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# Prediction and optimization of nitrogen losses in co-composting process by using a hybrid cascaded prediction model and genetic algorithm

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ABSTRACT

In this study, the effects of co-composting of food waste and poultry waste on nitrogen losses and maturity were investigated. The different mixture ratios were used and the effectiveness of co-composting was compared with mono-composting of each waste. Also, a linear and nonlinear hybrid tool based on a cascaded forward neural network was used to estimate nitrogen losses of all reactors. The proposed hybrid tool produced predictions with mean absolute percentage error (MAPE) values of approximately 1–2% on all data points containing the training, validation, and test datasets. These results can be considered outstanding, especially when compared to Response Surface Methodology (RSM), which produces predictions with MAPE values of approximately 15% on all data points. The optimal values from the genetic algorithm (GA) were for poultry waste of 17.20%, for a duration of 97.64 days. These findings are invaluable, especially when it is costly and difficult to renew the composting process by creating a new experimental setup.

## 1. Introduction

An increase in population, migration to cities, and diversified consumption habits lead to the development of new technologies in industries and as a result, the formation of solid waste in large quantities and various characteristics [1]. Solid wastes consist of organic wastes, metal, paper, plastic, glass, and other wastes. Organic waste has a large share with 44%, followed by 38% of recyclable wastes [2]. Among solid waste technologies such as landfill, composting, non-oxygen digestion, and incineration, composting is a sustainable method that has recently gained popularity in the removal of organic waste that has a high share in the solid waste composition. The most important advantages of this method are making the wastes hygienic, solving the disposal problem, obtaining value-added products, reducing greenhouse gas emissions, and low cost [3]. Composting is the process of forming a humus-rich product called compost as a result of the biological decomposition of organic wastes in the air environment. This low-cost waste disposal strategy needs to be completed in all stages (mineralization and humification stages), as it is necessary to conform with the minimum time conditions required even in well-designed composting technology applications for the production of a stable and quality product. The composting method to be applied is preferred depending on the usable land, availability of personnel, amount of organic matter, and budget. In all methods, moisture content, temperature, pH, ventilation, porosity, C/N ratio, particle size, porosity, and processing time are monitored during the process [4,5]. Finally, depending on the quality of the produced compost, it is possible to use it in sectors such as agricultural areas, gardens, forest areas, erosion control, road stabilization, airports, cemeteries, golf courses [1]. The researchers have published research on the composting of all types of biodegradable waste, such as food waste [6], swine manure [7], sewage sludge [8], municipal solid waste [9], green waste [10], sheep manure [11], poultry manure [12], olive mill waste [13], pruning waste [14], pulp/paper mill waste [15], etc.

In order to reduce the negative impact of the livestock sector on the environment, it is necessary to manage large amounts of biodegradable wastes generated by appropriate disposal methods. The composting method is of course not a new technology. However, the composting method for animal wastes management is an appropriate disposal method in the production of environmentally profitable fertilizers due to reducing the risk of spreading harmful microorganisms and weed seeds, reducing volume and moisture, easing storage/transportation/use, controlling odors, and microbial stabilization [16]. Agriculture is one of the important sectors in Turkey. Crops and livestock are almost 90% of this major sector. An important part of livestock consists of cattle, sheep

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and goats, and poultry [17]. According to Turkish Statistical Institute (TURKSTAT) data, the number of cattle in 2020 increased by 1.6% compared to the previous year rose to 18 million 158 thousand head. This value reached a total of 72.27 million along with the small cattle. The number of poultry was also 348 million 784 thousand 885 in 2019 [18]. The management of animal manure generated in large quantities is usually by using it as fuel or by storing it. The composting of poultry manure (PM) attracts attention as an environmentally friendly disposal method due to biodegradable organic matter and nutrient content such as phosphorus, potassium, and nitrogen [19]. PM contents can vary according to many different parameters such as seasonal conditions, the type of animals, the weight of animals, nutritional conditions, type and amount of litter material used in the poultry house. Waste generated in poultry production can also change according to the purpose of production (meat and egg production) and the conditions of production. The amount of poultry manure composed is almost 5.5 million tons per year in Turkey. It will be a great benefit if these wastes are stabilized and used to improve the soil's physical/chemical structure. The compost that will be produced by recycling the poultry manure instead of storing it or using it as fuel can be used to improve the soil quality [20].

The results are evaluated with a limited number of experimental sets established to optimize the composting process that is a complex biological process. Together with the experimental data obtained, the predictions produced by using mathematical models can support the optimization of the process [21,22]. These prediction models make it possible to decrease the number of experiments, cost, time, and manpower required for experiments, and determine the results for experiments that are technically inapplicable. Statistical-based models like Response Surface Methodology (RSM) and machine learning-based models like Artificial Neural Networks (ANNs) have been used in engineering applications as effective experimental modeling and optimization methods. Thanks to its hidden layers, machine learning-based models that learn the data structure and produce new information are more successful than statistical-based models in data sets that programming is hard. In the literature, while many ANN models have been used for various purposes [23–26], the number of studies focusing on the optimization and modeling of the composting process by using ANNs is quite limited [21,22,27–34].

In the present study, the composting of poultry wastes together with food wastes was investigated. Poultry wastes and food wastes were mixed at different rates and additionally, control groups in which the composting process of only food waste and only poultry waste were monitored. The goals of the study were as follows: (i) to investigate maturation parameters, (ii) to compare the performances of different mixture ratios on composting, (iii) to predict the nitrogen loss in the composting process by using a hybrid tool based on CFNN (iv) to specify the inputs of the prediction tool objectively instead of subjectively or arbitrary, by taking advantage of RSM (v) to model the data by taking into consideration the linear and non-linear relations between input parameters and output in a more rationalist way (vi) to determine the best prediction tool among RSM, feed-forward neural network (FFNN), a hybrid cascade forward neural network prediction model (H-CFNN-PM) by addressing root mean square error (RMSE) and MAPE criteria (vii) to determine the statistical effects of the poultry waste ratio on the nitrogen loss (viii) to determine the optimal parameter values by using a genetic algorithm in a way to minimize the nitrogen loss in the composting process.

## 2. Materials and methods

### 2.1. Materials

In this study, the poultry waste (PW) was obtained from Ernur Poultry Husbandry firm located in Kavak of Samsun city, Turkey. Food waste (FW) samples used in the study were collected from a fruit and vegetable market located in Samsun city of Turkey. The food wastes were placed in bins by taking equal amounts of the same species. The food waste was shredded before being placed in the bins. The materials were taken in 10 L plastic containers and set in the bins within a maximum of 4 h. The properties of raw materials used in the composting process are given in Table 1.

### 2.2. Methods

#### 2.2.1. Process design

Pilot-scale continuously aerated in-vessel reactors were used for the composting processes. The composting systems have a surface area of 1200 $cm^2$ (width: 40 cm, length: 30 cm) and a depth of 25 cm. The air distribution pipes were situated in both horizontal and vertical positions. These pipes with a diameter of 2 cm from PVC were mounted 5 cm above the base. 3 mm of diameter holes were drilled in all pipes. During the composting process, 10 L / min of air was supplied to all systems by the aeration pump. The pipe in the cover part was used for gas output and temperature measurement. The schematic view of the pilot composting reactor is given in Fig. 1.

#### 2.2.2. Experimental design

A total of three co-composting reactors were set up including 10% (Reactor 1), 25% (Reactor 2), and 40% (Reactor 3) of PW ratios, and additionally, only control groups in which the composting process of PW (Reactor 4) and FW (Reactor 5) were monitored. Before each sampling, the materials in the reactors were mixed and then were taken approximately 100 g of samples. Parameters were analysed in duplicate and their averages were used to evaluate the composting processes. The sampling times were once a week and continued for 105 days (15 weeks).

During the composting process, the temperature of compost was measured daily by using a temperature probe that was put into the middle of each reactor at a depth of 0.10 m (Loyka-9263 digital stem thermometer). The first part of the sample divided into two groups was used to determine pH, EC, and MC of compost. The second part was air-dried, ground, sieved (0.5 mm), and used to analysed total nitrogen (TN), and total organic carbon (TOC) contents. MC was determined by drying the sample at 105 °C for 24 h in an oven (Nüve-FN400). pH and electrical conductivity (EC) parameters were measured in the aqueous extract using 1:10 w/v (Orion Star™ A325 pH/conductivity portable multiparameter meter). Total nitrogen and carbon contents were analysed according to the APHA Standard Methods [35].

#### 2.2.3. Cascaded forward neural network

As one of the Machine Learning techniques, ANN has been designed as a quite simple simulation of the human brain to be able to solve common problems in the fields of AI. ANNs, just like a human who has the skills such as deriving and discovering new information through learning, realize the task of problem-solving by mimicking the brain. The Feed-forward neural network (FFNN), which is a kind of multilayer perceptron proposed by Werbos [36] and re-considered by Rumelhart et al. [37], is the most common used ANN in the modeling of the composting process, such as food waste composting, solid waste vermicompost, mixed municipal waste composting, and sewage sludge and

**Table 1**
Properties of raw materials used in the composting process.

| Parameter | PW | FW |
|---|---|---|
| pH | 8.44 ± 0.35 | 4.17 ± 0.27 |
| Electrical conductivity (mS/cm) | 3.56 ± 0.04 | 1.46 ± 0.02 |
| Moisture content (%) | 26.45 ± 1.02 | 69.12 ± 2.11 |
| Dry matter content (%) | 73.50 ± 1.02 | 30.90 ± 2.11 |
| Organic matter (%) | 84.75 ± 2.24 | 93.20 ± 2.62 |
| Total nitrogen (%) | 3.25 ± 0.58 | 2.40 ± 0.45 |
| Total organic carbon (%) | 56.31 ± 1.78 | 76.52 ± 2.01 |
| C/N | 17.33 ± 3.07 | 31.88 ± 4.47 |

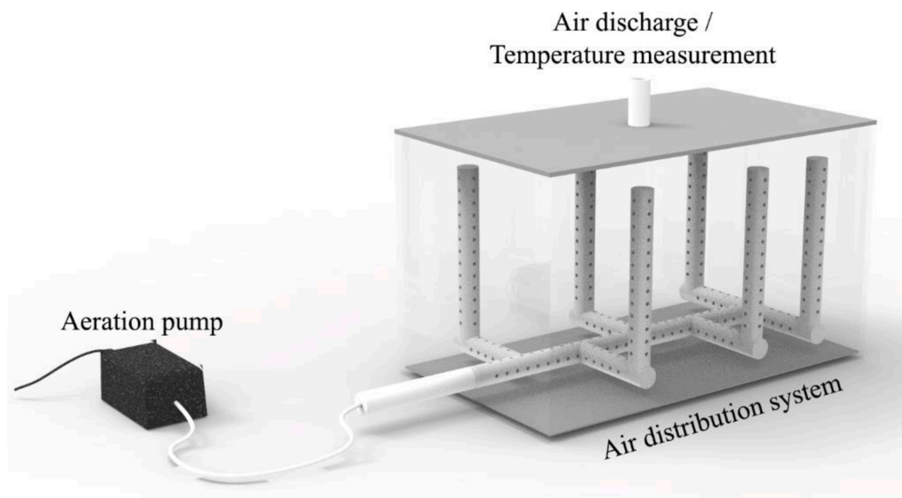


**Fig. 1.** A schematic representation of the composting process.

rapeseed straw composting, as in most other areas. FFNNs, unlike RSM which is a statistical-based modeling tool in all these areas, perform the modeling processes in a non-linear manner. It is a fact that both RSM and FFNNs generate successful results in composting process modeling, however, especially in consideration of the existing relationship between inputs and outputs of the composting process, being able to model both linear and nonlinear relationships together simultaneously will improve the results. Thanks to the sigmoid activation function used in the hidden layers and the linear activation function used in the output layer, and also since it's each layer is fed by all previous layers, CFNN has these abilities. CFNN was proposed by Demuth and Beale [38] inspired by the cascade correlation approaches of Fahlman and Lebiere [39]. Similar to classical FFNNs, CFNN has an architectural structure consisting of input, output, and hidden layer(s) [40]. Having the architectural structure that each neuron layer has a connection to all previous layers is the main distinguishing feature of CFNN from existing networks. It can be presented in Fig. 2 given as a CFNN prototype with two hidden layers.

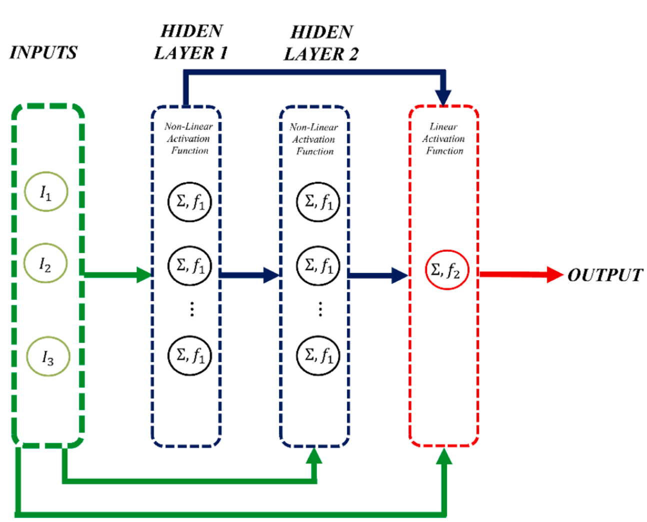


**Fig. 2.** A basic structure of CFNN.

## 3. Results and discussion

### 3.1. Changes in physico-chemical properties and nitrogen dynamics during composting

Temperature is a significant indicator used to evaluate whether the composting process has been completed successfully. Temperature profiles of the reactors were shown in Fig. 3a during the composting process. The temperature increased rapidly after the initial filling in all reactors. The rapid increase in temperature enhanced microbial metabolism and thus promoted heat production [41–43]. The maximum temperature values of 54.1, 66.5, and 68.3 °C were observed in reactors 1, 2, and 3, respectively. However, the thermophilic temperatures (>40 °C) were not recorded in both reactors 4 and 5. This was probably because of the higher MC of FW and the greater free air space of PW. The temperatures of all reactors decreased gradually to ambient levels in all reactors after the third week. The variation in the temperature values indicated that co-composting of FW and PW provided more suitable conditions for the process. Nitrogen losses were the highest during the first three weeks when the temperature increased. Approximately half of the nitrogen losses occurred during this period. A linear dependency was found between the nitrogen loss and the rate of heat generation during the composting processes. Similar results have been reported by Bryndum et al. [44], who indicated that the high nitrogen losses were observed at high temperatures during the early stages of composting.

pH is one of the indicators of compost maturity. However, it is not pondered at the initial stage of composting because most of the raw materials are within the recommended range which is 7.0–8.5 for efficient composting [45–48]. The evolution of the pH values for all reactors during the composting process was shown in Fig. 3b. As seen in Fig. 3b, the pH of all reactors decreased in the first weeks, as time went by, it dropped to the lowest level at the third week, and then it fluctuated for the rest of the composting period. The decrease of pH in the early stage of composting may be related to the ammonia volatilization, biodegradation of organic acid, and $CO_2$ emission [49,50]. At the end of the process, the pH values of all reactors were relatively stable and increased compared with the initial values. The increase in pH might be attributed to the consumption of short-chain organic acids and the formation of ammonium ($NH_4^+$) ions [51]. The final pH values of all composts, except for reactor 4 with only PW, were in the range of satisfactory pH value limits [16,52]. It was found that the pH value of the compost obtained from the Reactor 4 was highly alkaline (10.3), which resulted in more nitrogen loss. The loss of nitrogen decreased rapidly at pH $<$ 8 and increased significantly at pH $>$ 8. Therefore, pH is a key factor to reduce nitrogen loss.

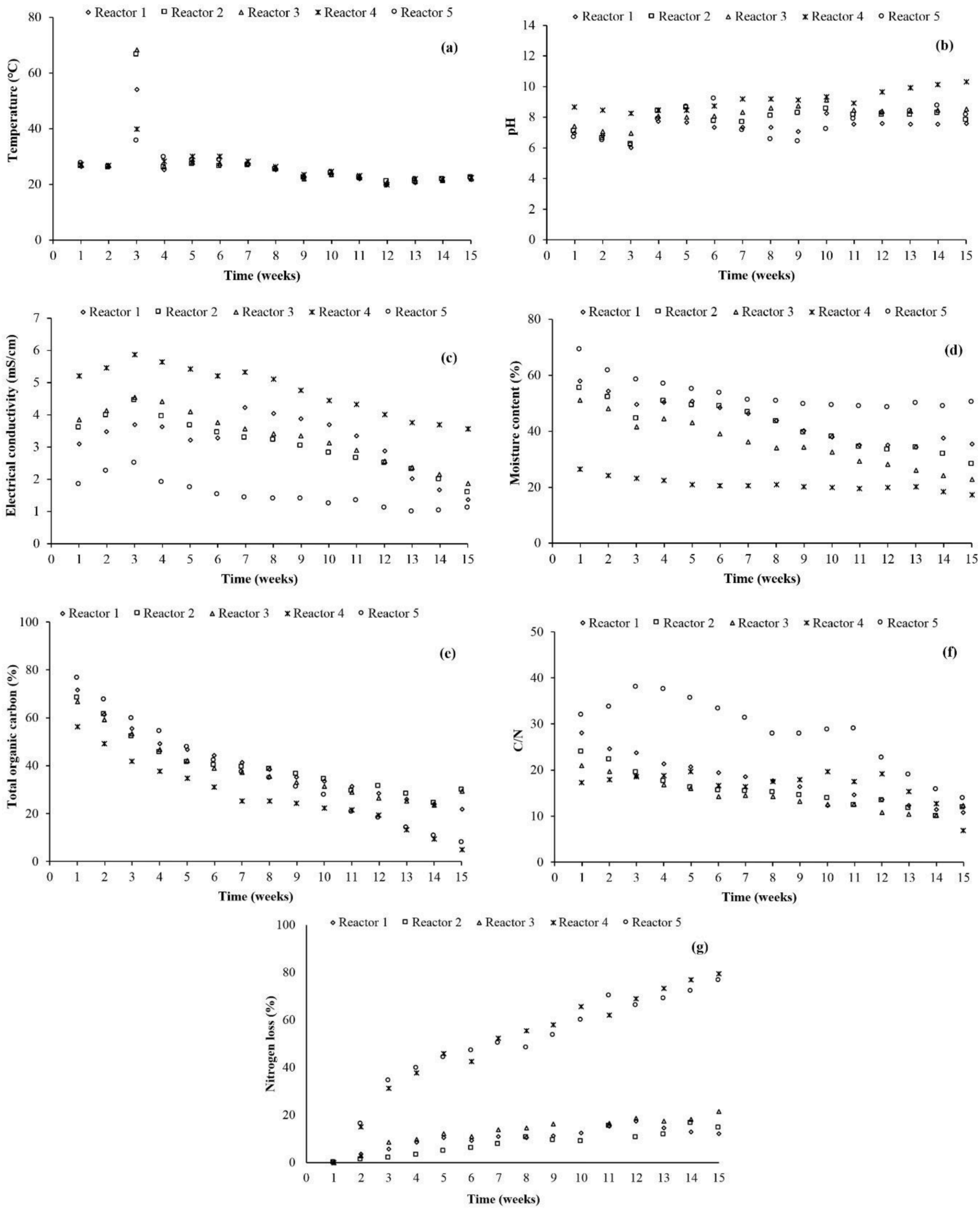


**Fig. 3.** Evolution of compost temperature (a), pH (b), EC (c), MC (d), total organic carbon (e), C/N (f), and nitrogen loss (g) in the reactor during the composting process.

EC can directly reflect the salt content of the compost. The higher EC value of final compost can cause phytotoxicity or inhibit plant growth [16,53]. Fig. 3c shows the changes in EC for all reactors. As seen in Fig. 3c, EC values increased in all reactors in the first three weeks due to an influence of temperature increased with the higher microbial activity [54]. EC values in each reactor gradually decreased after the third week. At the end of the composting process, the highest EC value was observed with 3.56 mS/cm in Reactor 4. The EC values of the final composts amended with FW were significantly lower than that of the only poultry waste compost, and the final ECs with FW decreased with an increase in the poultry waste proportion. This may be because of the substantial amount of salt ions due to the structural characteristics of poultry waste [48]. In general, compost can be safely applied to the soil as organic fertilizers only when the EC of the products is<4 mS/cm [55]. Therefore, the EC values of all the final composts in this study are suitable for compost quality criteria. While EC values increased in the thermophilic phase, a similar increase was observed in nitrogen losses. However, after that, there was a decrease in the EC values, but an increase in nitrogen losses.

MC is also an important factor for the microbial activity of the composting. MC should be in the range of 50–60% for optimal microbial activity at the beginning of composting. A low MC could decrease the distribution of soluble nutrients and slow microbial activity [56]. A high MC could decrease the $O_2$ concentration and become anaerobic. At the beginning of composting, MC was higher than the optimal range for Reactor 5 containing only FW (69.12%), and lower than that of Reactor 4 containing only PW (26.45%). However, all co-composting reactors (1, 2, and 3) meet the optimal initial range. The dynamic change of the MC during the composting is shown in Fig. 3d. It can be seen from Fig. 3d that all of the reactors had similar MC distribution patterns. The MC in the reactors was reduced by evaporation in the form of water vapor because of the combined effect of heat and ventilation. Organic substrates having higher MC required more processing time for completion of the maturation phase. High MC and great free air space of FW led to increased nitrogen loss. Therefore, the addition of PW to FW was found to reduce from 67.08 to 84.44% in the co-composting reactors. Previous studies had also shown that high MC with > 65% increased total nitrogen loss during the composting process [57–59].

TOC content decreased constantly in all reactors during the composting process (Fig. 3e). For all reactors, the greatest reduction in TOC content was observed during the first three weeks, which is by the rapid breakdown of easily biodegradable compounds in the initial stage of composting process [60]. After the third week, TOC content values ranged from 21.8 to 29.9% in reactors 1, 2, and 3 with co-composting, while it was below 8% in reactors 4 and 5 with mono-composting. In mature compost, TOC value should have to between 8 and 35%. Accordingly, TOC values of the composts obtained from Reactors 4 and 5 are below the ideal range. This was mainly due to co-composting promoting active microorganisms for the disintegration of organic carbonaceous material into $CO_2$ and water [61]. It was seen that there was an inverse relationship between TOC and nitrogen loss. While TOC values decreased during the composting process, nitrogen losses increased.

The initial C/N ratio is an even more important parameter that may influence ammonia emission [34]. High nitrogen content and low C/N ratio of the composting materials cause more ammonia volatilization and nitrogen loss [62]. The optimum initial C/N ratio is generally considered to be between 20 and 35 [63]. Experimental results indicated that the initial C/N ratios met the optimum range of C/N ratio in all the reactors except in Reactor 4 (Fig. 3f). The initial C/N ratio was<20 in this reactor. The initial C/N ratios decreased in all reactors at the end of the process. However, C/N ratios in reactors showed different variations during the composting process. In all co-composting reactors (1, 2, and 3), the C/N ratios decreased during the process, while in mono-composting reactors (4 and 5) they increased during the thermophilic phase and then decreased unevenly. At the end of the process, The C/N ratios were 8.7, 12.6, 14.5, 7.0, and 13.9 in the reactors 1, 2, 3, 4, and 5, respectively. A C/N ratio below 20 is acceptable for maturity, with a ratio of 15 or even less being preferable [64]. The C/N ratios were below 15 in all reactors. The composting of materials with a low C/N ratio resulted in more N losses than with high C/N ratio wastes [65,66].

It is reported that the total nitrogen loss is approximately 40–70% of the initial nitrogen [48,67–69]. In the study, the total nitrogen losses were within the range of 11.93–79.38% from all reactors. A lower total nitrogen loss could be achieved with the co-composting of FW and PW. Among them, nitrogen losses were 11.93, 14.44, and 21.48% for reactors 1, 2, and 3, respectively. However, nitrogen losses were above 70% in the mono-composting reactors (4 and 5). This was mainly because ammonia was the predominant nitrogen compound emitted. It was shown that nitrogen loss increased rapidly during the first three weeks, and then gradually increased until the end of composting (Fig. 3g).

### 3.2. Modeling and optimization of the nitrogen loss in the composting process

In this study, to predict the nitrogen losses displayed by certain poultry waste ratios within a certain period, a linear and non-linear hybrid prediction process based on CFNN was run. The proposed prediction process, which includes a hybrid approach, consists of three main stages; (i) determining the inputs composed of the process parameters' linear and quadratic functions, by RSM, (ii) prediction of nitrogen loss by the H-CFNN-PM, and evaluation of the results, (iii) specifying the proper parameters which will produce minimum nitrogen loss by genetic algorithm.

The modeling performance of the proposed hybrid prediction tool based on CFNN has been tested by comparing the results generated by a statistical-based RSM which has a linear structure, and by a machine learning-based FFNN with a nonlinear structure. Besides being a performance comparison, this comparison also provides an opportunity to evaluate the constructs of the proposed predictor, which can model both linear and nonlinear relationships together with tools that can model only linear or only nonlinear relationships.

#### 3.2.1. Determining the inputs

The proposed prediction tool that its main component is composed of CFNN uses the parameters' linear and quadratic forms as inputs. The main issue here is how to determine these inputs, in other words, which form or forms of which parameter should be used as inputs. In this stage, RSM was used to determine the form or forms of the parameters that have statistically important contributions to the modeling process. The results produced by RSM, with just statistically significant ($p < \alpha = 0.05$) components of the model, are summarized in Table 2.

#### 3.2.2. Prediction of nitrogen loss by the H-CFNN-PM

By using the statistically significant components of the RSM, to predict the nitrogen losses displayed by certain poultry waste ratios within a certain period, CFNN was run. A hypothetical architecture of CFNN including seven input layer neurons and one hidden layer is given in Fig. 4.

Here, $w^{ij}$ and $b^{i}$ are the weight between $j^{th}$ input layer neuron and $i^{th}$ hidden layer neuron $(i = \overline{1,K}; j = \overline{1,13})$ and the bias for $i^{th}$ hidden layer neuron $(i = \overline{1,K})$ . $Hw^{i}$ is the weight between $i^{th}$ hidden layer neuron and the output layer neuron $(i = \overline{1,K})$ . Moreover, IW is the vector of weights between input layer neurons and the output layer neuron $\left(IW = \left[Iw^{1}\ Iw^{2}\right]\right)$ and $b^{o}$ is the bias of output layer neurons. $f_1$ represents the sigmoid activation function and $f_1(x) = \frac{1}{1+\exp(-x)}$ . $f_2$ is the linear activation function and $f_2(x) = x$ .

Let input vector, for any implementation, is $[x_1, x_2, \cdots, x_{13}]$ . In this

**Table 2**
The statistically significant ($p < \alpha = 0.05$) components of RSM model

| Source | *F*-Value | *p*-Value |
|---|---|---|
| Model | 62.33 | 0.000 |
| Square | 1.98 | 0.082 |
| MC × MC | 11.4 | 0.002 |
| Two-Way Interaction | 5.43 | 0.000 |
| PW × Duration | 8.34 | 0.006 |
| PW × MC | 9.42 | 0.004 |
| PW × C/N | 7.71 | 0.008 |
| Duration × MC | 7.05 | 0.011 |
| EC × C/N | 6.55 | 0.015 |

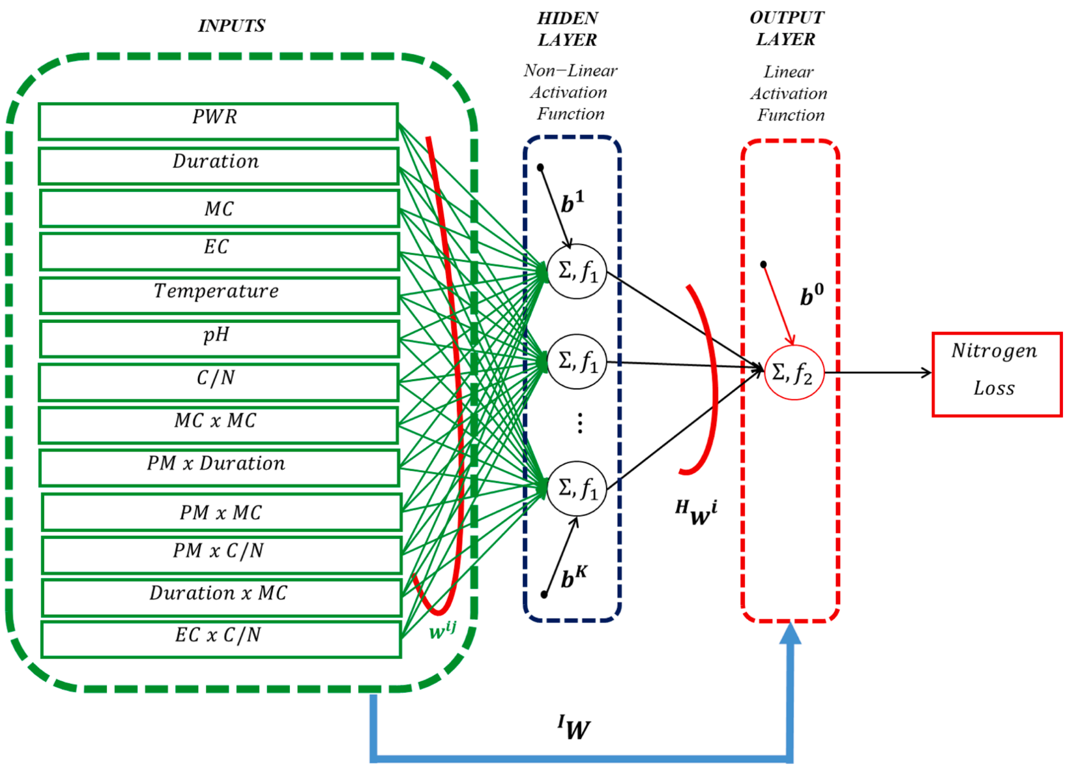


**Fig. 4.** A hypothetical architecture of modeling process.

case the calculations of outputs of the CFNN can be represented by Eq. (1–4).

$$net_i = \sum_{j=1}^{13} x_j w^{ij} + b_i; i = \overline{1, K} \tag{1}$$

$$o_i = f_1(net_i) = \frac{1}{1 + \exp(-net_i)}; i = \overline{1, K} \tag{2}$$

$$net_o = \left[ \sum_{i=1}^{k} o_i Hw^i + \sum_{j=1}^{13} x_j Iw^j \right] + b_i \tag{3}$$

$$o_o = f_2(net_0) \;= net_0 \tag{4}$$

Thus, the CFNN generates a function of linear and non-linear relationships between inputs and outputs.

In the prediction process of the nitrogen loss, there were thirteen inputs of CFNN; PWR, duration, MC, EC, temperature, pH, and C/N parameters, the quadratic form of MC parameter, and five interactions of the parameters as PWR × duration, PWR × MC, PWR × C/N, duration × MC, and EC × C/N. The number of hidden layer units of the CFNN was taken by changing from 6 to 13. 70 experiments from 5 reactors have been randomly divided into Training, Validation, and Testing sets. For each different case of the hidden layer unit, 30 analyses were done. The characteristics of the analysis process are summarized in Table 3.

### 3.2.3. Evaluation of the results produced by the H-CFNN-PM

To evaluate the modeling performance and the generalization ability of hybrid modeling procedure, basically, two well-known evaluation criteria, root mean square error (RMSE) and mean absolute percentage error (MAPE) were considered over the training, validation, and test sets of the experiments. In the benchmark process, two modeling tools, RSM as statistical-based, and FFNN as a machine learning-based, were used. RSM results were generated only once and for all experiments due to the nature of RSM, whereas FFNN was generated 30 times for the training, the validation and the test sets, just like the proposed hybrid procedure.

**Table 3**
The features of modeling process

| | | | |
|---|---|---|---|
| # Input | 7 | i. PWR | viii. MC × MC |
| | | ii. Duration | ix. PWR × Duration |
| | | iii. MC | x. PWR × MC |
| | | iv. EC | xi. PWR × C/N |
| | | v. Temperature | xii. Duration × MC |
| | | vi. pH | xiii. EC × C/N |
| | | vii. C/N | |
| # Output | 1 | *i.* Nitrogen loss | |
| # Hidden Layer Neuron | from 6 to 13 | | |
| # Experiments | 70 | | |
| # Training Set | 50 | | |
| # Validation Set | 10 | | |
| # Test Set | 10 | | |
| # Repetition | 30 | | |

Among the 30 different results obtained for FFNN and the proposed hybrid procedure, the best and worst cases were used to compare and the results, in terms of MAPE measure, were summarized in Table 4.

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

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

The findings in Table 4, in both the best and the worst cases of the models and for each hidden layer number, it is clearly shown that the H-CFNN-PM has a better prediction/modeling ability than the FFNN which is a classical computational-based modeling tool. With a deeper perspective, the worst cases among 30 analyses for the H-CFNM-PM can be examined in terms of the values of MAPE criterion which gives a percentage measure of the prediction error as independent of the measurement size. Considering these values, it is seen that H-CFNM-PM, with about 2% and lower MAPE values, displayed outstanding and

**Table 4**
The results of the FFNN and the proposed H-CFNN-PM, in terms of MAPE

| # Hidden Layer Neuron | Data Set | FFNN | | H-CFNN-PM | | Progress | |
|---|---|---|---|---|---|---|---|
| | | The best (%) | The worst (%) | The best (%) | The worst (%) | In the best (%) | In the worst (%) |
| 6 | Tr. | 0.9497 | 3.3686 | 0.8033 | 0.5374 | 15.4154 | 84.0468 |
| | Val. | 0.6251 | 4.3047 | 0.2306 | 1.1269 | 63.1099 | 73.8216 |
| | Test | 8.8530 | 13.1703 | 7.3781 | 8.1155 | 16.6599 | 38.3803 |
| | ALL | 2.0324 | 4.9025 | 1.6608 | 1.7042 | 18.2838 | 65.2381 |
| 7 | Tr. | 1.0258 | 1.9482 | 0.6522 | 0.6213 | 36.4204 | 68.1090 |
| | Val. | 0.8663 | 1.8710 | 0.5363 | 1.1476 | 38.0930 | 38.6638 |
| | Test | 15.2979 | 12.3885 | 7.5907 | 7.2491 | 50.3808 | 41.4852 |
| | ALL | 3.0419 | 3.4286 | 1.6269 | 1.6433 | 46.5170 | 52.0708 |
| 8 | Tr. | 1.1541 | 1.1523 | 0.1594 | 0.9080 | 86.1884 | 21.2011 |
| | Val. | 0.6155 | 1.5511 | 0.0715 | 1.2063 | 88.3834 | 22.2294 |
| | Test | 10.3644 | 15.7094 | 6.5652 | 7.8514 | 36.6562 | 50.0210 |
| | ALL | 2.3930 | 3.2889 | 1.0620 | 1.9425 | 55.6206 | 40.9377 |
| 9 | Tr. | 1.1476 | 1.5236 | 0.8318 | 0.7153 | 27.5183 | 53.0520 |
| | Val. | 0.8907 | 1.7430 | 0.6215 | 0.8332 | 30.2234 | 52.1974 |
| | Test | 16.7637 | 12.5502 | 7.4900 | 7.5456 | 55.3201 | 39.8767 |
| | ALL | 3.3418 | 3.1302 | 1.7530 | 1.7079 | 47.5432 | 45.4380 |
| 10 | Tr. | 1.0821 | 0.8528 | 0.8400 | 0.6810 | 22.3732 | 20.1454 |
| | Val. | 0.8194 | 1.1523 | 0.2453 | 0.9129 | 70.0635 | 20.7758 |
| | Test | 15.2833 | 11.8611 | 6.5591 | 6.0564 | 57.0832 | 48.9390 |
| | ALL | 3.0733 | 2.4682 | 1.5721 | 1.4820 | 48.8465 | 39.9562 |
| 11 | Tr. | 1.1559 | 0.7155 | 1.0523 | 0.6962 | 8.9627 | 2.6974 |
| | Val. | 0.6855 | 0.9491 | 0.3679 | 1.2847 | 46.3311 | −35.3598 |
| | Test | 15.1764 | 9.3752 | 7.0825 | 5.6656 | 53.3321 | 39.5682 |
| | ALL | 3.0916 | 1.9859 | 1.8160 | 1.4902 | 41.2602 | 24.9610 |
| 12 | Tr. | 1.2710 | 0.7563 | 0.4848 | 0.9313 | 61.8568 | −23.1390 |
| | Val. | 0.9926 | 0.8819 | 0.2221 | 0.9225 | 77.6244 | −4.6037 |
| | Test | 11.8741 | 13.9166 | 7.3520 | 4.1896 | 38.0837 | 69.8949 |
| | ALL | 2.7460 | 2.6543 | 1.4283 | 1.3955 | 47.9862 | 47.4249 |
| 13 | Tr. | 0.8437 | 0.6110 | 0.0453 | 0.5605 | 94.6308 | 8.2651 |
| | Val. | 0.5692 | 1.0426 | 0.0396 | 1.0196 | 93.0429 | 2.2060 |
| | Test | 11.6219 | 11.5730 | 7.6481 | 7.5652 | 34.1923 | 34.6306 |
| | ALL | 2.3442 | 2.2387 | 1.1306 | 1.6268 | 51.7703 | 27.3328 |

satisfactory modeling performance even in the worst cases. Considering the best cases, it is concluded that the proposed hybrid procedure produces nitrogen loss estimates for nearly all hidden layer unit counts, with MAPE values of about 1–2%. Moreover, these values were observed even below 1.5% in some cases (where the number of hidden layer units is 8, 12, and 13). Furthermore, in many cases, it can be said that the percentile errors were much lower than 1% for the training and validation sets, and also quite satisfactory at around 6–8% for the test set. When the results of all experiments for each number of hidden layer units are considered, it is seen that H-CFNM-PM produced the best predictions, in which the case of the hidden layer unit number was 8.

In this case, H-CFNN-PM produced predictions with MAPE values of 0.15% in the training, 0.07% in the validation sets, and 6.56% in the test set. In this scenario, all of the experiments, that is, a whole of training, validation, and test sets, are considered together, it can be seen that the predictions are produced by H-CFNN-PM with an error of about 1% (1.06%). FFNN, on the other hand, was able to produce predictions with an error of approximately 2.03%, even at its best (where the number of hidden layer units is 6), when all experiments were taken into account. Thus, it is concluded that the proposed H-CFNN-PM produces 18% better predictions than FFNN, even in this case. When each case of the hidden layer unit numbers is considered separately, it can be seen from the percentage progress values in the progress columns that the proposed H-CFNN-PM exhibits considerably superior predictive performances compared to FFNN, for both the best cases and the worst cases. For example, these progressions were around 55 and 41% when the proposed method was at its best (where the number of hidden layer units is 8). Moreover, 18 and 65% even when FFNN is at its best (where the number of hidden layer units is 6).

In addition to all these findings, some performance measures for the best results produced by FFNN and the proposed H-CFNN-PM, together with the results produced by the RSM, which is a statistical-based model, were given in Table 5.

From Table 5, it is seen that the hybrid procedure, proposed to predict the amount of nitrogen loss in the composting process, has the best prediction/modeling ability in terms of both RMSE and MAPE criteria.

The success rankings created by considering the performance of all three models according to the RMSE and MAPE criteria were found to be the same (Fig. 5). These figures show that the proposed H-CFNN-PM

**Table 5**
The results of the FFNN and the proposed H-CFNN-PM, in terms of RMSE and MAPE

| Criterion | Data Set | RSM | | FFNN (architecture of 13–6-1) | | | | H-CFNN-PM (architecture of 13–8-1) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | — | Rank | The Best | Rank | The Worst | Rank | The Best | Rank | The Worst | Rank |
| RMSE | Tr. | — | — | 0.2813 | 3 | 0.7620 | 4 | 0.0330 | 1 | 0.2028 | 2 |
| | Val. | — | — | 0.1274 | 2 | 0.8167 | 4 | 0.0291 | 1 | 0.3234 | 3 |
| | Test | — | — | 4.6228 | 3 | 6.1460 | 4 | 2.3364 | 1 | 2.5789 | 2 |
| | ALL | 3.0954 | 5 | 0.8795 | 3 | 1.5390 | 4 | 0.3615 | 1 | 0.5595 | 2 |
| MAPE | Tr. | — | — | 0.9497% | 3 | 3.3686% | 4 | 0.1594% | 1 | 0.9080% | 2 |
| | Val. | — | — | 0.6251% | 2 | 4.3047% | 4 | 0.0715% | 1 | 1.2063% | 3 |
| | Test | — | — | 8.8530% | 3 | 13.1703% | 4 | 6.5652% | 1 | 7.8514% | 2 |
| | ALL | 15.1244% | 5 | 2.0324% | 3 | 4.9025% | 4 | 1.0620% | 1 | 1.9425% | 2 |

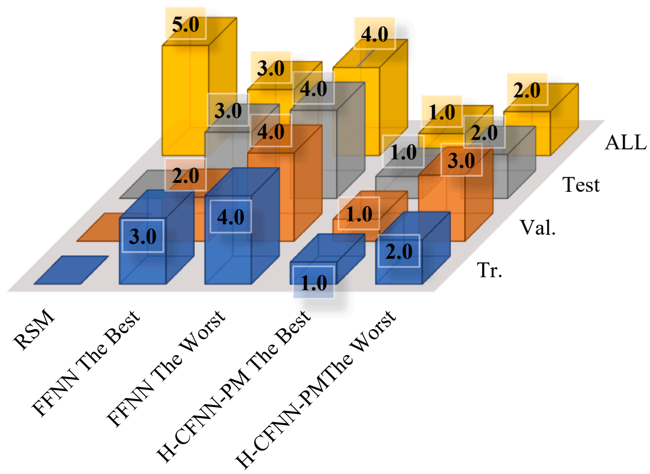


**Fig. 5.** The performances of the prediction tools, in terms of RMSE and MAPE.

displayed better prediction ability than both RSM and FFNN, even in its worst-case in 30 runs for all data sets, according to the RMSE. In terms of the RMSE criterion, the proposed H-CFNN-PM had the best two success rankings in the best and worst cases, in other words, it showed the best second performance even in its worst case, compared to RSM and FFNN.

Another perspective in evaluating the results of the estimator used to predict nitrogen loss is investigating consistency/reliability and validity. It is a fact that the performances of the prediction tools will vary because of chance and random effects that are always present in a modeling process in the different analyses. Keeping these variabilities within narrow limits from one implementation to another is a success criterion for a modeling/prediction tool and is known as the reliability of the modeling tool. Also, validity that measures the closeness of the predictions to the target values is a measure of accuracy for a prediction or modeling tool. Both reliability and validity are the looked-up properties for a satisfactory modeling tool.

In this perspective, to evaluate the reliability and the validity of the H-CFNN-PM, 30 times running was carried out and the obtained results were compiled and evaluated, over the best case of validation sets. For this purpose, in consequence of the 30 times run, the standard deviation statistics of the RMSE criterion were given in Table 6, together with the minimum, maximum, and mean statistics. By running the proposed H-CFNN-PM to predict nitrogen loss in composting process 30 times, from Table 6, it is seen that the proposed H-CFNN-PM generated the predictions with rather small RMSE values for each number of hidden layer neurons, even considering maximum statistics. These findings indicate that the obtained predictions have the property of validity, i.e., the H-CFNN-PM proposed to predict nitrogen loss in composting process is a valid prediction tool for this problem. Moreover, observing the pretty low standard deviations is also an indication of the reliability of the proposed prediction tool.

Moreover, the distribution of MAPE values obtained from 30 repetitions in the prediction of nitrogen loss in the composting process can be presented with the graphs given in Fig. 6(a-h). The reason why the distribution of the MAPE values for the test set, which has higher values than the training and validation sets, has a systematic appearance is that the results are ordered in descending order to be more easily observed and interpreted. These scatter plots constructed with MAPE values also contain and display information about the reliability and validity of the proposed H-CFNN-PM. 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 these plots, for all hidden layer neurons numbers, it is observed that the MAPE values of predictions of the H-CFNN-PM are scattered between 0.00 and 0.04% for the training sets, the validation sets, and the entire data. In the meantime, for the test sets, for all hidden layer unit numbers,

**Table 6**
Some statistics for RMSE criterion from 30 runs

| # Hidden Layer Neuron | Data Set | Statistics | | | |
|---|---|---|---|---|---|
| | | Min. | Max. | Mean | Std. Dev. |
| 6 | Training | 0.2074 | 0.2892 | 0.2550 | 0.0255 |
| | Validation | 0.0556 | 0.4376 | 0.1963 | 0.0988 |
| | Test | 1.6211 | 6.4048 | 3.1875 | 1.2328 |
| | ALL | 0.4348 | 1.1377 | 0.6655 | 0.1816 |
| 7 | Training | 0.2016 | 0.2870 | 0.2515 | 0.0237 |
| | Validation | 0.0530 | 0.4736 | 0.2201 | 0.0910 |
| | Test | 1.3003 | 5.7194 | 3.0159 | 0.9522 |
| | ALL | 0.4088 | 1.0343 | 0.6419 | 0.1384 |
| 8 | Training | 0.0330 | 0.2895 | 0.2433 | 0.0497 |
| | Validation | 0.0291 | 0.3234 | 0.1838 | 0.0687 |
| | Test | 1.4235 | 5.8271 | 3.0470 | 0.8587 |
| | ALL | 0.3615 | 1.0513 | 0.6353 | 0.1363 |
| 9 | Training | 0.1924 | 0.2830 | 0.2525 | 0.0226 |
| | Validation | 0.1237 | 0.3968 | 0.2306 | 0.0676 |
| | Test | 1.3000 | 5.9780 | 2.6542 | 0.9822 |
| | ALL | 0.4034 | 1.0460 | 0.5925 | 0.1377 |
| 10 | Training | 0.0706 | 0.2930 | 0.2315 | 0.0496 |
| | Validation | 0.0515 | 0.4165 | 0.1931 | 0.0944 |
| | Test | 1.4823 | 4.9075 | 2.8556 | 0.7078 |
| | ALL | 0.4253 | 0.9177 | 0.6009 | 0.1122 |
| 11 | Training | 0.1548 | 0.2912 | 0.2360 | 0.0375 |
| | Validation | 0.0770 | 0.5034 | 0.2395 | 0.1111 |
| | Test | 1.3452 | 4.6326 | 2.8006 | 0.8153 |
| | ALL | 0.3998 | 0.8860 | 0.6029 | 0.1280 |
| 12 | Training | 0.0577 | 0.2922 | 0.2365 | 0.0522 |
| | Validation | 0.0546 | 0.4185 | 0.1902 | 0.0960 |
| | Test | 1.2605 | 5.8721 | 2.7534 | 1.0104 |
| | ALL | 0.3571 | 1.0226 | 0.5894 | 0.1484 |
| 13 | Training | 0.0129 | 0.2886 | 0.2284 | 0.0580 |
| | Validation | 0.0081 | 0.3784 | 0.1902 | 0.0918 |
| | Test | 1.6802 | 6.2082 | 2.9352 | 1.0198 |
| | ALL | 0.3770 | 1.0295 | 0.6096 | 0.1445 |

the MAPE values ranged from 0.04 to 0.08%, an indication that the estimates are quite reasonable both in terms of pure value and variation.

In the light of all these findings, it is clearly said that RSM does not have a modeling/prediction ability at a level of competing with the proposed H-CFNN-PM. As for FFNN, although it is relatively successful in the prediction task of nitrogen loss in the composting process, still, it lacks competition with the proposed H-CFNN-PM. The main reason for this is that while RSM focuses on linear and FFNN or focuses on nonlinear relationships, the proposed approach handles both linear and nonlinear relationships together and simultaneously. Moreover, there is no concrete information about the generalization ability of the RSM in the prediction process since RSM does not use a part of the realized experiments as an out-of-sample data set. Moreover, there is no concrete information about the generalization ability of the RSM in the prediction process since RSM does not use a part of the realized experiments as an out-of-sample data set. This issue, particularly when creating and designing new experiments is difficult or costly, poses a problem. Thus, the proposed H-CFNM-PM has proven to be a very valid model, producing exceptionally reliable results.

### *3.2.4. The statistical effects of the poultry waste ratio on the nitrogen loss*

In an experimental design, the reason for alteration in the values of dependent variables is different levels of independent variables. In other words, it is expected that the different levels of independent variables in the different designs cause different dependent variable values. In this respect, it can be investigated the statistical effects of the independent variable (in this study; poultry waste ratio with the level of 10, 25, 40, 100, and 0% ratios) on the dependent variable (in this study; nitrogen loss). For this purpose, a two-way univariate analysis of variance (ANOVA) was performed. In the ANOVA analysis, the levels of poultry waste ratio were taken as 0, 10, 25, 40, and 100%. In ANOVA, the composting period, on the other hand, was taken as a covariate as day.

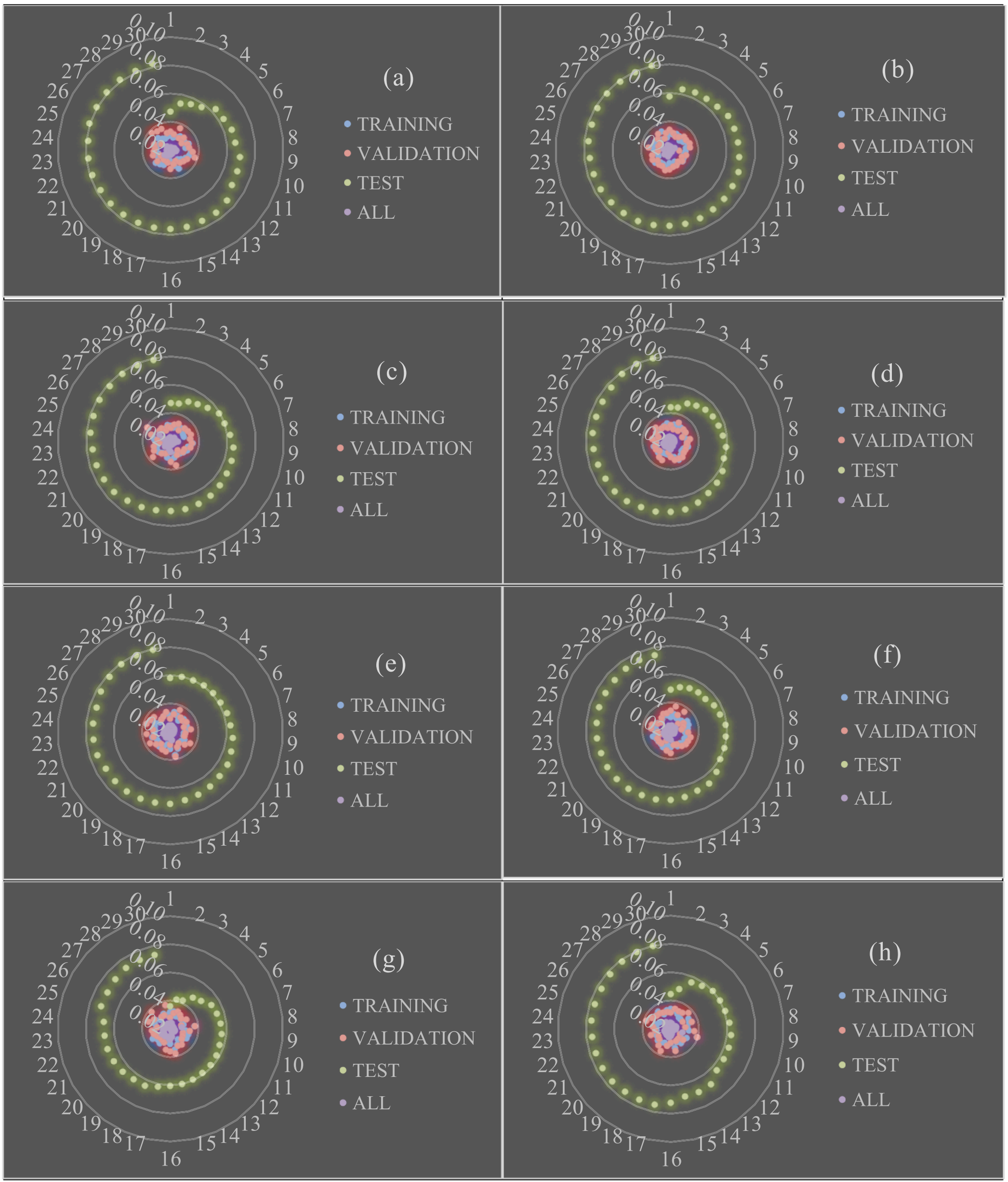


**Fig. 6.** The distribution of MAPE for 6 HLN (a), for 7 HLN (b), for 8 HLN (c), for 9 HLN (d), for 10 HLN (e), for 11 HLN (f), for 12 HLN (g) and for 13 HLN (h).

The results of the ANOVA analysis are given in Table 7.

From ANOVA results given in Table 7, it is seen that the poultry waste ratio had statistically significant effects on the dependent variable, nitrogen loss ($p < 0.001$). The greatness of this effect was measured as 0.803, this Partial Eta Squared value indicates a strong influence on the nitrogen loss in composting process. The question that comes to mind at this stage, nitrogen loss differs at what levels of the independent variable. Binary comparisons can be used to answer this question. In 5% levels of significance level, the pairwise comparison results with Bonferroni adjustment are given in Table 8.

As a result of the pairwise comparisons, in 5% level of significance

**Table 7**
The results of ANOVA

| Source | *F*-Value | *p*-Value. | Partial Eta Squared |
|---|---|---|---|
| Intercept | 10.350 | 0.002 | 0.130 |
| Day | 103.979 | <0.001 | 0.601 |
| Poultry waste ratio | 70.332 | <0.001 | 0.803 |

**Table 8**
The pairwise comparison results

| (I) | (J) | Mean Difference (I-J) | *p*-Value | 95% Confidence Interval for Difference | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| 0% | 10% | 38.141 | <0.001 | 28.091 | 48.191 |
| | 25% | 39.471 | <0.001 | 29.421 | 49.521 |
| | 40% | 32.168 | <0.001 | 22.118 | 42.218 |
| | 100% | −1.162 | 1.000 | −11.211 | 8.888 |
| 10% | 25% | 1.330 | 1.000 | −8.720 | 11.380 |
| | 40% | −5.973 | 0.893 | −16.023 | 4.077 |
| | 100% | −39.302 | <0.001 | −49.352 | −29.252 |
| 25% | 40% | −7.303 | 0.387 | −17.353 | 2.747 |
| | 100% | −40.632 | <0.001 | −50.682 | −30.582 |
| 40% | 100% | −33.329 | <0.001 | −43.379 | −23.279 |

level, it was observed that there were statistical differences between 0 and 10, 25, 40, and 100% poultry waste ratios, in terms of nitrogen loss ($p < 0.001$). Similarly, in terms of nitrogen loss, there were statistical differences between 10 and 100% ratios, 25 and 100% ratios, and 40 and 100% ratios ($p < 0.001$).

### 3.3. Optimization of the parameters by genetic algorithm

In this study, the H-CFNN-PM was proposed to predict nitrogen loss in the composting process. Thanks to its feature to model both linear and nonlinear relationships together and simultaneously, the proposed H-CFNM-PM demonstrated unsurpassed prediction capabilities. However, it can still be mentioned a problem that needs to be solved in order to model the nitrogen loss in the composting process. This is a problem of determining independent variable values that will minimize nitrogen loss during the composting process. So, it is an optimization problem to minimize nitrogen loss. In a general manner, an optimization problem with N decision variables, and J +K constraint can be given as follows.

$$\min/\max\left(f_1\left(\underset{-}{x}\right)\right)\quad\left(\underset{-}{x}=[x_1x_2\cdots x_N]\right)$$

$$\begin{array}{rlll} & g_j(\underline{x})\leqslant 0 & ; & j=1,2,\cdots,J \\ subject\ to & h_k(x)=0 & ; & k=1,2,\cdots,K \\ & x_i^{(L)}\leqslant x_i\leqslant x_i^{(L)} & ; & i=1,2,\cdots,N \end{array} \tag{3}$$

In this study, this optimization problem is addressed by a genetic algorithm. The outputs of the trained H-CFNN-PM, i.e. the predictions of nitrogen loss, constitute the objective function values of the optimization process. The decision variables also compose of 7 parameters; PWR, duration, MC, EC, temperature, pH, and C/N.

To evaluate the results of the optimization transaction the desirability level given in Eq. 4 is considered. In this equation, while S is the importance level of dependent variables in the optimization process, $Min_m$ and $Max_m$ represent the limit values of dependent variables.

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

GA produces optimal values with a desirability of 0.99998 for minimizing nitrogen loss. In optimum case, when PWR is 17.20%, duration is 97.64 days, MC is 42.87%, EC is 1.20 mS/cm, pH is 6.50, and C/N ratio is 15.02, the minimum nitrogen loss can be obtained as around 0.00188. Thus, it can be said that GA reached nearly the best values of decision variables with the desirability level of 0.99998.

## 4. Conclusions

In this study, the effects of some physical and chemical parameters affecting the maturation of compost were investigated on nitrogen loss in the co-composting of PW and FW, and compared to the mono-composting of PW and FW. It was observed that nitrogen losses increased with the increase in temperature in all reactors. The pH values of the final composts were found in the desired range, except for Reactor 4. While co-composting arranged the pH of the composts, it also caused a decrease in nitrogen losses. Nitrogen losses increased significantly, especially at pH $>$ 8 values. It was observed that when EC and TOC values decreased in all systems, nitrogen losses increased. A lower C/N ratio resulted in greater nitrogen loss. In addition, MC values above 65% led to an increase in nitrogen loss. Co-composting of PW and FW resulted in reaching the thermophilic temperatures and reduction of high MC and nitrogen loss. The lowest nitrogen losses were found to be 11.93 and 14.44% for 10 and 25% PW ratios, respectively. In addition to these experimental design findings, this study was aimed both to predict nitrogen loss in the co-composting process and to optimize the process parameters. The existing ANN-based approaches put forward for this purpose only consider the marginal effects of each parameter. However, it is clear that their interactions will have a significant contribution as well as their marginal effects on the process. Besides that, although RSM considers the effects of the interactions of the parameters, it is only based on the linear combination of them. From this point of view, a hybrid model was created in which all interactions that could contribute to the model were included in the system and CFNN's contribution to the analysis as a machine learning method was utilized to overcome these shortcomings of both models. Also, an optimization process using a genetic algorithm was carried out to obtain the parameter values that would give the minimum nitrogen loss. It was possible to consider the values other than the existing experiments by this process. Thus, it is desired to create a tool where researchers can consider all the situations in the experiments in detail without the need for a new experimental design in their new research.

For the different hidden layer neuron numbers of CFNN, the proposed prediction tool produced predictions with MAPE values of approximately 1–2% on all data points containing the training, validation, and test datasets, even for the worst cases. These results can be considered outstanding, especially when compared to RSM, which produces predictions with MAPE values of approximately 15% on all data points. In addition, the proposed H-CFNN-PM also generated the predictions for out-of-sample data, unlike RSM, with MAPE values of about 6–8%. The reliability and the validity of the H-CFNN-PM were proved by results of the 30 times running. MAPE values obtained from 30 times running were scattered between 0.00 and 0.04% for the training sets, the validation sets, and the entire data. This range for the test set was between 0.00 and 0.08% that is rather reasonable and narrow. The statistical effects of PW with the different ratios on nitrogen losses were investigated. Moreover, by ANOVA analysis, it is exhibited that PW ratios had statistically significant effects on the dependent variable, nitrogen losses ($p < 0.001$). Finally, GA was used to determine optimum values of the decision variables to minimize nitrogen loss amount in composting process. The optimal values were found as PWR of 17.20% and a duration of 97.64 days.

As a result, it has been revealed that the proposed H-CFNN-PM in this study can be used as a reliable and valid tool for predicting nitrogen loss, and by optimizing this tool, parameter values that will produce the minimum nitrogen loss can be determined. These findings are invaluable, especially when it is costly and difficult to renew the composting process by creating a new experimental setup.

## 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.

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