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Research article

Evaluation of a cascade artificial neural network for modeling and optimization of process parameters in co-composting of cattle manure and municipal solid waste

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

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

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ABSTRACT

The present study was carried out to improve, test, and validate the Cascade Forward Neural Network (CFNN) for co-composting of municipal solid waste (MSW) and cattle manure (CM). Composting was performed in vessel pilot-scale reactors with different CM rates for 105 days. The CFNN used 5 input variables containing CM and MSW mixture combinations, and 1 output for each of the compost quality parameters. The CFNN results were compared with Response Surface Methodology (RSM) and Feed Forward Neural Network (FFNN) results. Multi-objective optimization process using Genetic Algorithm (GA), the total desirability, which has a much better value than the RSM, was obtained as 0.4455 and the CM ratio and processing time were determined as approximately 23.39% and 104.86 days, respectively. It is concluded that CFNN is a unique modeling tool, exhibiting superior modeling and prediction performance in MSW and compost modeling for CM.

1. Introduction

Currently, 2.01 billion tons of waste are produced, 33% of which cannot be managed safely, worldwide. It is reported in the researches that the world population will be 8.6 billion in 2030 and 9.8 billion in 2050 and that the contribution of developing countries will be higher in this rapid growth. It is indicated that the amount of waste to be generated in proportion to population growth will also reach 3.4 billion tons in 2050 (Wang et al., 2020).

Composting is gaining importance day by day for the disposal of organic wastes. Besides obtaining value-added products with this low-cost solid waste technology, it is possible to do the wastes hygienic, solve the disposal problem, increase the life of the landfill, and reduce greenhouse gas emissions (Chen et al., 2020; Reyes-Torres et al., 2018). Composting is the process of decomposing the organic part of waste by microorganisms in the presence of oxygen in order to enrich the soil used in farms, parks, agriculture, and home gardens. The composting process differs from natural rot due to the regular monitoring of moisture, temperature, oxygen, nutrients, and chemical content. This monitoring process is very important in determining the stages of the decomposition process, intervening in the process and determining the quality of the finished compost (Kaza and Bhada-Tata, 2018). The researchers have conducted many studies related to the composting of several types of organic wastes, such as pig manure and industrial sludge (Arias et al., 2017), vegetable waste and tree leaves (Kalamdhad et al., 2009), pup/paper mill waste (Aycan et al., 2014), agricultural waste (Külcü and Yaldiz, 2014), sewage sludge and green plant waste (Jouraiphy et al., 2005), biowaste (Francou et al., 2008), animal manures (Bernal et al., 2009), food wastes (Cerda et al., 2018), municipal solid waste (Wu et al., 2013), beer vinasse (Wang et al., 2017), etc.

In order to reduce or eliminate the negative impact of waste from the livestock sector on the environment, it should be managed appropriately waste produced in a great quantity and biodegradable. Composting of animal waste is a feasible waste management method to better control odor and mosquitoes and to protect water quality. In this way, it can be ensured that the weight and volume of wastes are reduced, weeds are destroyed and the nutrients are kept in a more stable organic form. The composted manure can be applied in many places (settlement places, parks, gardens, etc.) where raw manure cannot be used. Also, seedling cultivation can be done by mixing the composted manure with soil or plants. According to the data from the Turkish Statistical Institute (TUIK), the population of cattle was 18 million 158 thousand in 2020

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* Corresponding author. Department of Environmental Engineering, Faculty of Engineering, Giresun University, Turkey.
E-mail address: fulya.temel@giresun.edu.tr (F. Aydın Temel).

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(TUIK, 2020). And a study reported that this population will reach 18 million 700 thousand in 2026 (Melikoglu and Menekse, 2020). And the quantity of only cattle manure composed is also almost 40 million tons per year in Turkey (Ozturk and Yuksel, 2016). Treatment of cattle manure with the composting process and the usability of the resulting compost will be an important investment for the environment, instead of storing it or using it as fuel. While the agricultural production in Turkey is approximately 123 million tons, the amount of waste generated during the production and consumption of these products is approximately 16 million tons (Cakar et al., 2020). From a study conducted by TUIK that the municipal waste amounts of 36 countries were compared, Turkey ranks 25th with 421 kg of waste production per person (TUIK, 2020).

In order to determine the optimum conditions in composting, which is a complex biological process, evaluations are generally made by establishing a limited number of the experimental setups. Using these results instead of limited information obtained from experimental data is supported to optimize the composting process with estimates produced by mathematical models (Boniecki et al., 2013; Sharma et al., 2021). In this way, it is possible to predict the results of the experimental setups that cannot be technically installed/applied, the number of experimental setups to be installed, the cost required for configuration and operation, and time and labor. Recently, statistical-based models such as Response Surface Methodology (RSM) and machine learning-based models such as Artificial Neural Networks (ANNs) have been used to model and optimize the experimental setups. Machine learning-based models are models that learn the data structure thanks to their hidden layers, generate new information using this information, and are more successful than statistical-based models in cases where programming is difficult. In the literature, there are limited studies focusing on ANNs in modeling and optimizing the composting process (Boniecki et al., 2013; Hosseinzadeh et al., 2020; Kujawa et al., 2020; Sharma et al., 2021; Sidełko et al., 2019). Therefore, modeling and optimizing the findings with Cascade Forward Neural Networks (CFNN) by following the composting process in experimental setups created under laboratory conditions was the focus of the present study.

Both current statistical-based and NN-based modeling tools have a fundamental problem. Statistical-based tools such as RSM rely solely on the linear modeling approach, while NN-based tools use the approach with the nonlinear structure for modeling composting. Whereas, like many modeling problems, the composting modeling problem also often involves linear and nonlinear relationships together. This proposed modeling tool, which uses CFNN in modeling, can model both linear and non-linear relationships simultaneously by means of its cascading structure. CFNN was used to model co-composting of municipal solid waste and cattle manure in different analyzes and perspectives and the results were compared with both Response Surface Methodology (RSM) and Feed Forward Neural Network (FFNN). In addition, a multi-objective optimization process was run using a genetic algorithm (GA) to answer the questions of what should be the mixture ratio of the materials and the processing time in the composting.

2. Material and methods

2.1. Raw materials in composting process

Cattle manure (CM) used in the present study was obtained from the Faculty of Agricultural in Ondokuz Mayıs University located in Samsun/Turkey. The organic fraction of municipal solid waste (OMSW) was collected from the wholesale market hall in Samsun, Turkey. Non-biodegradable items such as glass, metal, and plastics were manually removed in the laboratory. OMSW consisted of 63.9% vegetables, 24.4% fruits, and 11.7% peels (on the wet weight basis). OMSW was cut into small particles and a size of less than 60 mm was used for experiments. Some physicochemical properties of raw materials are given in Table 1.

Table 1
Some physicochemical properties of raw materials.

Parametre	CM	OMSW
pH	8.15	4.17
Electrical conductivity (mS/cm)	0.77	1.46
Moisture content (%)	58.41	69.12
Organic matter (%)	74.52	93.23
Total Nitrogen (%)	1.73	2.41
Total Organic Carbon (%)	39.17	76.52
C/N	22.64	31.75

2.2. Experimental set up

The pilot composting reactor was composed of a rectangular prism-shaped plastic vessel reactor with dimensions of 40 (L) x 30 (W) x 25 (H) cm. The effective volume of the reactor was 30 L. Five in-vessel reactors were organized for the experiments that consisted of five treatments in the proportions (fresh weight basis). Mixture ratios of 10, 25, and 40% by mass were used as CM in three reactors. In order to demonstrate the effectiveness of co-composting, the composting process was also performed in two reactors containing only CM and only OMSW. The schematic view of the pilot composting reactor is given in Fig. S1.

At the bottom of the reactor, the distribution pipes were installed vertically. Aeration pumps were connected to the main distribution pipe and the air was supplied to all reactors at a flow rate of 10 L/min during the process. The gas formed during the composting process was discharged with the pipe on the cover of the reactor. The compost temperature was measured with a digital thermometer (Loyka-9263) by way of the pipe on the cover of the reactor. The duration of composting was 105 days. Composting matrix was manually mixed before the sampling for analysis.

pH, EC, and moisture content (MC) were directly determined by using fresh compost samples. pH and EC were measured in aqueous extract (1:10 (w/v)) by a multifunctional pH-EC meter (Orion Star™ A325) (FCQAO, 1994). The MC of samples were detected by oven-drying at 105 °C (Nüve-FN400). The dried samples were used to measure total organic carbon (TOC) and total nitrogen (TN) contents. TOC and TN contents were analyzed and calculated according to the standard methods (Baird et al., 2017).

2.3. Artificial neural networks

Artificial neural networks (ANNs) have been created with the aim of allowing computer programs to generate solutions for common problems in the fields of AI and machine learning etc. by simulating the human brain. ANNs, just like a human, have the skills such as deriving and discovering new information through learning. The most widely used ANN in these fields is Feed-Forward Neural Network (FFNN), which is a kind of Multilayer Perceptron proposed by Werbos (1974) and re-considered by Rumelhart et al. (1986). These ANNs produce successful results in the solution of nonlinear problems thanks to their structure. FFNNs were used, even in limited for composting processes modeling such as food waste composting, vermicomposting, mixed municipal solid waste composting, and sewage sludge and rapeseed straw composting. FFNNs, which are used as an alternative to RSM, which is a statistical-based modeling tool in all these areas, have a non-linear modeling process, unlike RSM. Although both RSM and FFNNs have produced successful results in this field, it is a fact that the use of a tool that can model both linear and nonlinear relationships together simultaneously in the modeling process will further increase the efficiency and modeling ability. Cascade Forward Neural Network (CFNN) which is another multilayer Feed Forward Neural Network, proposed by Demuth (Demuth and Beale, 2009) inspired by the cascade correlation approaches (Fahlman and Lebiere, 1990), can model both linear and nonlinear relationships together thanks to the sigmoid activation function it uses in the hidden layer and the linear activation function it uses in the output layer. Like other classical FFNNs, the architecture of CFNN consists of input, output, and hidden layer(s) (Alkhasawneh, 2019). However, the main feature that distinguishes CFNN from the current networks is that each layer of neurons is related to all previous layers of neurons. A prototype of CFNN having two hidden layers can be illustrated in Fig. S2.

3. Results and discussion

3.1. Changes in temperature and moisture content

Temperature is a significant parameter that represents microbial activity and degradation rate, shows the process efficiency, and specifies whether the composting could progress smoothly (Nie et al., 2020; Yu et al., 2017). The changes in temperature were similar form to a typical composting process. At the beginning of the process, a rapid temperature rise occurred for all reactors, remarking an apparent microbial activity. However, thermophilic temperatures were observed differently in all treatments. The maximum temperature value was 35.6 °C for treatment 5. This fact could be because of the high moisture content of OMSW. The maximum temperature reached was 48.8 °C in treatment 4. The high temperatures (>60 °C) were recorded in the co-composting OMSW and CM mixtures within approximately 3 weeks (Fig. 1(a)). The thermophilic phase (>60 °C) was maintained for a week in these treatments, which were similar as compared to previous studies on composting (Awasthi et al., 2015; Wang et al., 2016; Zeng et al., 2010). During the composting process, if the temperature is 55 °C and above for at least 3 days, pathogens can be destroyed (Bernal et al., 2009). After 4 weeks, the temperature decreased gradually to ambient levels in all treatments. The reason for this may be the depletion of easily degradable matters and the composting process pass through to the curing stage (Awasthi et al., 2016).

MC is also a critical parameter in the composting process. MC affects the temperature, microbial activity, and oxygen transfer to the process (Haug, 1993). The optimum MC is between 50 and 60% for composting (Epstein, 2011). The evolution of MC in all treatments is given in Fig. 1(b). As it is seen in Fig. 1(b), the inlet MCs in all treatments containing OMSW were between 60 and 70%, while it was 58.41% in the treatment containing the whole CM. It was indicated that the heat released by decomposition caused the MC notably to decrease through evaporation during the maturation phase. At the end of the process, MC values for treatments from 1 to 4 were less than 30%, whereas the MC of treatment 5 was approximately 50%. According to the national legislation, MC in compost should be less than 30%. The treatment 5 exceeded the maximum permitted by current legislation. Similar results were reported for MSW composting in previous studies (Montejo et al., 2015; Turan and Ergun, 2008).

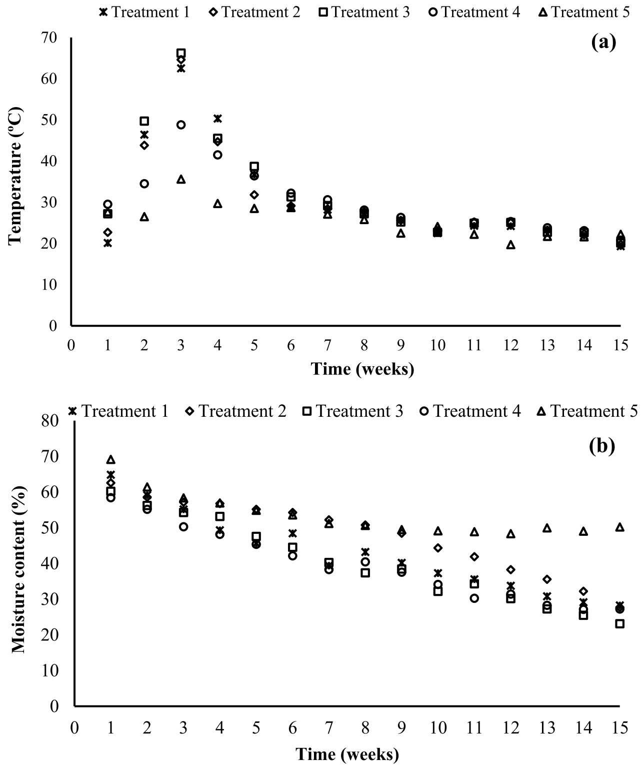

Fig. 1. Changes of T and MC profile during the composting process.

3.2. Changes in pH and EC

In the composting process, pH value of the compost provides information about the microbial activity and the degradation of organic matter (Yu et al., 2017). The pH in all treatments presented a downward decreasing trend during the early composting stage (0–3 weeks) due to the production of organic acids by the decomposition of organic matter (Jiang et al., 2016). Then, pH followed an upward trend in the treatments (Fig. 2(a)). After 8 weeks, the pH did not show a significant variation until the end of the process in the treatments containing CM. However, in treatment 5 containing only OMSW, pH level did not remain at a constant level during the process. The pH values of final composts were 6.46 in treatment 1, 6.82 in treatment 2, 7.01 in treatment 3, 8.93 in treatment 4, and 8.14 in treatment 5. The optimum pH should exist between ranges of 6.5–7.2 for the final product (Singh et al., 2012). The results indicated that the final pH values of treatments 4 and 5 were above the permissible range, while the other treatments were in the ideal range. Similar results were obtained by Gil et al. (2008) who tested the pH in CM composting during 75 days and observed an increase in pH from 7.3 to 9.6 (Gil et al., 2008). Another study reported that the pH was above 8.0 in dairy CM compost (Wang et al., 2015). A research also notified that the pH values of municipal solid waste changed from 5.0 to 8.7 (Onwosi et al., 2017).

EC is a parameter related to organic matter degradation and the concentrations of dissolved nutrient matters/minerals in composting process. EC indicates possible phytotoxic-inhibitory effects or phytotoxic (Meng et al., 2019). EC values ranged from 0.77 mS/cm to 1.83 mS/cm for different compost types at the beginning of the process. During the composting process, the variation in EC is given in Fig. 2(b). As seen in Fig. 2(b), EC showed the opposite trend to that indicated by pH. In the first three weeks, EC values increased due to the organic matter decomposition and water loss via evaporation (Bustamante et al., 2008; Silva et al., 2009). Then, EC values decreased during the process. This trend is thought to be a result of ammonia evaporation and precipitation of mineral salts (Meng et al., 2019). Similar results were notified in the literature by Hachicha et al. (2009), Paredes et al. (2002), and Said-Pullicino et al. (2007). EC value of final compost is used to evaluate compost quality. The EC value of compost should be less than 4 mS/cm because of the negative effect on plants growth and crop yield, such as low germination rate and wilting (Li et al., 2007; Yao et al., 2015; Zhang and Sun, 2016). The results indicated that EC values of all treatments were within the permissible limit.

3.3. Changes in TOC, TN and C/N ratio

During the composting process, carbon and nitrogen are the most important nutrients used by microorganisms for energy production and cell growth. In the composting process, biodegradation of organic matter and conversion of carbon by microbes and fungi to gaseous compounds such as CO_2 and CH_4 results in carbon loss (Epstein, 2011; Khan et al., 2009; Tittonell et al., 2010). At the beginning of the composting process, TOC contents were 39.17% and 76.52% in treatments 4

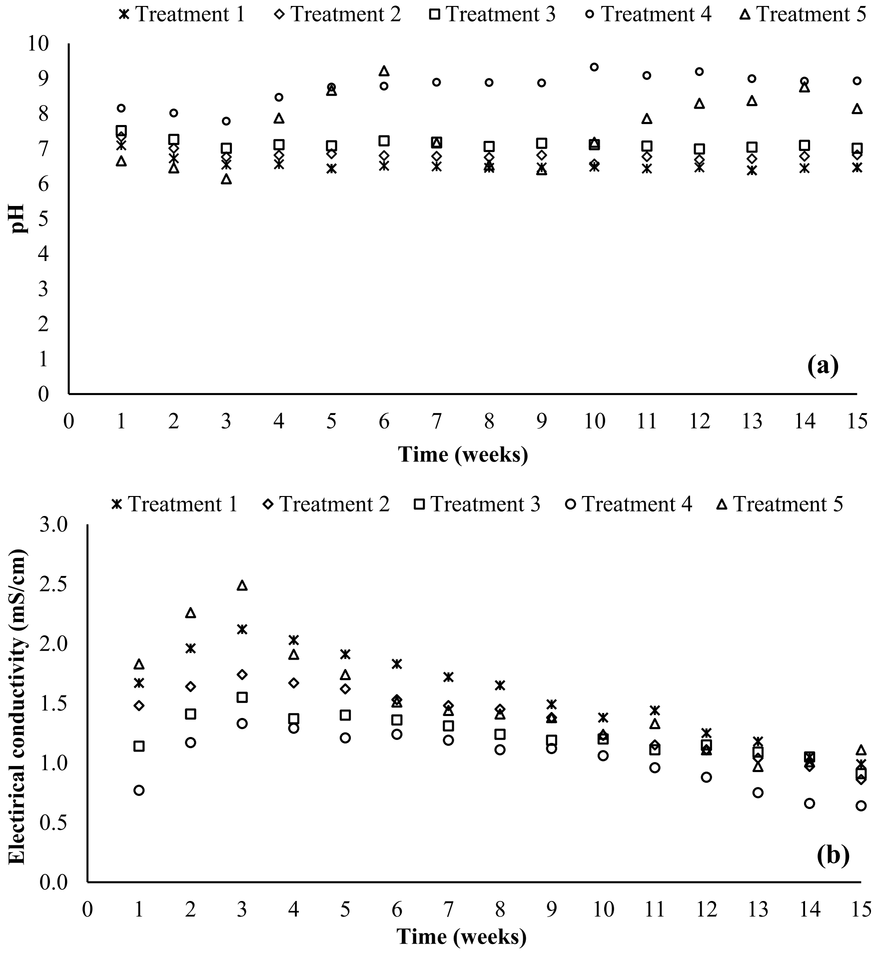

Fig. 2. Changes of pH (a) and EC (b) during the composting process.

and 5, respectively (Fig. 3(a)). In the co-composting treatments, TOC varied within the 55.14–69.14% range. TOC contents of all treatments reduced until the end of the process. TOC was consumed more in treatment 5 than in other treatments since it had more biodegradable substances with the whole of OMSW. At the end of process, TOC contents were observed in the subsequent order as treatment 5 (7.78%) < treatment 4 (10.22%) < treatment 3 (11.56%) < treatment 2 (14.71) < treatment 1 (15.12). Similar dynamics of TOC was found in composting of different organic wastes (Goyal et al., 2005; Meena et al., 2016). It is known that 60–70% of the carbon contained during the breakdown of organic compounds turns into CO_2 and the remaining part is used in the cellular components of microorganisms (Milán et al., 2002).

All the treatments containing OMSW had similar TN contents at the beginning of the composting process; they varied in range from 2.04 to 2.41% (Fig. 3(b)). In treatment 4 containing only CM, the initial TN content was 1.73%. TN contents decreased during the process in all treatments. This trend might have resulted from the volatilization of NH_3. A large amount of TN loss occurred when temperature and pH were more than 45 °C and 7.7, respectively. Similar results were reported by Cáceres et al. (2018) and Zhou et al. (2018). The least nitrogen losses were found as 32.48 and 33.49% in the treatments containing CM of 10 and 25%, respectively. On the other hand, the highest losses (nearly 75%) were observed in treatments 4 and 5. Young et al. found similar losses of TN (68.1 ± 10.4%) with poultry manure in their research (Young et al., 2016).

An initial ideal C/N ratio is between 25 and 30 in the active composting phase (Kumar et al., 2010). A lower C/N ratio increases nitrogen loss (Ren et al., 2010; Zhang et al., 2020) and the release of more soluble basic salts (Awasthi et al., 2014). A higher C/N ratio can lead to slower decomposition and a prolongation of the composting process due to the insufficient supply of nitrogen for supporting optimum microbial growth (Qiao et al., 2019). In this study, the initial C/N ratios were 22.64 and 31.88 for treatments 4 and 5, respectively (Fig. 3(c)). However, the initial C/N ratios were within the optimum range in the co-composting treatments 1, 2, and 3. C/N ratios reduced during the composting process because the rate of organic N mineralization was lower than organic carbon (Onwosi et al., 2017). C/N ratio is generally used to assess the maturity of compost. A C/N ratio of 20 or less is accepted as mature compost (Awasthi et al., 2016; Bernal et al., 2009; Muktadirul Bari Chowdhury et al., 2013). It was shown that the final composts containing CM had acceptable C/N ratios for maturation, whereas C/N ratio of the final compost containing only OMSW was higher than 20.

3.4. Statistical results

In this study, CFNN was used to be able to model composting together with OMSW for the treatment of CM. The results of CFNN were compared two basic modeling tools, RSM and FFNN (Fig. 4). Thus, besides the modeling performances of the modeling tools, the modeling structures were also compared. Because, while RSM uses a linear structure in the modeling process, FFNN has a non-linear structure. CFNN, on the other hand, has a structure that can model both linear and nonlinear relationships with its superior aspect. In CFNN structure, sigmoid activation function was used in the hidden layer neurons and linear activation function was used in the output layer neuron. A hypothetical architecture of CFNN including two input layer neuron and

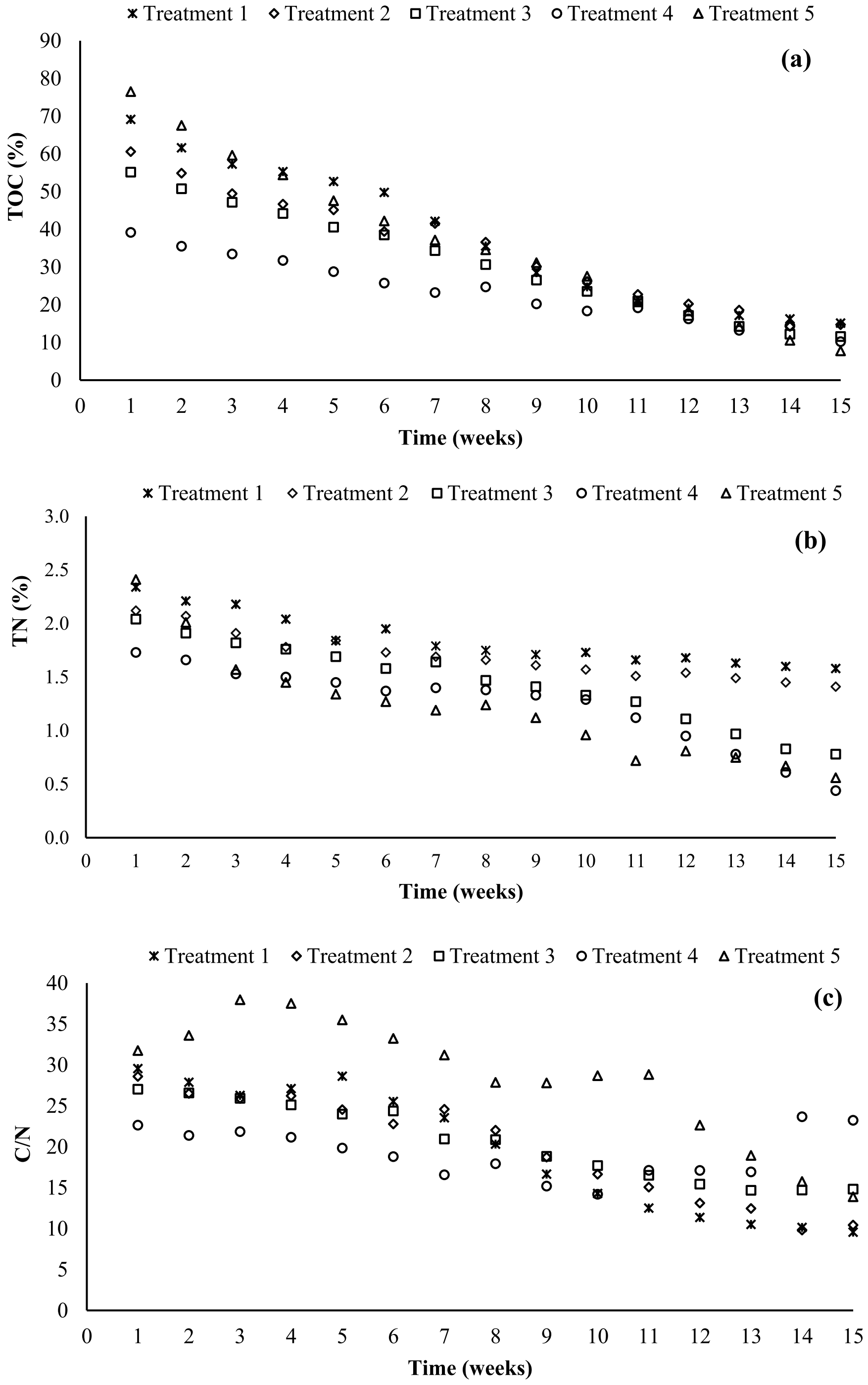

Fig. 3. Changes of TOC (a), TN (b), and C/N (c) during the composting process.

one hidden layer is given in Fig. S3.

Here, w^{ij} and b^i are the weight between jth input layer neuron and ith hidden layer neuron ($i = 1, 2, \ldots, K; j = 1, 2$) and the bias for ith hidden layer neuron ($i = 1, 2, \ldots, K$). $^{H}w^{i}$ is the weight between ith hidden layer neuron and the output layer neuron ($i = 1, 2, \ldots, K$). Moreover, ^{I}W is the vector of weights between input layer neurons and the output layer neuron ($^{I}W = [^{I}w^{1}\ ^{I}w^{2}]$) and b^{o} is the bias of output layer neuron. f_1 represents the sigmoid activation function and $f_1(x) = \frac{1}{1+exp(-x)}$. f_2 is the linear activation function and $f_2(x) = x$.

The modeling process cattle manner ratios, and time (as days) were taken as inputs of CFNN. Six different parameters, temperature (T-°C), pH, electrical conductivity (EC-mS/cm), moisture content (MC-%), total nitrogen (TN-%), and C/N ratio (C/N-%), formed the outputs of CFNNs. 30 analyses were made for each of 6 parameters and the number of hidden layer units of the neural networks was taken as 5 in each analysis. The characteristics of the analysis process are summarized in Table S1. For this task, the modeling performance of CFNN was evaluated from several different perspectives.

i. Evaluation of error criteria over the training, the validation and the test sets of experiments

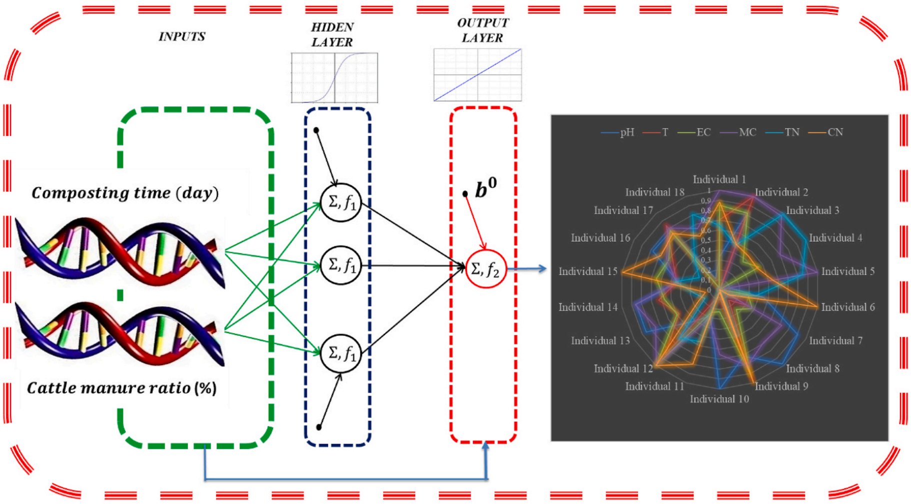

Fig. 4. The diagram of statistical evaluations.

This can be seen as evidence of the generalization ability of the modeling tools. Here, two basic performance measures, root mean square error (RMSE) and mean absolute percentage error (MAPE), were used. In addition to the best performances obtained from 30 repetitions, the worst performances were also taken into account.

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

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

In comparison, RSM which is well known statistical-based modeling tool and FFNN which is also well known computational-based modeling tool were used. The prediction/modeling performances of the models, in terms of MAPE measure, were given in Table S2. In Table S2, the values of “Rank” represent the rankings of the models in modeling or prediction performances. From the findings in Table S2, it was clearly seen that the CFNN had the better prediction/modeling ability than both RSM and FFNN. In particular, from the MAPE values which gives a percentage measure of the prediction error as an independent of the measurement size, even in the worst situation among 30 analysis it was evident that the CFNN displayed the outstanding and remarkable modeling performance comparing to RSM and FFNN.

In terms of temperature, while RSM produced a prediction error of around 15%, FFNN, in its best situation, showed a prediction performance with an error of around 6%. While CFNN performed modeling with a prediction error of around 4% in the best case, it still outperformed both RSM and FFNN with an error rate of around 5.5% even in the worst case. For pH, while the RSM had an error of around 5.5%, FFNN, in its both best and worst situation, showed a modeling performance with an error of between 2.5 and 3%. While the CFNN, in the prediction of pH, displayed an outstanding performance with a prediction error of around 1.25% in the best case, it still produced a competitive performance with an error rate of around 2.8% even in the worst case. For EC prediction, RSM gave the predictions with an error of around 9%. While FFNN put predictions out with an error of around 4.5% and 5.5% in the best and the worst case, respectively, for CFNN these error rates were around 2.9% and 3.5%. In the prediction of MC and TN, with prediction errors of 8.25% and 17.23%, RSM was able to produce very poor results from both neural networks. The proposed prediction procedure using CFNN, on the other hand, had the best performances among the prediction tools even in its’ worst cases, with 2.15% and 2.77% prediction errors for MC and TN estimation, respectively. There was a similar situation in C/N prediction, that is, RSM, which produced only predictions based on a linear model, gave the worst result among the prediction tools with 13.74% error, while FFNN, which produced predictions only based on a nonlinear model, was able to make predictions with an error of 6% even in its best case. CFNN, which performed the analysis process based on both linear and non-linear models, showed superior performance with 4.42% error even when it produced the worst results among 30 different analyses.

In the light of all these findings, in the modeling of 6 different parameters, it was observed that RSM could not produce predictions that can compete with both FFNN and the CFNN-based prediction model proposed in this study. Moreover, there is no concrete positive evidence about the generalization ability of the RSM in the prediction process since RSM uses all of the observed data as an in-sample. This phenomenon indicates an important question mark how the RSM will perform for unobserved data sets particularly when creating and designing new experiments is difficult or costly. On the other hand, although classical FFNN has a satisfactory generalization ability thanks to the training, validation and test set it uses in the analysis process, it can be insufficient in some modeling problems such as composting modeling problems because it can only model the non-linear relations. As a composting modeling tool, CFNN, on the other hand, has both superior generalization ability and outstanding prediction performance, thanks to its superiority to these two estimation tools.

ii. Evaluation of the proposed cascade modeling tool in terms of consistency/reliability and validity

Due to chance and random effects that are always present in a modeling process, it is inevitable that performances in different analyzes will vary. What is expected from a superior modeling/prediction tool is that its predictions are to fall within narrow limits from one model implementation to another. This situation is considered as the reliability of the modeling tool. On the other hand, validity is a measure of accuracy for a prediction or modeling tool and can be expressed by the closeness of the predictions to the target values. A satisfactory modeling tool should be able to produce both reliable and valid predictions.

From this point of view, the proposed cascaded modeling tool was run 30 times. For all analyzed cases, and the obtained best results for validation test sets were compiled and evaluated. The standard deviation statistics of RMSE values, as a measure of variability, were calculated and evaluated (see Table S3). Considering that the observed standard deviation values are quite small, there is no hesitation in saying that the prediction models have a very high level of reliability. By running the proposed cascade prediction tool to model composting together with OMSW for the treatment of CM 30 times, it is clear from

Table S3 that predictions with rather low RMSE values were obtained. In addition, when the standard deviation is considered, it is observed that the variation of the prediction errors is pretty few. These two findings are noble evidence of the reliability and validity of the proposed model. Moreover, the distribution of MAPE values obtained from 30 repetitions in the prediction of 6 parameters can be presented with the graphs given in Fig. 5.

The scattering of MAPE involves and exhibits information about the reliability and validity of the proposed cascade modeling tool. As mentioned before, for reliable modeling tools at a satisfactory level, the values of error metrics should be scattered to vary within narrow ranges from one implementation to the other. From Fig. 5, for all parameters, it is observed that the MAPE values of predictions produced by the CFNN are scattered between 0.00% and 0.06% for training, validation, and test sets in addition to the entire data. It has also been observed that these ranges are much narrower, especially in TN and MC modeling. These findings are proof that the CFNN produces extraordinarily reliable results. Moreover, the prediction errors obtained for each data set in the modeling of all parameters were mostly around 0.02% while the largest one was observed to be around a very low error value of 0.06% which is proof that the CFNN can be used as a very valid model.

iii. General comparison of the results over success rankings

In this study, CFNN, which can pay regard to both linear and non-linear relations together simultaneously by using a cascaded modeling approach, was used to model composting with OMSW for the treatment of CM. The performance of the CFNN was compared with a classical statistical-based modeling tool, RSM, and a classical computational-based modeling tool, FFNN from different viewpoints. Findings from all these comparison perspectives revealed that CFNN gave much better prediction results than both RSM and FFNN in predicting 6 parameters for CM processing, which is an important part of composting with OMSW. This sub-section presents an illustration created by using the averages of success rankings established by considering the performance of all models, according to the MAPE (see Fig. S4). This illustration shows that CFNN had better prediction ability than both RSM and FFNN, even in its worst-case in 30 runs for all data sets. CFNM, for the training set and the entire data set, had the best performance with average success rankings of 1 obtained for its best case. This situation was the same, for the validation and the test sets, with average success rankings of 1.8 obtained for its best case. Even in CFNN's worst case in the 30 runs, it had a better performance than both RSM and FFNN performance with average success rankings of 2.3, 2.7, 2.5, and 2.2 for the training,

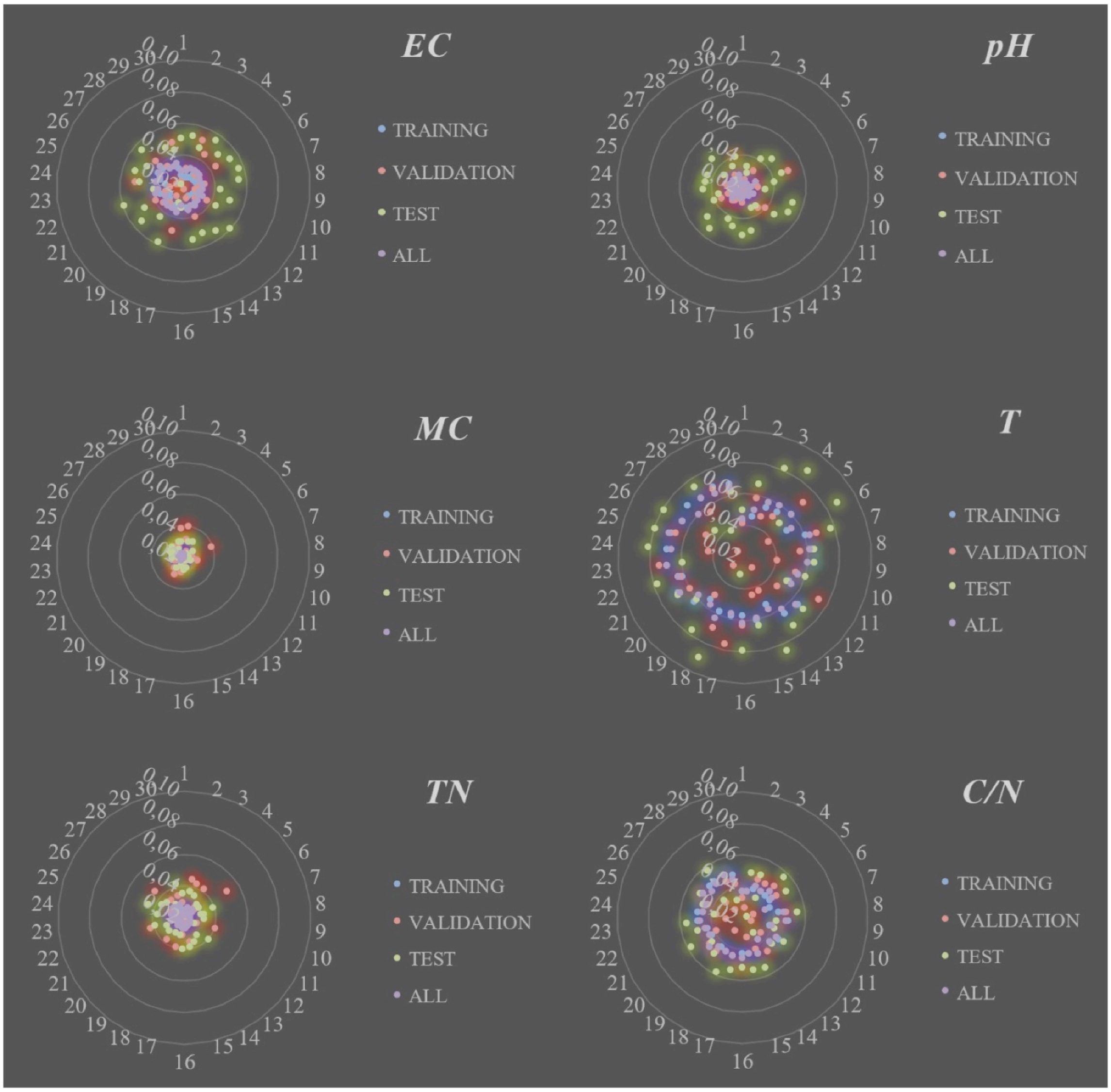

Fig. 5. The distributions of MAPE for all parameters.

validation, test sets, and the entire data set, respectively.

iv. The Statistical Effects of CM Ratio on the Parameters

Experiments created in different designs in an experiment design problem are expected to produce different dependent variable values. In other words, different levels of independent variables cause different values of dependent variables. This section is devoted to investigating the statistical effects of independent variable (in this study; CM ratio) levels on dependent variables (in this study; T, pH, EC, MC, TN, C/N). For this purpose, a two-way multivariate analysis of variance (MANOVA) was performed. In the MANOVA analysis, the levels of CM ratio were taken as 0%, 10%, 25%, 40%, and 100%. In MANOVA, the composting period, on the other hand, was taken as a covariate as day. The results of MANOVA analysis are given in Table S4.

From MANOVA results, it is proven that CM ratio had statistically significant effects on the set of dependent variables, according to both Pillai's Trace and Wilks' Lambda tests. The greatness of this effect was measured as 0.5365 by the Pillai's Trace test and 0.6730 by the Wilks' Lambda test, which proved that these Partial Eta Squared values had a strong influence on the composting process of the material, once again. These findings indicate that the CM ratio had a significant effect on at least one of the 6 parameters. However, on which parameter or parameters this effect is statistically significant can be revealed by an ANOVA analysis. The results of ANOVA analysis are given in Table S4.

From ANOVA results, it is proven that CM ratio had statistically significant effects on the set of dependent variables except temperature. These results mean that different levels of the ratio had different values of the other 5 parameters except temperature. But at what levels does this difference exist. This question can be answered with binary comparisons. As a result of the pairwise comparisons, in %5 level of significance for pH, it was concluded that the 25% CM ratio level and 10% and 40% CM ratio levels were not statistically different ($p = 0.114$; $p = 0.090$), while the other levels contained statistical differences in terms of pH values. For EC, in %5 level of significance again, it was concluded that the 0% and 10% CM ratio levels ($p = 0.357$) and also 25% and 40% CM ratio levels ($p = 0.066$) were not statistically different, while the other levels contained statistical differences in terms of EC values. For MC, in %5 level of significance, it was observed that the 40% CM ratio level and 10% and 100% CM ratio levels were not statistically different ($p = 0.059$; $p = 0.582$), while the other levels contained statistical differences in terms of MC values. For TN, it was seen that the 10% CM ratio level and 100% CM ratio level were not statistically different ($p = 0.572$), while the other levels contained statistical differences in terms of TN values. Finally, for C/N, it was observed that the 0% CM ratio level and the other CM ratio levels were statistically different ($p < 0.001$), while the other levels did not contain statistical differences in terms of C/N values.

3.5. *Multi-objective optimization of the parameters by genetic algorithm*

In this study, a cascaded modeling approach based on CFNN proposed to model composting with OMSW for the treatment of CM. Thanks to the superior features of CFNN, outstanding prediction results can be obtained for the composting process parameters, namely the dependent variables. However, there is still a fundamental problem to be solved for modeling the composting process. This is which the best values of the dependent variables are during the composting process and with which values of the independent variables these best values can be obtained. In short, this is a multi-objective optimization problem in which the best values of the dependent variables are tried to be obtained. In a general manner, a multi-objective optimization problem with N decision variables, M objective function and $J + K$ constraint can be given as follows.

$$
\begin{aligned}
&min\Big/max\left(f_1\left(\underline{x}\right), f_2\left(\underline{x}\right), \cdots, f_M\left(\underline{x}\right)\right) \quad \left(\underline{x} = [\,x_1\; x_1\; \cdots\; x_1]\right)\\
&subject\ to \quad
\begin{array}{lll}
g_j\left(\underline{x}\right) \le 0 & ; & j = 1, 2, \cdots, J\\
h_k(x) = 0 & ; & k = 1, 2, \cdots, K\\
x_i^{(L)} \le x_i \le x_i^{(L)} & ; & i = 1, 2, \cdots, N
\end{array}
\end{aligned}
\tag{3}
$$

In this study, this multi-objective optimization problem was tackled by a genetic algorithm. The objective function values of the multi-objective optimization process were values of six dependent variables (pH, T, EC, MC, TN, C/N) i.e. the outputs produced by trained CFNNs corresponding to the independent variable values.

For the multi-objective optimization problem having these features, the results produced by GA were compared with the optimization results generated by the classical approach, RSM. In the comparison, the individual desirability and overall desirability, which are given by Eqs. (4)–(6) were used. In these equations, while S is the importance level of dependent variables in the multi-objective optimization process, Min_m and Max_m represent the limit values of dependent variables. The comparison findings are summarized in Table 2.

$$
d_m^{max} = \left\{
\begin{array}{lll}
0 & ; & f_m\left(\underline{x}\right) < Min_m\\
\left(\dfrac{f_m\left(\underline{x}\right) - Min_m}{Max_m - Min_m}\right)^S & ; & Min_m < f_m\left(\underline{x}\right) < Max_m\\
1 & ; & f_m\left(\underline{x}\right) > Max_m
\end{array}
\right\}
\tag{4}
$$

$$
d_m^{min} = \left\{
\begin{array}{lll}
1 & ; & f_m\left(\underline{x}\right) < Min_m\\
\left(\dfrac{f_m\left(\underline{x}\right) - Max_m}{Min_m - Max_m}\right)^S & ; & Min_m < f_m\left(\underline{x}\right) < Max_m\\
0 & ; & f_m\left(\underline{x}\right) > Max_m
\end{array}
\right\}
\tag{5}
$$

$$
D = \left(\prod_{m=1}^{M} d_m\right)^{1/M}
\tag{6}
$$

The findings in Table 2 show that GA generated optimal values with higher individual desirability for all parameters except temperature. GA particularly had a maximum desirability level for pH (almost 100%) while, for EC and TN, it produced satisfactory optimal parameter values with around 70% and over desirability level. Moreover, the desirability level of C/N is also satisfactory level, with over 55%. When examining the overall desirability level, GA reached around 45% desirability while RSM can reach only 7% desirability levels. Thus, it can be said that GA reached a better overall desirability level of approximately 3.8 times than RSM. As a result, GA determined the optimum values of decision variables CM ratio and process period as 23.39% and 104.86 days, respectively, to reach these optimum parameter values and desirability levels.

From another perspective, the optimized CFNN produced a TN value of 2.1192 for the inputs which are contained %23.39 CMR and seven days. And thus, when a TN value of 2.1192 is initially set, the TN loss at the end of the determined optimal period will be around 26.86%.

4. Conclusion

In the present study, the co-composting of CM and OMSW was investigated for improving compost quality and maturity. The addition

Table 2
The optimization results.

	RSM			GA		
Variable	Optimum Values	Result	Desirability	Optimum Values	Result	Desirability
T	CMR = 36.36364%	27.62993	0.41737	CMR = 23.38375%	20.84468	0.31487
pH	t = 76.29293 days	6.93857	1.00000	t = 104.86386 days	6.58218	1.00000
EC		1.15828	0.61391		0.98919	0.67027
MC		29.99998	0.00003		27.30531	0.08982
TN		1.40125	0.67575		1.54998	0.73140
C/N		15.85354	0.20732		8.72147	0.56393
	Overall Desirability		0.06540			0.44551

of CM to OMSW significantly reduced TN loss and MC, provided to reach thermophilic temperatures of compost materials. Moreover, the co-composting processes improved compost quality and maturity. From the experimental studies, an efficient mixture ratio was found as 25% CM.

On the other hand, with a basic computational perspective, a cascaded modeling approach was used to model composting together with municipal solid waste for the treatment of CM. The prediction performance of CFNN, obtained from 30 runs, was compared with RSM and FFNN and it was concluded that CFNN outperformed both modeling tools in terms of RMSE and MAPE performance measures. As for the reliability and the validity which are required specifications for a modeling tool, in the prediction of each composting process parameter, rather low RMSE values and also rather low standard deviation of RMSE were obtained as a consequence of 30 times running of the proposed cascade prediction tool. This was also supported by illustrations that gave the distribution of MAPE values obtained as a result of 30 analyzes for the entire data set, as well as training, validation and test sets. All these are proofs that CFNN can be used as a reliable and valid prediction and modeling tool in the composting process problems.

MANOVA as a multivariate statistical analysis was performed and the results showed that CM ratio had statistically significant effects on the set of dependent variables according to both Pillai's Trace and Wilks' Lambda tests ($p < 0.001$). Moreover, which parameter or parameters this effect is statistically significant was investigated by an ANOVA analysis. The ANOVA results indicated that CM ratio had statistically significant effects on the set of dependent variables ($p < 0.001$) except for T ($p = 0.246$). The multi-objective optimization results showed that the overall desirability was determined as 0.44551. For the optimum case, CM ratio was about 23.39% and the processing period was about 104.86 days.

In future studies, computational-based and statistical-based modeling tools can be intercrossed within a hybrid approach and so the predictive ability of the model can be improved.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.115496.

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