

Modeling of solid waste composting under uncertainty

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Abstract

Effectiveness in reflecting uncertainties in a modeling process is critical for ensuring forecasting accuracy and improving process efficiency. However, few previous studies made efforts toward incorporating uncertainties into composting modeling systems. The purpose of this study is to develop a methodology based on Monte Carlo simulation and factorial design to reflect uncertainties in the modeling process. The uncertain parameters under consideration include temperature, moisture content, free air space, and oxygen concentration. Monte Carlo simulations are undertaken based on composting kinetic simulator, and a set of 2^4 factorial experiments are conducted to examine the effects of the input uncertainties and their interactions. The results indicate that complexities of the system uncertainties have been effectively addressed through the developed modeling approach. The proposed method offers an effective tool for composting process simulation and control under uncertainty.

1 Introduction

Efficiency of solid waste composting is determined by physical, chemical, and biological characteristics of microbes and solid wastes, as well as a series of process parameters that control the ultimate organic transformation extent [1]. In order to maintain effective operation of the composting system, an appropriate process control scheme is desired. In fact, it is recognized that any feasible process control should depend on reliable dynamic simulation models to capture bio-complexities that exist in the system [2]. Various research works have been

conducted to develop models to simulate composting processes. These models were primarily based on mass balance and energy conservation principles, and/or experiential biodegradation kinetics [3]. For example, Kaiser [4] analyzed the thermodynamics and kinetics of composting processes and proposed a model that reflected mass transfer, heat transfer, and bio-transformation of organic materials. Stombaugh and Nokes [5] developed a model based on Monod microbial growth kinetics, and differential equations describing microbial, substrate and oxygen concentrations, as well as moisture and temperature profiles in composting processes were derived. Some other similar works can be found in Das and Keener [6], Seki [7], and Kim et al. [8].

Among these various models, kinetic models (e.g., Monod models) can be conveniently used for simulating the biochemical reactivity in composting processes [9, 10, 11]. For example, Keener et al. [12] developed an analytical model to examine the interactions among biological and physical factors based on kinetic expressions, and the effects of temperature, compost depth, and degradation rate on system performances. Due to complexities within the composting processes, the modeling efforts usually need a large number of input variables including microbial specific growth rate, biodegradation coefficient, temperature, moisture content, oxygen concentration, and free air space in the compost. In reality, these parameters are usually associated with different degrees of uncertainties. Some uncertainties are due to the difficulties in making accurate measurements, and the others may result from physical, chemical and biological complexities and dynamics [13]. Taking all of these uncertainties into account in the modeling efforts will be beneficial for reducing system cost and improving operating efficiency. However, few previous research efforts have been made toward incorporating these uncertainties within the composting modeling systems. In addition, the simulation models often exhibit various sensitivities to changes in system parameters. As a result, an effective sensitivity analysis is desired to identify key parameters.

The probabilistic analysis is the most commonly used approach to account for uncertainties in environmental simulations, and a primary approach has been the Monte Carlo simulation associated with various environmental models [14]. The Monte Carlo method was successfully applied to many engineering fields [13]; however there were few applications to composting modeling studies. In addition, conventional sensitivity analysis only considers changing one factor at a time, and the joint effects among factors cannot be examined. Fortunately, the factorial design approach can be applied to the sensitivity analysis for considering many interactive factors [15]. However, this technique was seldom applied to composting simulation studies.

This paper attempts to systematically study the influence of various uncertainties on composting modeling, through a kinetic composting modeling approach. A series of Monte Carlo simulations and a set of factorial experiments will be conducted based on the developed kinetic model to examine effects of the input uncertainties on the modeling outputs, as well as to identify key sources of uncertainties that are critical for improving system performance.

2 Methodology

2.1 Development of the kinetic composting model

Assume that homogeneous composted solid wastes consist of biodegradable solids that can be decomposed by microbes, as well as non-biodegradable solids that do not participate in the bio-reaction. The fate of solid wastes in an aerobic composting system can then be described by a first-order kinetic equation [16]:

$$\begin{cases} dM_c / dt = -K(M_c - M_e) \\ M_c = M_0 & \text{at } t = 0 \\ M_c = M_e & \text{at } t = \infty \end{cases} \quad (1)$$

where M_c is the total mass of dry compost in the system (kg), M_e is the non-biodegradable total mass (dry basis) in the system (kg), t is process time, and K is the composting rate (day^{-1}).

The concept of equilibrium mass ratio ($\beta_0 = M_e/M_0$) is used to represent the fraction of materials remaining after a long period of composting. The solid waste degradation ratio can then be described as follows:

$$C_r(t) = \frac{\Delta M(t)}{M_0} = \frac{M_0 - M_c(t)}{M_0} \quad (2)$$

where C_r is waste degradation ratio, and M_0 is initial dry mass in the composting system (kg).

By substituting equation (2) with equation (1), the following can then be obtained:

$$\begin{cases} dC_r / dt + KC_r = K(1 - \beta_0) \\ C_r = 0 & \text{at } t = 0 \\ C_r = 1 - \beta_0 & \text{at } t = \infty \end{cases} \quad (3)$$

The solution to the above problem can then be obtained as follows:

$$C_r(t) = (1 - \beta_0)(1 - e^{-Kt}) \quad (4)$$

Equation (4) can be solved to obtain the waste degradation ratio C_r when the equilibrium mass ratio β_0 and the composting rate K are known.

The composting rate K is a function of substrate compounds, microbial populations, temperature, moisture content, oxygen concentration, and free air space [17]. For example, degradation rate may exhibit significant variations for various wastes and microbial populations. In addition, suitable temperature can provide higher rate of decomposition, while inappropriate temperature would lead to reduction in microbial diversity; proper oxygen supply is important for maintaining effective microbial growth and aerobic biodegradation activities; biodegradation kinetics are also affected by moisture through changes in oxygen diffusion, water activity, and microbial growth rates; free air space is also a

critical factor for oxygen transfer that further influences heat transfer in the composting process [18].

Following Haug [1], the composting rate K can be represented by multiplicative sub-factors for temperature, oxygen, moisture content, and free air space as follows:

$$K = K_T K_{H_2O} K_{FAS} K_{O_2} \quad (5)$$

$$K_T = K_{dR1} [1.066^{T-20} - 1.21^{T-60}] \quad (6)$$

$$K_{H_2O} = \frac{1}{e^{[-17.64(1-m)+7.062]} + 1} \quad (7)$$

$$K_{FAS} = \frac{1}{1 + e^{[-23.675 * FAS + 3.4945]}} \quad (8)$$

$$K_{O_2} = \frac{(O_2 \%) }{(O_2 \%) + 2} \quad (9)$$

where K_T , K_{H_2O} , K_{FAS} , and K_{O_2} are temperature, moisture content, free air space, and oxygen concentration correction terms, respectively; K_{dR1} is the biodegradation coefficient which is related to substrate types (e.g., organic solid wastes) and microbial population; T is composting temperature ($^{\circ}C$); m is moisture fraction (wet basis) of the solid wastes in the composting system; FAS is free air space (fraction) in the compost; and $O_2\%$ is the percentage of oxygen (e.g., oxygen concentration) in the gas that is within the free air space.

2.2 Two-level full factorial design and Monte Carlo simulation

Factorial design is a classical experimental design method that allows determination of coefficients like b_i and b_{ij} , in a linear model with interactions as follows:

$$y = b_0 + \sum_i b_i x_i + \sum_{i \neq j} \sum_{j \neq i} b_{ij} x_i x_j + \dots \quad (10)$$

where y is the response of the simulation model by changing input parameters x_i and x_j , b_0 is the average effect, b_i is the main effect of parameter x_i , and b_{ij} is a second-order interactive effect between x_i and x_j . The idea of a factorial design is to arrange the simulations in such a way that variations in simulation response obtained under different settings of the factors can be traced back to those of the factors. By proper arrangement of the factor settings, it will be possible to determine not only the main effect of each factor but also the joint effects between factors on the response (y).

If the simulations are implemented at the minimum and maximum values (two levels) of each of the k factors, the design is called 2^k factorial design that needs 2^k sets of experimental tests. Through factorial design, the main effect of each factor can be determined, which is the difference between two averages:

$$b_i (\text{main effect}) = \bar{y}_+ - \bar{y}_- \quad (11)$$

where \bar{y}_+ is the average response to factors that take maximum values and \bar{y}_- is for those taking minimum ones. The measure of the interactive effect of

$A \times B$ is defined as half of the difference of the effects from factor A under conditions when factor B is at its maximum and minimum levels:

$$AB = \frac{1}{2}[A_{B+} - A_{B-}] \quad (12)$$

Rapid calculation of effects is possible using Yates's algorithm described in detail in Box et al. [15]. If there is an interactive effect $A \times B$, this means that the influence of changing factor A will depend on the setting of factor B.

In this paper, four input parameters of the developed kinetic model, including composting temperature T , moisture content m , free air space FAS , and oxygen concentration $O_2\%$, are considered uncertain, while the biodegradation coefficient K_{dRI} is considered to be a deterministic parameter. The uncertain parameters are assumed to be normal-distributed with known means and standard deviations. A set of 100 Monte Carlo simulation runs are then implemented based on the developed model to examine the effects of input uncertainties, and 2^4 factorial experiments are conducted to examine the effects of these factors and their combinations on the system performance.

3 Case study and results analysis

A windrow composting system is considered based on extensive literature review to examine uncertainties within the composting process. The C/N ratio of the waste is in a suitable range for composting, and the solid wastes are homogeneous. The non-biodegradable solids fraction (dry basis) is assumed to be 60%. The input parameters for the kinetic composting model are listed in Table 1.

Table 1 Input parameters of the kinetic composting model

Parameter	Value	
Biodegradation coefficient K_{dRI}	$4 \times 10^{-3} \text{ day}^{-1}$	
Equilibrium mass ratio β_0	60%	
Parameter	Mean	Standard deviation
Temperature (T)	50 °C	5 °C
Moisture content (m)	50%	5%
Free air space (FAS)	35%	5%
Oxygen concentration ($O_2\%$)	12%	4%

In order to examine the effects of uncertainties of these input parameters on the modeling output (e.g., degradation ratio C_r), a series of 100 Monte Carlo simulations are conducted. Thus, 100 sets of T , m , FAS , and $O_2\%$ values are generated by the normal-distributed-random-number generator at first, and then the composting simulator is implemented 100 times to obtain relevant sets of modeling outputs. The corresponding means, standard deviations, and coefficients of variation (CV) ($CV = \text{standard deviation} / \text{mean}$) are also obtained from these simulations.

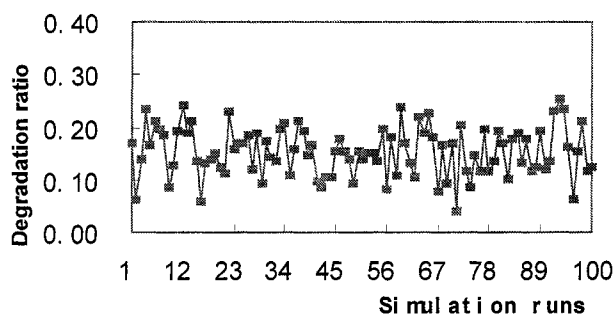


Figure 1 Degradation ratio at the 20th day

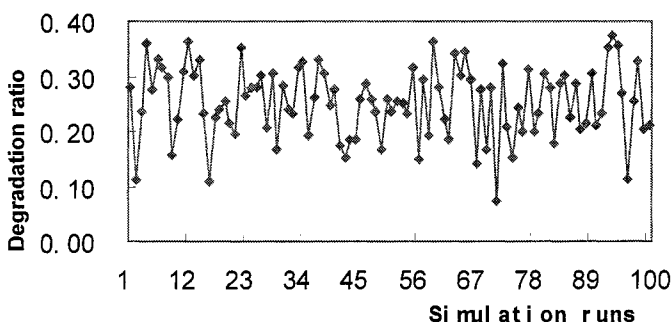


Figure 2 Degradation ratio at the 40th day

Figures 1 and 2 present the Monte Carlo simulation results of degradation ratio at the 20th and 40th days after initiation of the composting process, respectively. They reveal that uncertainties in the input parameters will have significant impacts on the modeling outputs (degradation ratios). For example, at the 20th day, the minimum and maximum values of the simulated degradation ratio are 0.039 and 0.25, respectively; in comparison, at the 40th day, these values are raised to 0.074 and 0.375. Figures 3 and 4 present results from several simulation runs, as well as the relevant means, standard deviations, and corresponding coefficients of variation (CV). It is indicated that there are significant variations of the simulated results among different runs, with the standard deviation increasing slightly with time. The variations of the simulated degradation ratio are also significant and have a tendency of slightly decreasing with time. For example, at the 10th and 20th days, the averages of degradation ratios are 0.0834 and 0.151, respectively, and the standard deviations are 0.0279 and 0.0463, respectively; in comparison, the coefficients of variation are 0.335 and 0.306, respectively. Therefore significant uncertainties exist in the model outputs from the Monte Carlo simulations.

In order to test which uncertain parameters have the most significant effects on the modeling outputs, and to examine interactions among these parameters, a set of 16 factorial experiments are implemented based on the 2⁴ factorial design.

Table 2 lists the combination of factor settings from the factorial design. The kinetic composting model is then implemented for every combination of parameters.

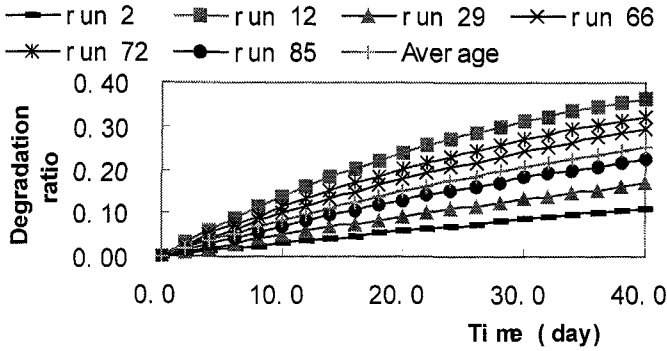


Figure 3 Degradation ratio versus time

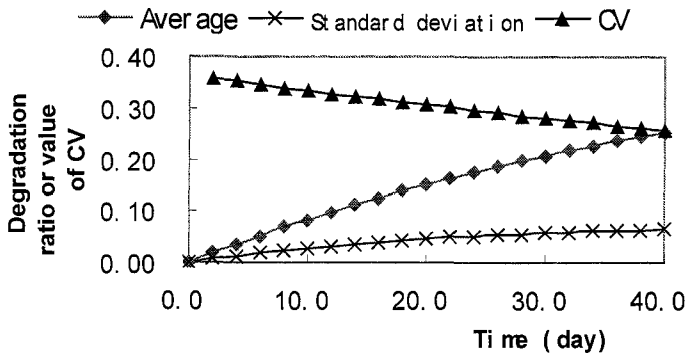


Figure 4 Average, standard deviation, and coefficient of variation for degradation ratio versus time

In order to gain insight of the sensitivity of the modeling response to various factors, the main and interactive effects should be quantified. Table 3 lists the magnitudes of various effects of the 4 factors and their combinations, where factors A, B, C, and D represent oxygen concentration, free air space, moisture content, and temperature, respectively.

It is indicated from Table 3 that the composting temperature has the largest main effect on the degradation ratio, while oxygen concentration and moisture content also have considerable levels of main effects. Through examining the effects of various factors at the 30th day, it is indicated that (a) the main effects from oxygen concentration, free air space, and temperature are 0.0388, 0.0109, and 0.0883, respectively, demonstrating that increases of these three factors will lead to increase in the degradation ratio, due to the enhanced microbial activities under improved conditions in terms of oxygen concentration, free air space, and

composting temperature; (b) the main effect from moisture content is -0.0873, indicating that this increase will lead to significant decrease of the degradation ratio, since 60% of moisture content is inappropriate for microbial activities.

Table 2 Combinations of impact factors in the 2⁴ factorial design

Set No.	Temperature <i>T</i> (°C)	Moisture content <i>m</i>	Free air space <i>FAS</i>	Oxygen concentration O ₂ %
1	40	40%	25%	6%
2	40	40%	25%	18%
3	40	40%	45%	6%
4	40	40%	45%	18%
5	40	60%	25%	6%
6	40	60%	25%	18%
7	40	60%	45%	6%
8	40	60%	45%	18%
9	60	40%	25%	6%
10	60	40%	25%	18%
11	60	40%	45%	6%
12	60	40%	45%	18%
13	60	60%	25%	6%
14	60	60%	25%	18%
15	60	60%	45%	6%
16	60	60%	45%	18%

Table 3 Estimated effects on degradation ratio

Factors	Degradation ratio ($\Delta M/M_0$)			
	t=10 days	t=20 days	t=30 days	t=40 days
Average	0.0757	0.136	0.184	0.223
A	0.0202	0.0320	0.0388	0.0428
B	0.0056	0.009	0.0109	0.0117
C	-0.0440	-0.0712	-0.0873	-0.0963
D	0.0453	0.0729	0.0883	0.0953
AB	0.0007	0.0009	0.0007	0.0003
AC	-0.0053	-0.0061	-0.0057	-0.0037
AD	0.0094	0.0125	0.0117	0.0094
BC	-0.0014	-0.0018	-0.0016	-0.0008
BD	0.0026	0.0035	0.0031	0.0026
CD	-0.0206	-0.0283	-0.0277	-0.0229
ABC	-0.0001	0.0002	0.0002	0.0003
ABD	0.0002	0.0001	-0.0002	-0.0006
ACD	-0.0021	-0.0009	0.0012	0.0039
BCD	-0.0005	-0.0002	0.0006	0.0011
ABCD	0.0	0.0003	0.0003	0.0004

The effects from interactions among the factors can also be examined. The interaction effects of AD and CD are 0.0117 and -0.0277, respectively at the 30th

day. These are comparable to the main effects of A, C and D, indicating that these interactions can significantly affect the degradation ratio. In comparison, the third and fourth-order interactions among the impact factors are negligible. As shown in Table 3, composting temperature has the most significant effects on the system performance, while oxygen concentration and moisture content also have considerable levels of impacts. Therefore, input uncertainties in composting temperature, oxygen concentration, and moisture content would lead to considerable output uncertainties in the predicted degradation ratio. Thus it is important for a composting system to maintain proper conditions of temperature, oxygen, and moisture levels.

4 Conclusions

An integrated system based on kinetic modeling, Monte Carlo simulation and factorial design is proposed for composting-process analysis under uncertainty. The system can facilitate examination of effects from parameter uncertainties through stochastic and multivariate-analysis approaches. Four uncertain input parameters, including oxygen concentration, free air space, moisture content and composting temperature, are assumed to have normal distributions. A set of 100 Monte Carlo simulation runs and 2^4 factorial analyses are implemented to evaluate effects of these four factors and their interactions. The results indicate that composting temperature, oxygen concentration, and moisture content have significant effects on the prediction results, while free air space has a relatively minor influence. Also considerable interaction effects among the impact factors are also observed. The statistics (i.e., mean, standard deviation, and coefficient of variation) from the Monte Carlo modeling results also provide useful information for quantifying the effects and the associated uncertainties.

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