Journal of Applied Science and Environmental Studies
JASES
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Mixture design formulation for optimized composting with the perspective of using artificial intelligence optimization algorithms

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Received 26 Nov 2018 ; Revised 05 Jan 2019, Accepted 08 Jan 2019
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Keywords
Mixture design
Surface response
The composting process
optimization

Abstract

The increasing population size generates an increase in the amount of waste in the landfill. Most of this waste is biodegradable and its removal with traditional methods has many effects on the environment and public health. Thus, the composting process as new biotechnology allows the transformation of waste into a new useful product can be used in this case to produce the compost which can be used as bio-fertilizer in agriculture. The achievement of compost is a complicated task because of the non-linear interaction between biological and physic-chemical parameters in all steps of the process. Moreover, the composting process poses many other difficulties lies in the fact that it takes a long time for the degradation, maturity, and stability of organic matter and it has also the difficulty to find the bestformulation of feedstock leading to a C/N(Carbon/Nitrogen) ratio around 12 which is considered as a sign of maturity of the compost. That's why an accurate optimization of the composting process is necessary for predicting the process parameters such as pH, C/N, %M (Moisture), EC (Electrical Conductivity) ensuring a good quality of compost, and the efficiency of the process. In order to optimize our process, the mixture-designs have been used in this article. The performance of the predictive models of C/N ratio and %OM will be a function of the rate of the different substrate of feedstock and will be measured using the coefficient of determination (R2) which is 85,31% for C/N and 71.64% for %MO.

1. Introduction

The agriculture context of Morocco is currently favorable to a significant insertion of new fertilizing products based on recycling organic waste such as compost. Therefore, an accurate prediction of the composting process parameters is an ultimate objective in order to minimize the timing of the compost production management. Generally, producing an accurate and reliable forecast of composting parameters is of a great importance for all the markets of biotechnological industry, such as programming the production of energy and fertilizing products, the maintenance and operation of composting machines, and design of adequate strategies to introduce the bio-fertilizing products resulting of composting operation as a strategic level in order to reply to two goals: contributing on Morocco Green Plan (MGP) and reducing waste as well as pollution. A wide variety of mathematical models have been developed for the prediction of composting process parameters using traditional and intelligent models. In this paper, the determination of the optimal formulation between different substrate of feedstock to obtain compost with the required characteristics in terms of C/N and % OM is carried out by a quadratic model based on mixture designs. The model was validated using an ANOVA analysis. The structure of this paper is as follows: Section 2 presents a review of the composting process. Section 3 is reserved for the definition of mixture designs experiment. Section 4 is destined of the finding results and discussion.

2. Composting process

Composting process is a physic-chemical and biological process which involves a consortium of bacteria for decomposing and stabilizing the organic matter containing in bio-waste[1].This process can be also considered as a spontaneous degradation of the organic matter by involving microbial population in a warm, moist, and aerobic environment given the right conditions. It can carry out into anaerobic or aerobic conditions [2].

The composting process is carried out by which the four following microbiological stages as a function of the temperature. These stages are mesophilic, thermophilic, cooling, and maturation [1] as shown in figure 1.

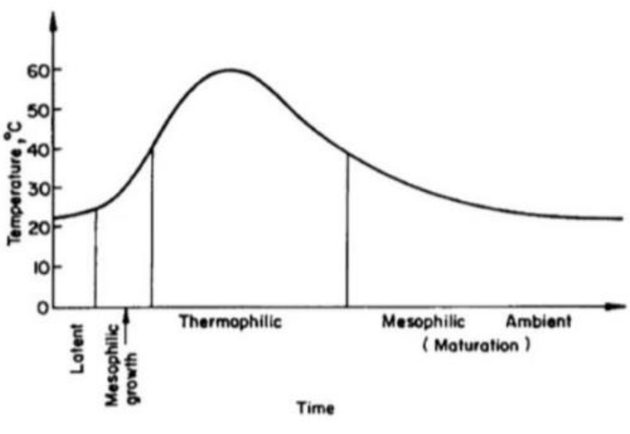


Figure 1: Temperature profile during the composting process time

The obtaining of compost with optimal qualities requires a careful control because of the change of their physical and chemical parameters with time. The quality of the compost is, also, evaluated by its maturity and stability which are depended on the quality of feedstock materials[3][4][5]. Before the application of the compost in agricultural land, it must take into consideration that it should be mature and the microbial activity is very reduced and stabilized. These requirements are evaluated by different physicochemical parameters defined in several studies[6][7][8]. The configuration of the case study of the present compost is shown in figure 2.

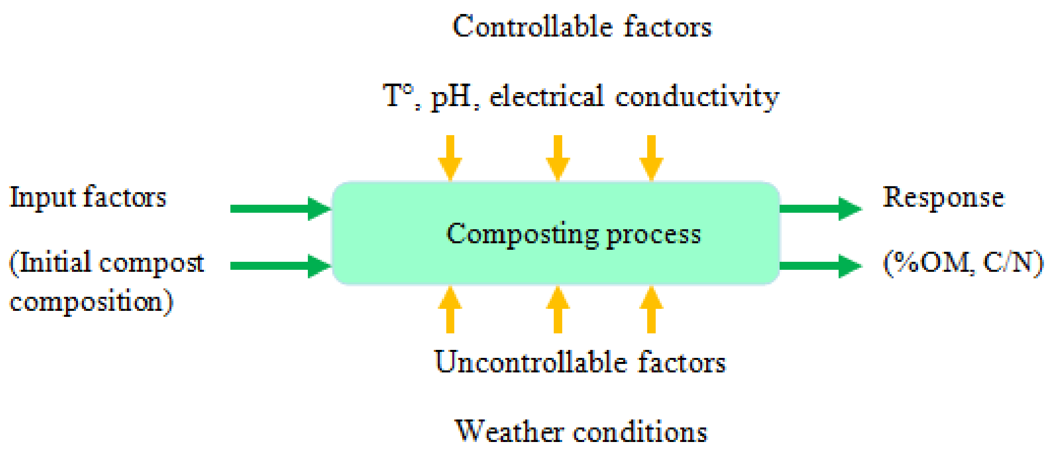


Figure 2: Configuration of the composting process

3. Physic-chemical parameters of the composting process

The composting process is influenced by various physic- chemical parameters which are important in the growth of the microbial population, such as pH, Temperature, C/N ratio, Electrical conductivity, moisture content. There are other factors influencing this process, such as aeration, initial particle size, and the frequency of turning. Indeed, the pH is a crucial factor in composting process which has an effect on microbial activities and can increase the NH3/NH4 ratio when it is in high level[9][10]. The moisture content has an impact on the oxygen consumption, microbial activity, free airspace, and temperature of the process. Its optimal range depends on the type and form of waste. Some studies revealed that the moisture content of the feedstock should be at 50%-60%[2][11]. The temperature is one of the most important parameters in the composting process which contributes in the speeding up of the biodegradability of organic matter by microorganisms[12]. The C/N parameter is a ratio composed of Carbon and Nitrogen which are the most important nutritional element for microorganisms. Indeed Carbon is used as an energy source while Nitrogen is used for building cell structure and the limitation of Carbon can lead to the decrease of microbial growth population[13][14][15]. Moreover, high N content and low C/N ratio leads to more ammonia volatilization in the composting process. The range of 20-30 was considered as the ideal in composting[16][17]. Electrical conductivity was defined as a numerical expression of conduction of electrical current by an aqueous solution[18]. It indicates the salinity of an organic amendment which rises during the composting process by the decomposition of complex organic matter[3][19].

4. Optimization tools applied to composting process

There is huge optimization methods applied to the composting process in the literature. Statistical approaches and advanced methods based on artificial intelligence or deep learning is the most evoked in scientific research. Optimization by Response Surface Methodology as a statistical tool is used to optimize moisture parameter and C/N ratio (C/N: 8.3) in the process of decomposition of kitchen waste to obtain stable and mature compost. Indeed, the mathematical model of ANOVA with p-value < 0.05 depicts a high accuracy for both moisture and C/N with a coefficient of correlation 99.58 % and 98.53 % respectively[14]. Simplex-centroid mixture is used to optimize the composting process of kitchen waste composed of vegetable scraps, fish processing waste, and newspaper or onion peels in order to determine the best formulation leading to the desired initial moisture content (50% to 65%) and C/N ratio (20–40) [20]. A central composite experimental design is utilized to optimize composting process conditions of leucaenas trimming residues shows satisfactory results for predicting Organic matter, Kjeldahl-N, C/N ratio, and N-losses parameters using as input parameters time, aeration, Moisture, and particle size [21]. Regression models based on mixture experimental design is used to predict the contribution of each organic component (dewatered sludge, food waste, mixed paper waste, sawdust, and branches) in the biodegradability of the global mixture. This study has also as the main focus to determine the influence of initial C/N and moisture content on the composting process of above-mentioned residues[22]. a central composite experimental design was also used to study the effect of control parameters such as moisture, aeration, and C/N ratio on the parameters of composting process monitoring as follows: temperature, pH, O2 and volatile compounds in the co-composting process of municipal solid waste and pine trimmings [23]. In the other hand, artificial intelligence is also more evoked in the field of the composting process. Indeed, Sun et al. devoted a part of their research to AI-based process control techniques by designing a Genetic-Algorithm (GA)-aided Stepwise Cluster Analysis (SCA) method to map the nonlinear relationship between the selected inputs variables and the C/N ratio in food waste composting. This coupling between GA and SCA shows a good agreement between the predicted and the experimental values of C/N[24]. Another study adopted a benchmarking between Artificial Neural Network (ANN)-based multilayer perceptron and the traditional Multiple-Linear Regression (MLR) in the efficiency of composting process monitoring parameters such as pH and temperature. The study shows that the prediction is more accurate using ANN than the traditional MLR, the figure 3 below illustrate the architecture of the adopted ANN pattern[25].

The ANN was used to predict the ammonia emissions from composted sewage sludge. Indeed, the study shows a high model accuracy which is between 0.972 and 0.981 and depicts the key parameters responsible for ammonia emissions released in composting are pH and C/N[26]. Chen et al. were achieved a comparative study between traditional MLR and Back Propagation (BP) artificial neural network model in the prediction of N2O emission and nitrogen loss from swine manure composting. The main characteristics of the prediction model such as MAPE(Mean Absolute Percentage Error) and MSE (Mean Square Error) using BP-ANN show a good performance in comparison with MLR [27] as depicted in the figure 4. The following sections of this paper will treat the optimization of the composting process using the mixture design.

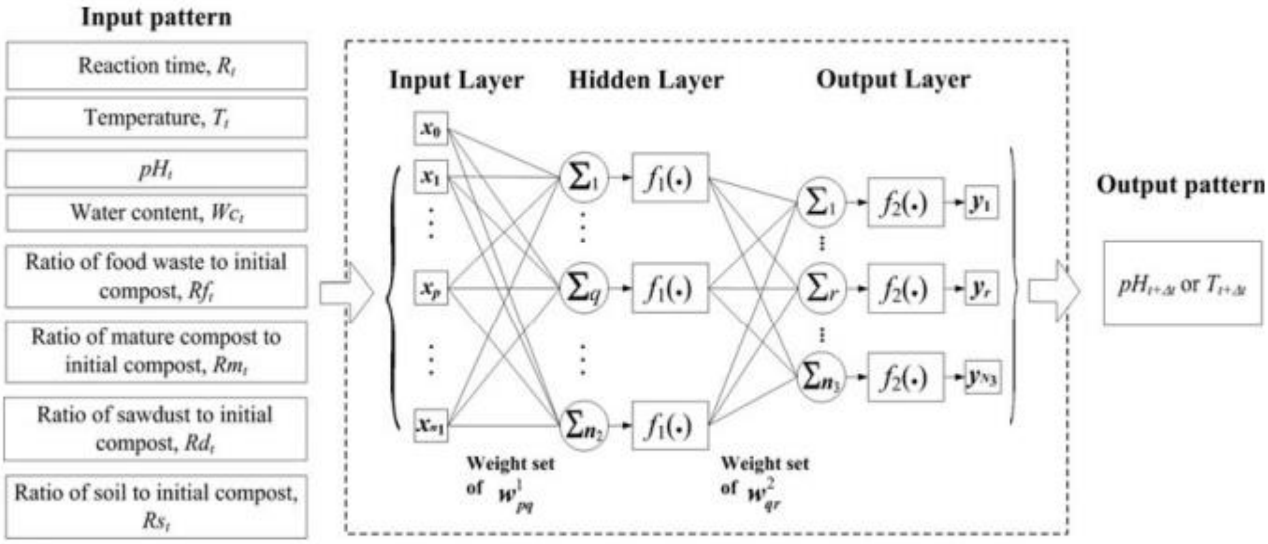


Figure 3: Architecture of Multi-Layer Perception Neural Network

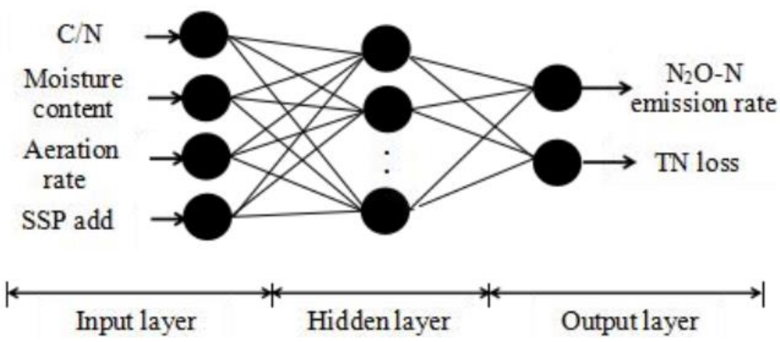


Figure 4: The sketch map of BP network

	Model	N_2O-N emission	TN loss
MAPE (%)	BP network	138.85	11.06
	Linear regression	250.82	19.28
MSE	BP network	1.17	24.72
	Linear regression	1.43	50.49

Table 1: Comparison between traditional multilinear regression and BP-ANN

5. Mixture designs experiment

Statistical techniques are destined to analyze the behavior of an experimental system in order to understand it and enhance its performance. Experimental design can be used as an optimization method of industrial processes as well as for making the formulation of products. To make an experimental design, it's necessary to have an experimental device which delivers one or several responses. The outputs of systems depend on a set of inputs parameters called "factors" characterized by the independent feature. The uses of experimental designs bring an optimal

number of experiences and capitalize knowledge by observing and understanding the impact of different ratios of inputs variables on the response (s). They also identify the optimal combination able to fulfil the desired objective. The mathematical model resulting from the experimental design is used to make a prediction without making experiences. The fitting multiple regression models with the intercept set to zero and the response surface system are the most tools used by mixture designs experiment to analyze formulation problem solving.

6. Methodology

Data used in the present study was the result of Ph.D. students of DHAR MEHRAZ, Fes, Morocco University. The compost was made from the combination of the following substrate: Poultry Litter (PL), Olive Mill Wastewater (OMW), Olive Mill Solid Waste (OMSW), and Green Waste (GW) as shown in figure 5. The Olive Mill Wastewater is used in the watering of the compost instead of using water. This solution saves water resources and reduces water steams pollution caused be the removal without treatment of OMW. To carry out this compost, 19 experiences have been launched in buckets of 10 Kg with a weekly follow-up of different physical-chemical parameters and aeration in order to avoid the generation of anaerobic environment caused by high moisture content of different substrate. Data analysis generated from these experiences has been made by mixture designs experiment with 4 factors and Simplex centroid network as a matrix of experience. Minitab 18 was used as data processing software.

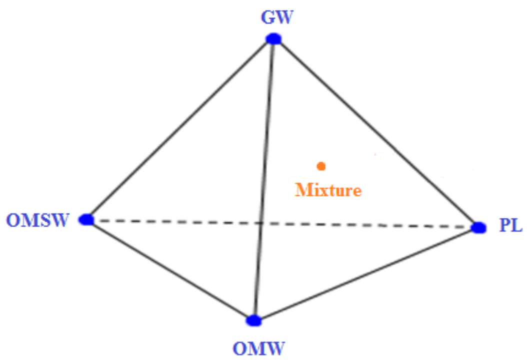


Figure 5: Graphic representation of a mixture with 4 compounds

7. Finding results

7.3 Experimental response

All the mixtures were made according to the dosages of the constituents defined in the matrix of experiences. The experimental responses obtained were used for the calculation of the coefficients of the polynomial. The results of C/N and %OM responses are illustrated in Figure 6 (a) and (b).

Based on these findings, as the proportion of GW, OMSW, and M in the mixture increase, the C/N and %OM increase rapidly, and as they decrease, the C/N and %OM decrease rapidly, while PL has a slow effect on both parameters. Indeed, as the proportions of C/N and %OM increase, the proportion of PL decreases. As a result, the obtaining of a C/N between 10-15 and %MO > 20%, the proportions of GW, OMSW, and OMW should be increased and PL decreased.

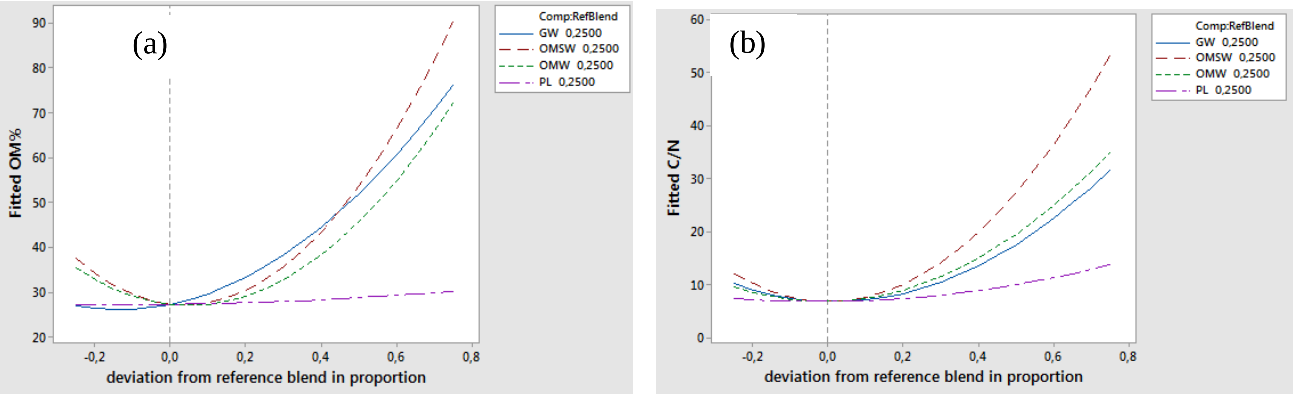


Figure 6: Cox response of fitted C/N (a) and fitted %OM (b)

7.4 The optimal solution

Desirability function deviates between 0 and 1 and reflects the degree of satisfaction of the decision-making. Desirability is 0 when the response is unsuitable, it equals 1 when the given response is very satisfactory, and it takes intermediate values for more or less satisfactory responses. The overall desirability required Dg for the desired optimum responses is a function of the elementary desirability d (%MO) and d (C/N). It is defined by the relation (1) below:

$$Dg = \sqrt{d(C/N) * d(\%OM)} \quad (1)$$

The application of a mixture design processing software allows a simultaneous optimization of both responses (C/N and %OM), it is a purely numerical procedure consisting of searching mathematically for a combination of parameters (formulation) for which the desired responses are either values optimal, either belonging to an interval of optimal values. This is the case of a multi-criteria optimization based on desirability function.

Before starting data simulation, the desired parameters were set up on the following targets:

	Goal	Lower	Target	Upper
OM%	Target	20	40	60
C/N	Target	10	12	25

The first solution given by the processing software is shown below with 1 as global desirability.

Global Solution

Components

GW	=	0,407477
OMSW	=	0,433570
OMW	=	0
PL	=	0,158953

This result shows a satisfactory solution with 1 as global desirability and 1 and 0.9999 as elementary desirability for C/N and %OM, respectively. This solution reveals the omission of OMW compound in the mixture for satisfying both responses parameters conditions. But this compound was used as a humidifier instead of using water in the present compost because it's economically and ecologically better to use OMW in the composting process to dispose of it instead to remove it directly in the soil as fertilizer because of its toxicity. Moreover, OMW is rich in biodegraded organic matter and through exothermic aerobic reactions, can produce carbon dioxide, water, mineral salts, and a stable and humified organic material[28] which are making the omission of this compound is inevitable. For this reason, another simulation was been achieved by adding 15.5% as a proportion of OMW to the mixture of the optimal solution. The carrying out of this simulation takes into consideration that the solution should belong to the optimal values interval and conserves the desirability value above 90% as shown in figure 7(b).

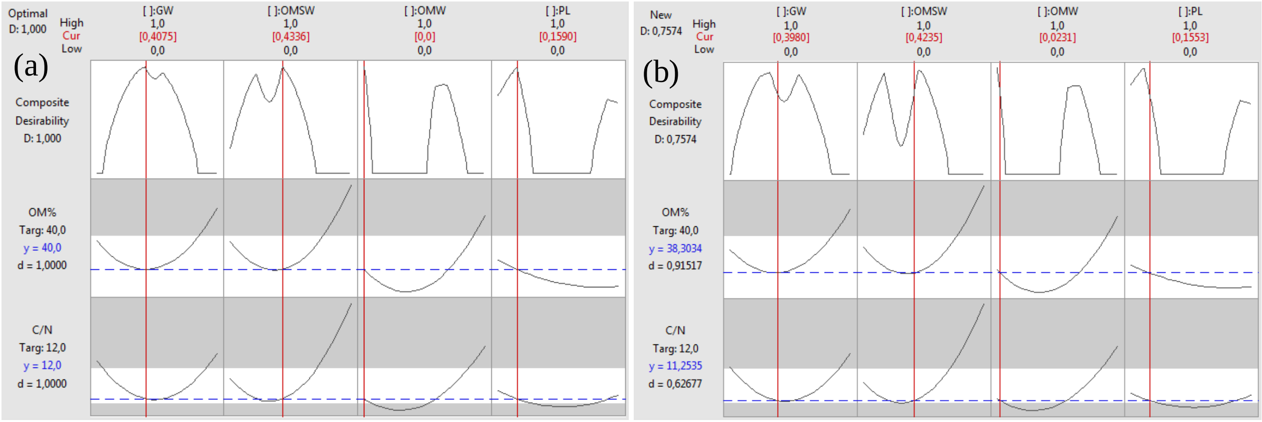
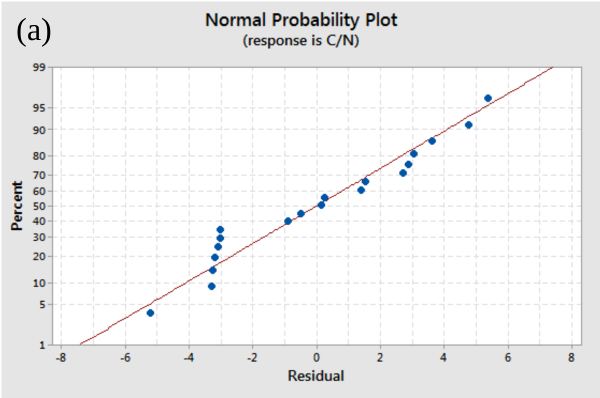


Figure 7: Optimal optimization responses (a) and with adding an amount of OMW (b)

7.5 The fitting models

The quality of the fitting model and response modeling is determined by the coefficient of correlation (R2) [29]. The responses obtained from experimentation and the experiment design data were presented in figure 8 and 9. These figures revealed that the resulting values of (R2) were 92,65 and 85, 82 for C/N and %OM, respectively, which show a fairly good agreement between the experimental and predicted values of C/N and %OM responses. According to ANOVA test, some interactions between the compounds of the fitting model were not statistically significant as the p values were 0.160 and 0.134 in C/N fitting model (figure 8b), also they were 0.470 and 0.073 in % OM fitting model (figure 9b).



(b)

Estimated Regression Coefficients for C/N (component proportions)

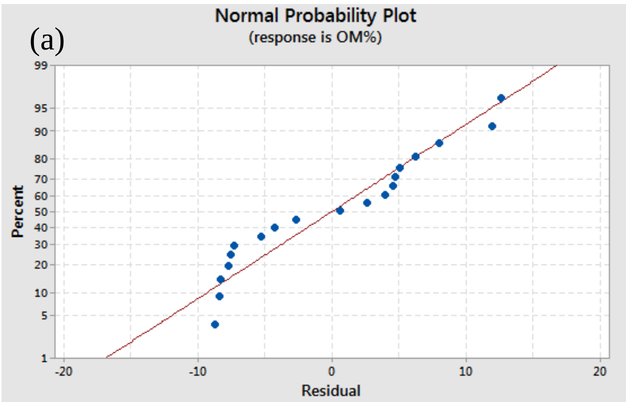
Term	Coef	SE Coef	T-Value	P-Value	VIF
GW	31,62	4,33	*	*	2,41
OMSW	53,14	4,33	*	*	2,41
OMW	34,88	4,33	*	*	2,41
PL	13,62	4,33	*	*	2,41
GW*OMSW	-109,0	19,0	-5,73	0,000	1,86
GW*OMW	-72,3	19,0	-3,80	0,004	1,86
GW*PL	-29,1	19,0	-1,53	0,160	1,86
OMSW*OMW	-110,9	19,0	-5,84	0,000	1,86
OMSW*PL	-71,8	19,0	-3,77	0,004	1,86
OMW*PL	-31,3	19,0	-1,65	0,134	1,86

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)
4,49105	92,65%	85,31%	3515,40	0,00%

Figure 8: The fitting model of C/N parameter

Based on the ANOVA test, the fitting model is significant when all model terms are significant which means they were all below 0.05 value. Thus, the “lack of fit fit” makes the prediction by using the multi-linear regression to non-linear process not adequate.



(b)

Estimated Regression Coefficients for OM% (component proportions)

Term	Coef	SE Coef	T-Value	P-Value	VIF
GW	76,14	9,83	*	*	2,41
OMSW	90,15	9,83	*	*	2,41
OMW	72,16	9,83	*	*	2,41
PL	30,04	9,83	*	*	2,41
GW*OMSW	-151,4	43,1	-3,51	0,007	1,86
GW*OMW	-118,3	43,1	-2,74	0,023	1,86
GW*PL	-32,5	43,1	-0,75	0,470	1,86
OMSW*OMW	-200,7	43,1	-4,66	0,001	1,86
OMSW*PL	-87,6	43,1	-2,03	0,073	1,86
OMW*PL	-47,9	43,1	-1,11	0,295	1,86

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)
10,1863	85,82%	71,64%	18693,8	0,00%

Figure 9: The fitting model of %OM parameter

7.6 Surface responses

Surface diagrams below illustrating the influence of each constituent parameter on the mixture. Indeed, four simulations were been achieved by setting one parameter and varying the others, their sum should be equal to unity. In each case, the fixed parameter was set on 0.25 as a reference value. The GW compound is overriding because the C/N response is more sensitive to the variations of this compound than to those of "OMW", "OMSW", or "PL". Furthermore, there would be interactions between "GW" and "OMSW" because the influence domain of "GW" is closer to the OMSW (figure10a, 10c) than the OMW (figure 10c), but the triple reaction between these compounds leads to a good result (figure 10 b). Otherwise, the influence domain of "GW" is fairly close with "PL" (figure 10a, 10c). Otherwise, a combination with only "PL" and "GW" was given a good result in a study done on the co-composting between 36% of GW and 64% of PL. The results of this study revealed 37% as a ratio of %OM and 17 as C/N ratio [30]. The analysis results of %MO response surface have the same reasoning as C/N.

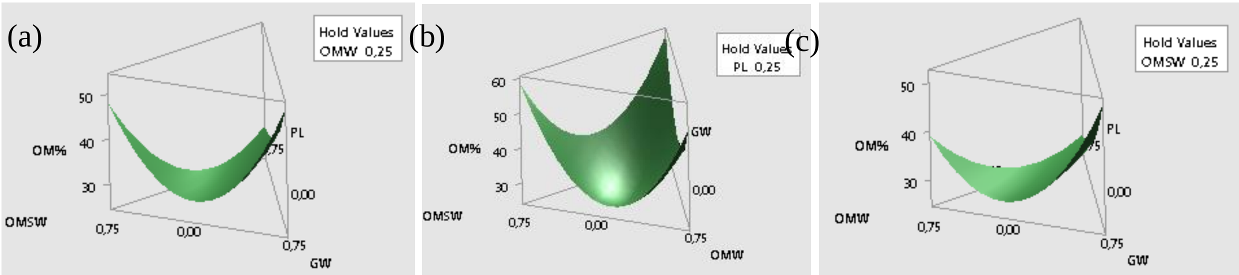


Figure 10: Surface diagrams of C/N as a function of GW, OMSW, OMW, and PL.

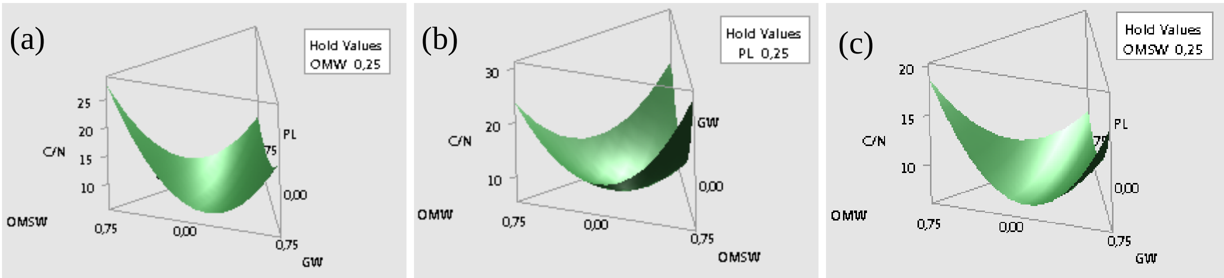


Figure 11: Surface diagrams of %OM as a function of GW, OMSW, OMW, and PL.

Conclusion

An overall satisfactory desirability of 100% has made it possible to define the optimal formulation within the experimental domain. An adding of an amount of OMW could be lead to making an optimized compost substrate. The surface response confirms the results given by Cox response which show a fair influence of PL on the formulation of the compost and there is a close correlation between the other there compounds. The fitting model of C/N and %OM revealed a fair satisfaction because of their low coefficients of correlation which were 92,65 and 85, 82 for C/N and %OM, respectively. As a result, our future work will consist of the using of Neural Networks as a simulation tool for the present data using Matlab Toolbox Software because of their adaptability with non-linear problems solving.

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