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A predictor model for the composting process on an industrial scale based on Markov processes[☆]

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ABSTRACT

The biochemical and physical characteristics of composting processes have been historically modeled from an analytic point of view. Recently, stochastic approaches pushed forward the short-term forecast for the observed behaviour, but no model deals well with long-term predictions, especially when dealing with industrial data. We present a new approach, based on Markov processes, that shows good accuracy when predicting the long-term evolution of composting processes on an industrial scale. The proposed model deals with incomplete industrial data even for unevenly spaced observations, learns from past observations improving accuracy as data grows, and shows excellent predictive capabilities for time spans larger than 200 days and for heterogeneous large scale compost windrows. With our model, predictions can be obtained in real-time using Monte-Carlo runs. The model may be extremely convenient for industrial environments where large amounts of incomplete available data make it very difficult to use other prediction approaches.

1. Introduction

Waste management is one of the main economic, social and environmental challenges of the 21st century. As the income level and rate of urbanisation keep increasing, the amount of waste produced is also greater. Organic solid waste management is especially demanding given its heterogeneous nature and diverse sources - agricultural, industrial and municipal.

In developed countries, the increasing adoption of regulations to divert organic waste from landfills has boosted technologies that use the susceptibility of organic matter to microbial degradation. One of these processes is the composting process, which can transform waste into a potential resource of nutrients and/or a stable material with various potential uses. As defined by Haug (1993), the composting process is the biological decomposition and stabilisation of organic substrates, under conditions that allow thermophilic temperatures as a result of biologically produced heat, to produce a final product that is stable, free of pathogens and plant seeds, and can be beneficially applied to land. As an alternative waste management method, composting not only diverts organic waste from landfill but it also mitigates groundwater contamination, reduces air pollution and greenhouse gas emissions, while generating useful products.

Composting facilities are large-scale professional facilities that have practices in place to ensure conditions are ideal for composting, fast degradation, good emission control and compost quality. Under these conditions composting is considered ”industrial”, a controlled biotechnological process, to distinguish it from ”home composting”. Composting is characterised by a high degree of intricacy related to the interactions of several biochemical and physical factors in a heterogeneous matrix of gas, liquid and solid phases, which fluctuate considerably over time. The composting process depends on many factors, especially oxygen levels, carbon-to-nitrogen ratios, moisture content, and temperature (Haug, 1993). Process parameters are controlled in industrial facilities and, at the end of the process, final compost is subject to quality control analysis to verify that it meets the regulated specifications. If oxygen levels are above 5%, aerobic microorganisms are favoured and the process is rapid and effective. If the process is oxygen deficient, anaerobic decomposition by a different group of microorganisms takes place, and undesirable byproducts and unpleasant odours are

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caused. Microorganisms require for their growth a carbon source and other nutrients such as nitrogen, phosphorus or potassium. Nitrogen is a critical element for microorganisms because it is necessary for their cell growth. If the nitrogen available is limited, the degradation process slows. However, if there is excess nitrogen, it is lost from the system as ammonia gas or other odorous nitrogen compounds. The optimum C/N ratio is around 30, but the values on an industrial scale might vary depending on the substrate.

During composting, different pools of microorganisms transform organic matter under controlled conditions. Composting stabilises organic matter, yielding a soil-like end product. An understanding of the composting process is important for producing a high-quality product and preventing operating problems. The microorganisms require oxygen and water, and produce compost, carbon dioxide, heat and water. The heat produced increases the temperature in the compost pile from near-ambient air temperature to as high as 70 C. The temperature rise results in increased water evaporation. As the process nears completion, the compost pile once again approaches ambient air temperature.

Composting may proceed effectively over a range of pHs without seriously limiting the process. Nevertheless, the anaerobic activity releases organic acids that lower the pH, though the release of ammonia may raise the pH during early stages of composting. Given the ease of measuring temperature and pH and the value of the information that both measurements provide, these are the two main parameters used in almost all facilities.

Mathematical modelling has been widely utilised in science and engineering in order to improve understanding of the behaviour of systems, establish control and operating strategies, predict system performance and optimise process engineering. The first mathematical models of the composting process were developed in the 1970s, and since then, a number of models for the composting process have also been published and reviewed (Mason, 2006). An overview of the modelling of the composting process is offered in section 2.

Markov processes may be good models in some scenarios dealing with uncertainty. Markov processes are random processes where transition probabilities among states do not depend on past events, but only the current situation. Once the transition probabilities are estimated, stochastic simulations can be run to predict the systems behaviour. A discrete time stochastic process is a sequence of events $\{X_n\}$ in which the outcome (or state) at any stage is finite or countably infinite and depends on a random variable (X_n). A discrete time stochastic process is said to have the Markov property if the outcome at any stage depends only on the outcome of the previous stage, i.e. $P\{X_n=i_n X_0=i_0,\ldots,X_{n-1}=i_{n-1}\}=P\{X_n=i_n|X_{n-1}=i_{n-1}\}$. In this case, it is referred as a discrete time (finite or infinite) Markov chain (Kemény and Snell, 1960; Allen, 2011). Transition probabilities in Markov chains play an important role in modelling processes, being defined as $p_{ij}(n-1)=P\{X_n=i_n|X_{n-1}=i_{n-1}\}$. When transition probabilities do not depend on time, $p_{ij}(n-1)=p_{ij}$ the Markov chain is said to be stationary. p_{ij} are the elements of the transition matrix (P) that will model our system. Thus, we model composting processes as stationary discrete time finite Markov chains, or Markov processes for short.

Markov process models have been applied to a wide range of fields, including waste treatment planning (Hansen et al., 1980), waste collection routing problems (Kim et al., 2006), anaerobic waste treatment processes (Haag et al., 2003), or warning and emergency responses for landfill operations (Dokas et al., 2009). To the best of our knowledge, the application of Markov models to composting processes has never been reported. Our work focuses on modelling composting processes as a discrete time finite state Markov process, with the aim of dealing with uncertainty over a long time span and tackling the challenge to predict the biochemical and physical characteristics of any arbitrary compost windrow, learning from measurements of a non-homogeneous core of previous measurements.

2. Overview of the modelling approaches

It is not the objective of this paper to review in depth the existing models of the composting process. Instead, a general overview is presented to frame the presented model. An extensive general review can be found in Hamelers (2004) or Mason (2006). As shown in this review, a number of models have been developed for the composting process. In addition, models describing biodegradation in a liquid phase, as wastewater treatment or anaerobic digestion, have provided some understanding of the composting system's behaviour. In general, two main strategies have been used to respond to the specific challenges of the process. The inductive strategy is data based using empirical kinetic expressions, while the deterministic approach focuses on the solution of equations that describe the process from a biological and/or physical point of view.

The deterministic approach has been the preferred strategy, and amongst them most models have been based on the solution of heat and mass balances in time (Bach et al., 1987; Haug, 1993; Van Lier et al., 1994a,b; Kaiser, 1996; Stombaugh and Nokes, 1996; Higgins and Walker, 2001; Bari and Koenig, 2012; Sole-Mauri et al., 2007; de Guardia et al., 2010; Fontenelle et al., 2011). The spatial solution has rarely been adopted (Smith and Eilers, 1980; Hamelers, 1993). Deterministic models are useful for detailing the biological, chemical or physical processes that take place during composting. The number of model parameters required in a model and the possibility to obtain their values determines its usefulness and whether a certain model can be used as an operational or research tool. Composting processes are normally complicated with a variety of uncertainties arising from incomplete or imprecise information obtained in real-world systems. Thus, deterministic models can require more than 30 parameters to respond to the detailed heat and mass calculations. Although this approach might be very useful from a research point of view, this huge number of constants and parameters makes its application on an industrial scale constrained by the lack of information.

On the other hand, the inductive strategy has proven to give a more accurate response for a certain set of data (Hamelers, 2004), but its applicability is limited when waste or operational conditions change. The first approaches used linear expressions (Kishimoto et al., 1987; Nakasaki et al., 1987), followed by polynomial (Van Lier et al., 1994a,b) and exponential (VanderGheynst et al., 1997) expressions. During the process, the chemical changes and complex biological processes vary with the composition of the initial waste. Even in a certain composting process, the entire system can change dynamically to reflect the variation of environmental factors. One important consequence of this is that the process evolution is specific to a particular waste under the given conditions of the treatment characteristics.

In the 2000s, the inclusion of a stochastic approach began to respond to the uncertainties from incomplete or nonexistent information in non-laboratory composting systems (Seki et al., 2000; Scholwin and Bidlingmaier, 2003; Xi et al., 2008; Giusti and Marsili-Libelli, 2010). In these models, fuzzy set theory was incorporated (Qin et al., 2007; Zhang et al., 2008; Kumar et al., 2009). Zhang et al. (2008) used the fuzzy set theory to assess the quality of the final compost product and Giusti and Marsili-Libelli (2010) modelled dynamically the composting process based on a fuzzy combination of clustered antecedents and linear autoregressive consequents. The model is based on airflow input data and temperature output data. The model is in good agreement with the observed behaviour,