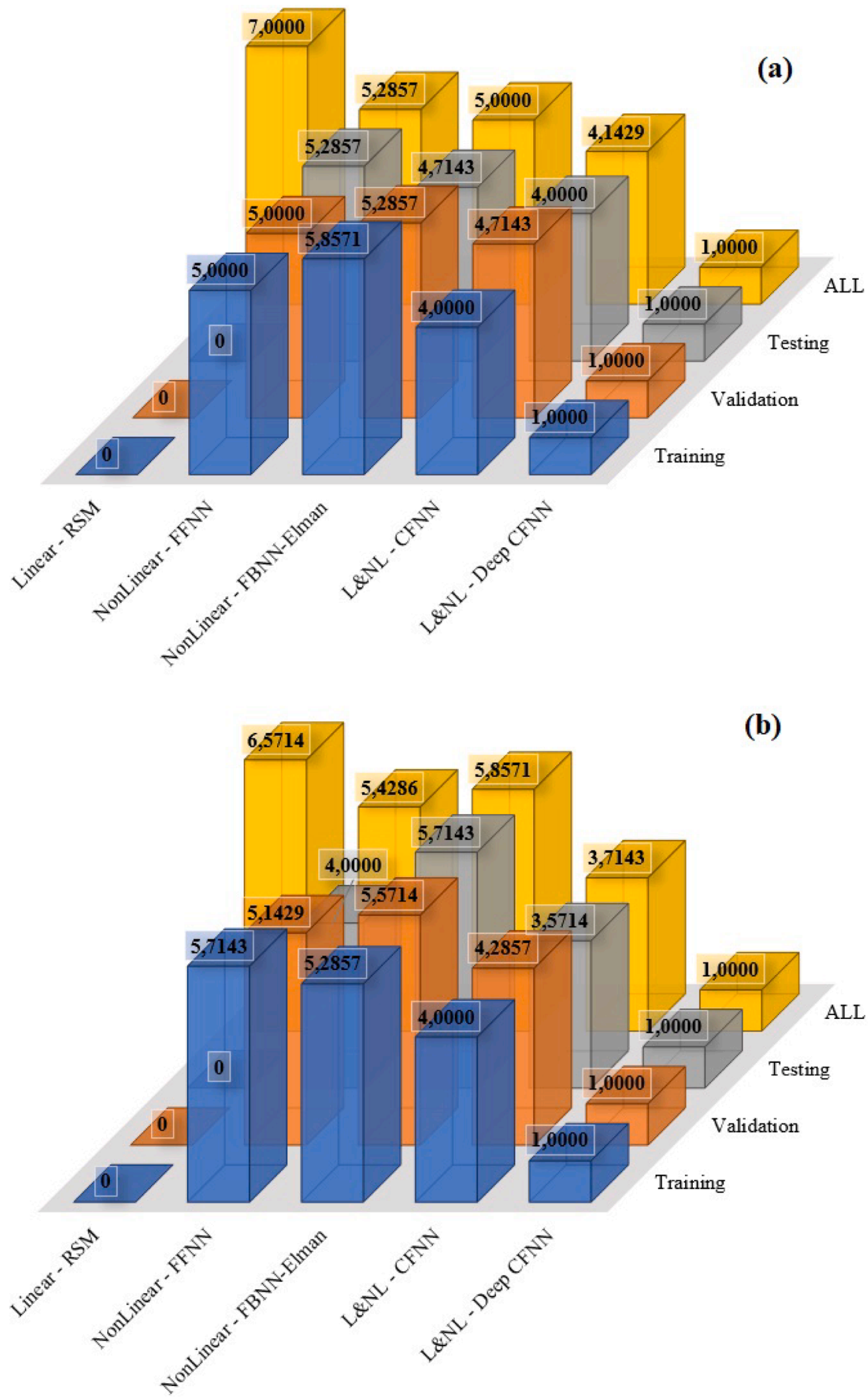

Fig. 4. The performances of the prediction tools, in terms of RMSE – by DSS (a) and SSS (b).

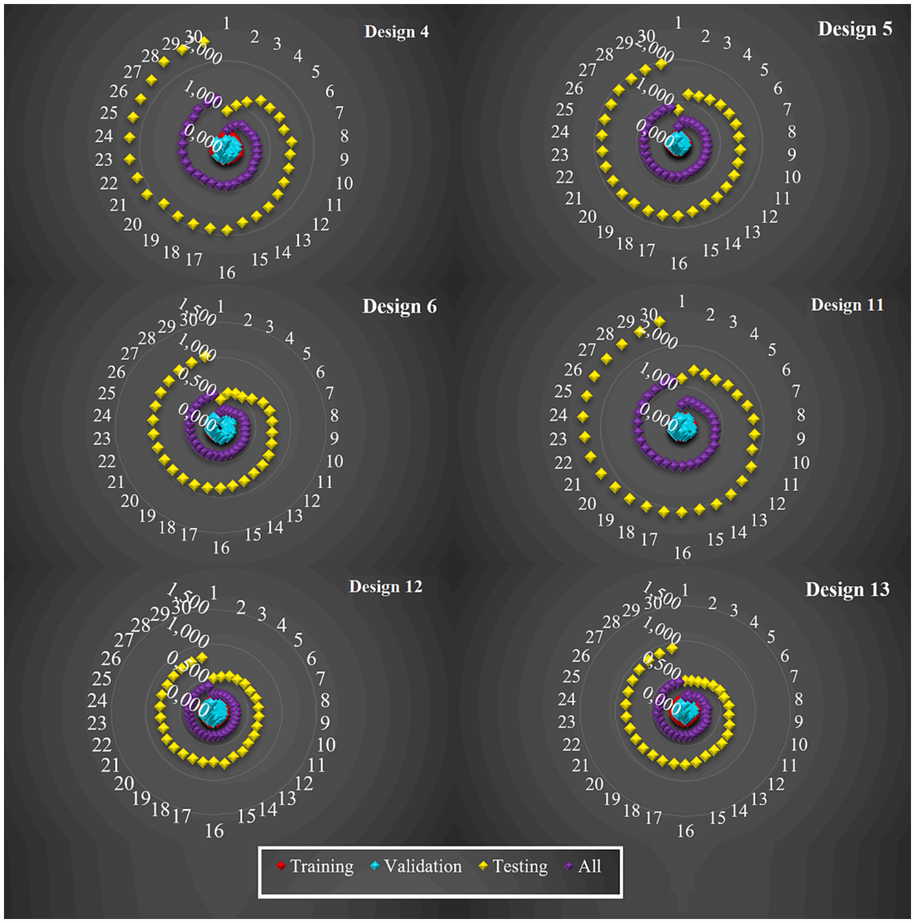

Fig. 5. Distribution of RMSE values for 30 runs.

$$RMSE = \sqrt{\frac{1}{n}\sum_{p=1}^{n}\left(Target_p - Output_p\right)^2} \tag{1}$$

$$MAPE = mean\left(\left|\frac{Target_p - Output_p}{Target_p}\right|\right) \quad , \; p = 1, 2, \cdots, n \tag{2}$$

$$Y_p = \beta \widehat{Y}_p + \varepsilon_p \tag{3}$$

3.3.2. Holistic comparison of the models over error metrics

Firstly, the predictors used in the analysis of the datasets of the experimental designs were compared in terms of the RMSE metric (see supplementary material). The results showed that DCFNN produced the best prediction performance for both sewage sludges. DCFNN used 4 hidden layers with deeper structures showed the best performance in test sets for all experimental designs from RMSE metric values. This indicates the exceptional generalization ability of DCFNN in the analysis of datasets related to the composting process. For the testing sets, in composting processes, RMSE values were below 0.5 for all experimental designs except for two of them (TN loss with RMSE = 0.5376; TOC loss with RMSE = 0.6110) while the error metric value was even below 0.1 in the prediction of the parameters of pH, EC, and NH_4^+-N/NO_3^--N ratio. Secondly, MAPE metric values produced for the analysis of the datasets of the experimental designs were determined (see supplementary material).

The findings of MAPE and RMSE metrics showed quite similar results. In composting processes, DCFNN with 4 hidden layers produced the best predictions according to MAPE metric for test sets in all experimental designs. DCFNN achieved predictions with lower than 1 % MAPE values for all test sets of experimental designs except one with a MAPE value of 1.99 %, in composting process realized by SSS. The average success rankings determined according to the RMSE criteria were shown in Fig. 4. DCFNN, capable of co-modeling both non-linear and linear relationships, exhibited the best predictive performance with an average success rank of 1 for all datasets.

3.3.3. Validity and reliability assessment of DCFNN

Two key features desired for predictors are reliability and validity. Validity is that predicts produced by predictors are satisfactorily low or high for different metrics under different conditions. Reliability is that the predictions produced by the prediction tool contain values that are satisfactorily close to each other in terms of any measurement under different conditions. In this study, DCFNN with 4 hidden layers in the best architectural conditions was run 30 times for parameter prediction of three basic experimental designs, and RMSE metric values obtained were visually evaluated by scatter plots. The scatter plots of RMSE values obtained for TN loss, TOC loss, and MC loss predictions were presented in Fig. 5. As seen in Fig. 5, RMSE values in training, validation, and test sets, and also in the whole data for all three designs created for modelling of the composting process were found as very low. This indicated the validity of the predictions produced by the deep predictor. The RMSE values of all sets and designs showed little variation in modeling the composting process. This also indicated the reliability of the predictions produced by the deep predictor.

Moreover, as a consequence of the 30 runs, some statistics of the RMSE criteria were calculated. Though the DCFNN model was run 30 times, it was able to reproduce estimates with very small RMSE values for each design. These results can also be seen as another proof of the validity of the DCFNN proposed to model composting processes. Also, very low values of standard deviations were further proof of DCFNN's

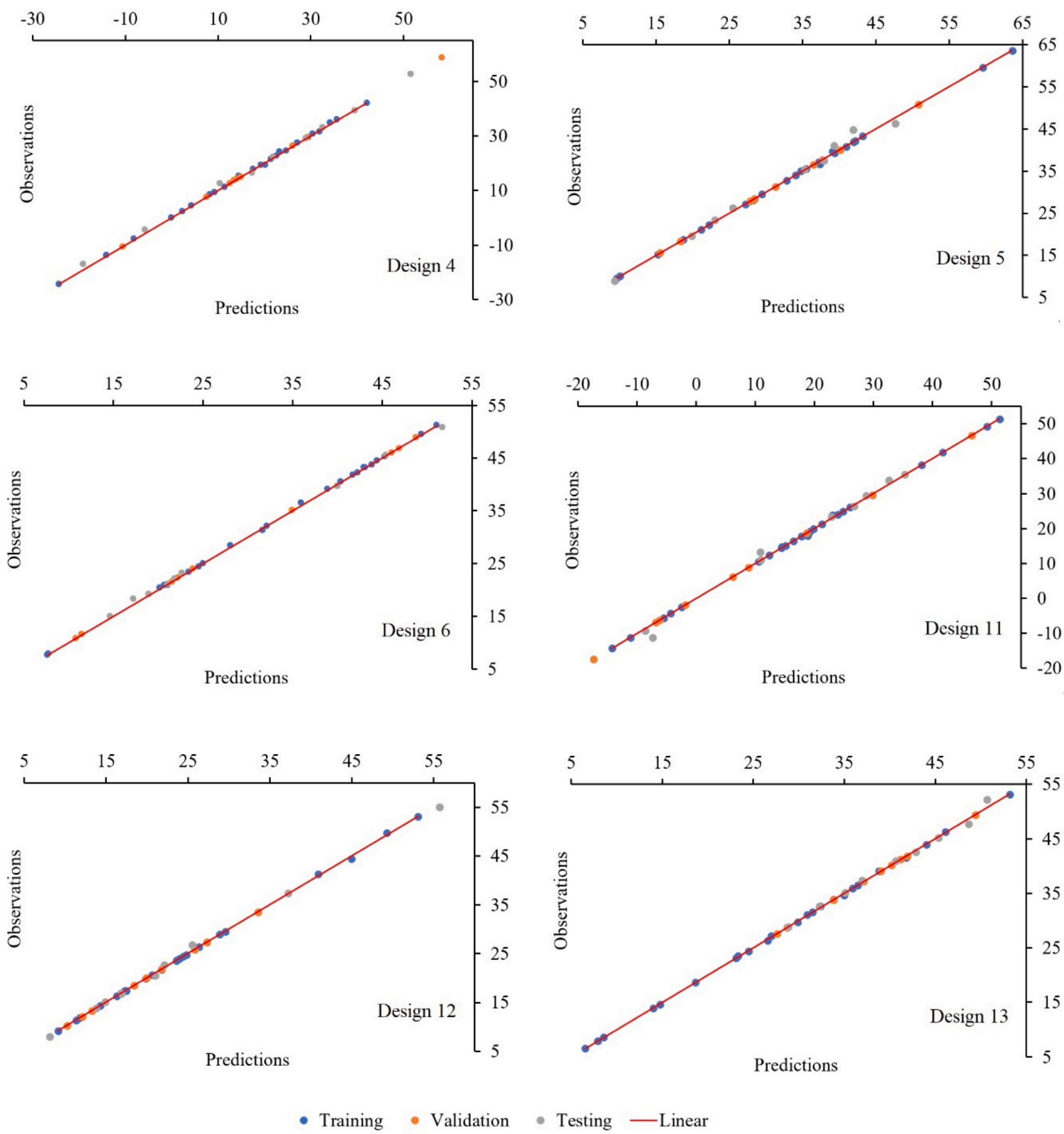

Fig. 6. Scatter plots of the produced predictions with real observations.

Table 3
Statistical evaluation of the difference for both composting processes.

Parameter	*t*- stat	*p* value	%95 Confidence interval of DSS (μ_1) - SSS (μ_2)	
			Lower bound	Upper bound
T (°C)	−0.4283	0.6695	−5.7156	3.6889
pH	0.9588	0.3403	−0.1321	0.3783
EC (mS/cm)	2.4891	0.0147*	0.0530	0.4728
MC loss (%)	−0.5553	0.5802	−6.8416	3.8554
TN loss (%)	0.5058	0.6143	−5.7506	9.6722
TOC loss (%)	3.3254	0.0013**	3.4852	13.8639
NH_4^+-N/NO_3^--N	1.6447	0.1036	−0.1139	1.2075

*: 5 % of importance level, **: 1 % of importance level.

reliability.

3.3.4. *Evaluation of the model fit ability of DCFNN*

The performance of the DCFNN was evaluated by examining both with visual graphics and some features of the regression analysis. The scatter plots of the produced predictions with real observations for TN loss, TOC loss, and MC loss parameter modelling were shown in Fig. 6. It was observed that the predictions produced by the deep prediction model with the real observations were an excellent fit, and hence the outstanding performance of the deep predictor from Fig. 6. The RMSE and MAPE values showed that the performance of DCFNN in estimating other parameters was similar to these three parameters.

On the other hand, all findings were supported by some features of a

Table 4
Some properties of the problem produced for process optimization.

Decision Variables	Search Area	Objective Functions	Dependent Variable	Goal	Min	Max
The ratio of sewage sludge (%)	$0 \le SS \le 100$	Functional structures of the corresponding trained DCFNNs	T	max	0	$Max_{observed}$
			pH	In Range	6.50	7.20
			EC	min	0	3
			C/N	min	1	20
Time (day)	$0 \le Time \le 105$		MC loss	max	0	20
			TN loss	min	$Min_{observed}$	$Max_{observed}$
			TOC loss	min	$Min_{observed}$	$Max_{observed}$
			NH_4^+-N/NO_3^--N	min	0	3

LR model created between actual observations and predictions given in Eq. (3). The results obtained from the regression models showed that both β and R^2 values were quite close to the desired 1 value. Accordingly, the harmony between the actual loss rate and the predictions produced by the model was quite high. However, the 95 % confidence interval of β showed that it had a very narrow framework.

3.3.5. The statistical comparative evaluation of composting processes

The statistical changes of composting parameters in case of using different sewage sludge were examined in this section. For this purpose, an independent two-sample *t*-test was performed for each parameter. The results obtained are presented in Table 3. It was observed that there was a noticeable difference between the two sewage sludges at the 95 % confidence level for the mean values of the EC (mS/cm) parameter ($p = 0.0147$). The EC value for sewage sludge dewatered by decanter was significantly higher than by separator. Although the situation was similar for TOC loss (%), it was the opposite for the C/N ratio. C/N ratio for sewage sludge dewatered by decanter was significantly lower than by separator.

Table 3.

3.3.6. Optimization of the parameters of composting processes

DCFNN generated outstanding parameter predictions for various mixture ratios. However, there was a fundamental difficulty in modeling composting processes that need to be overcome: detecting the independent variable values of the parameters that would provide the optimum process conditions and the maturity of the final compost. Thus, optimization was designed to determine the optimum parameter values. An optimization design with $J + K$ constraints and N decision variables was presented below (Eq. (4)):

$$min \Big/ max\left(f\left(\underset{-}{x}\right)\right)\left(\underset{-}{x} = [x_1 x_1 \cdots x_1]\right)$$

$$subjectto \quad \begin{matrix} g_j\left(\underset{-}{x}\right) \le 0 & ; & j = 1, 2, \cdots, J \\ h_k(x) = 0 & ; & k = 1, 2, \cdots, K \\ x_i^{(L)} \le x_i \le x_i^{(L)} & ; & i = 1, 2, \cdots, N \end{matrix} \tag{4}$$

GA was applied to optimize the process conditions as a metaheuristic search algorithm. The decision variables of the optimization transaction were the ratio of dewatered sewage sludge and the composting duration. Also, the parameters of pH, temperature, EC, C/N, TOC loss, TN loss, NH_4^+-N/NO_3^--N ratio, and MC loss were optimized. The values of these parameters formed the values of the objective function for the optimization process. These values representing the objective function values of optimization transactions were produced by trained DCFNNs. Some properties of process optimization were listed in Table 4.

Desirability coefficients were calculated to determine the optimization performance by Eqs. (5) and (6). In the equations, the framework of the search space for dependent variables was represented by min and max. In addition, GA was applied to determine the optimum process conditions according to certain hyperparameter values.

$$d^{max} = \left\{ \begin{matrix} 0 & ; & f\left(\underset{-}{x}\right)\Big\langle Min \\ \left(\dfrac{f\left(\underset{-}{x}\right) - Min}{Max - Min}\right) & ; & Min < f\left(\underset{-}{x}\right)\Big\langle Max \\ 1 & ; & f\left(\underset{-}{x}\right)\Big\rangle Max \end{matrix} \right\} \tag{5}$$

$$d^{min} = \left\{ \begin{matrix} 1 & ; & f\left(\underset{-}{x}\right)\Big\langle Min \\ \left(\dfrac{f\left(\underset{-}{x}\right) - Max}{Min - Max}\right) & ; & Min < f\left(\underset{-}{x}\right)\Big\langle Max \\ 0 & ; & f\left(\underset{-}{x}\right)\Big\rangle Max \end{matrix} \right\} \tag{6}$$

The composting process was modelled without the necessity for new experiments, since the performance of DCNN was based on out-of-sample observations. In addition, the process parameters were optimized by GA in order to increase the process efficiency and improve the quality of the final product. The optimal values of the parameters exhibited high desirability levels. Minimum TN losses for DSS and SSS were obtained with the addition of 1.819 and 3.382 % BFA, respectively. Minimum TOC losses were achieved with the addition of 3.995 % for DSS and 2.652 % for BFA for SSS. According to the NH_4^+-N/NO_3^--N ratio, which is one of the significant maturity parameters, BFA ratio in the feedstock mix was determined as 4.500 % and 2.764 % for DSS and SSS, respectively. In the evaluation of the optimization results, the desirability levels of the GA applied as a metric showed that the desirability levels were over 95 % in all designs. Moreover, 100 % of the desirability level was achieved in a few designs.

4. Conclusions

In this study, DCFFN model was investigated to predict compost maturity and identify key physicochemical parameters for the co-composting of dewatered sewage sludge and BFA. The modelling findings were evaluated in comparison with RSM, FFNN, FBNN-Elman, and CFNN. The proposed prediction tool exhibited the best predictive performance, very small standard errors (<0.20) and mean RMSE values (<1.00). The decision variables for composting processes were optimized by using GA. Optimal parameters for all composting processes were obtained very close to the desired values. Consequently, Deep-CFNN could be applied to model composting process parameters as a reliable and consistent tool.

CRediT authorship contribution statement

Hale Dogan: Performed the experimental studies, Investigation, Formal analysis. **Fulya Aydın Temel:** Data curation, Writing – review &

editing, Visualization, Investigation. **Ozge Cagcag Yolcu:** Data curation, Formal analysis, Investigation. **Nurdan Gamze Turan:** Supervision, Investigation, Writing – review & editing, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biortech.2022.128541.

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