Estimation of landfill emission potential with particle filtering

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ABSTRACT: The emission potential is a key factor controlling long-term emission from landfills. The uncertainty in quantifying the emission potential is high due to deterministic initial values and imperfect simulation models, which make the long-term prediction highly uncertain. This study investigates the feasibility of using the particle filter method to estimate the emission potential, in this paper represented by the mass of chloride present in the waste body. The particle filter was used to estimate the emission potential by assimilating leachate volume and concentration measurements. Our results show that the uncertainty in chloride mass is quantified and constrained. These results suggest that it is promising to use easily acquired time series measurements to estimate the emission potential related states.

Keywords: emission potential, water content, chloride mass, particle filter, uncertainties

1. INTRODUCTION

The primary aim of a sustainable landfill is to be a final and safe storage facility for municipal solid waste materials, where polluting and harmful emission will always be under required thresholds.

A convincing prediction of long-term emissions is required for developing a long-term aftercare strategy. The emission potential is a concept which is a key factor controlling the long-term concentrations in landfill leachate and the long-term gas production. It is related to the total amount of any pollutant of concern present in the waste body; in this paper, chloride is chosen as the leachate component of interest. In modelling long-term emissions, the total mass of solutes and the total volume of water in the waste body are treated as deterministic values which are updated with time by a forward model (Fellner et al., 2009; Fellner & Brunner, 2010; Laner et al., 2011; Zhang et al., 2021). However, the uncertainty in these values is large because it is unfeasible to accurately quantify these using direct measurements. Even if an accurate initial value is acquired, the uncertainty will increase during the state update because of the errors in input data and forward model. As a consequence, results from models simulating long-term emission behavior are also highly uncertain.

Data assimilation has been widely used in hydrological and geophysical modeling to address uncertainties in model states (Jiang et al., 2019; Weerts & El Serafy, 2006) because of its power to recursively assimilate new measurements. Particle filtering is one of the data assimilation methods that is especially suitable for nonlinear models and errors. In this paper we explore the use of a particle filter approach to quantify and possibly constrain the uncertainty in the values controlling emission potential.

2. Approach

2.1 Sequential data assimilation

Particle filters assimilate measurements recursively to estimate the unmeasurable states in a model. We apply particle filtering to estimate and quantify the uncertainties in emission potential in a relatively simple case, focusing only on water volumes and chloride mass in landfill waste bodies. The total water volume represents the water content in waste body that is possible to be discharged as leachate.

The idea behind data assimilation is Bayes' theorem. During the process of state estimation, both a model equation and a measurement equation are required (Arulampalam et al., 2002). We take X_t to represent the state vector that contains all model states at time step t. Firstly, the state vector will be propagated from current time step to next measurement step with model equation.

$$X_t = M(X_{t-1}) + \varepsilon_{model} \quad (1)$$

where $M(\cdot)$ denotes a deterministic model, and ε_{model}represents model errors caused by different sources of uncertainty. The state vector is then connected to the available measurements through the measurement equation.

$$Y_t = H(X_t) + \varepsilon_{mea} \quad (2)$$

in which $H(\cdot)$ denotes measurement operator that connect model states to measured states, and ε_{mea} represents measurement errors.

2.2 Model characteristics

The forward model used to simulate the water balance and chloride transport in this particle filter framework is a mass balance travel time distribution model. The landfill is simulated with one cover layer and one waste body layer. The states controlling the emission potential are total water volume and chloride mass in the waste body. The model is driven by known values of precipitation and potential evaporation from the nearest weather station, and the particle filter updates the model states using measured time series of discharged leachate volumes and chloride concentrations in the discharged leachate. Leachate volumes are measured daily, chloride concentrations are measured once every two weeks. The time series is available from June 2012 until the end of 2018.

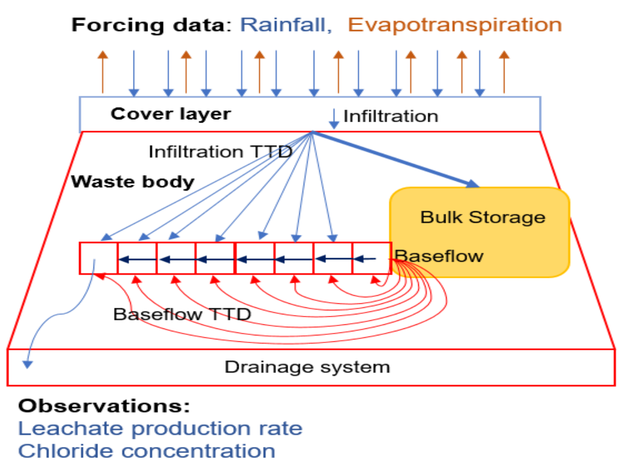

Figure 1. A schematic overview of model structure.

Firstly, the forward model we use is based on a one-way coupling between water volume and chloride mass. The leachate production rates only contain information on water volume states, while the concentration states depend both on water volume and solute mass.

Secondly, in the forward TTD model we use, we have explicit time lags between many model states and measurements because the travel time distribution considers the time information explicitly. For instance, the oldest cell states will only influence the measurements after 5 years. This time lag complicates the estimation of multiple hidden states using current measurements.

In particle filtering approaches, we can estimate hidden states in the model using measurements of observable states because the measurements contain some information about hidden states. When the model is not assumed to be entirely correct, the model errors will be added to model states during the state propagation process. If the errors are only added to observable states in the state vector, the diversity of hidden states may disappear with resampling. In other words, adding model errors to hidden states gives us the possibility to explore the hidden state space. The hidden states with model error will be assessed in the following time steps because it influences the measurable states. However, if this influence is weak or does not exist, the hidden states will be updated randomly, and the estimation will be poor.

In the TTD landfill model, the cell states are propagated with time. After P (the number of cells) days, there will be a connection among all cells and bulk states. We call this implicit relationship 'history'. We can estimate hidden states by current measurements if this' history' is maintained. Hence, the initialization of particles and the model errors should guarantee this 'history'. The implementation strategy is further explained.

2.3 Implementation

Initialization: from the model calibration results, we get one parameter set and initial states in 2003. The initial samples are sampled from Gaussian distributions where the means are selected as initial values. Initially, the corresponding standard deviations are set the same as truth generation. Subsequently, the standard deviations undergo adjustment to meet the ensemble spread criteria. With a warm-up simulation, the samples are propagated to 26th June 2012, a time step 7 days earlier than the first measurement date. The reason to perform this warm-up propagation is that we want to build connections among waste body states. Otherwise, the time lag between bulk states and measurements will make the estimation unreliable.

Update step: all the particles are propagated to the next assimilation step with the coupled TTD model. Considering the time lag issue, if we add independent model error to each state directly, the accumulation of errors of states like bulk water content will be huge after several years' lag. Therefore, we choose to add daily error to cover layer water content. The daily errors will be propagated to waste body states with time, which means we are adding correlated model errors to waste body states. Since the influence of error on fast flow cells can be estimated by measurements very quickly, we can avoid adding too many unreasonable errors to old states like bulk water content. Additionally, this error choice maintains the total mass balance of waste body volume states. No model error is introduced to concentration states directly. Once the initial concentration values are determined, the concentration variation is assumed to be determined by volume states.

Analysis step: the weights for particles should be calculated. In a coupled assimilation scenario, the weights for volume and concentration states are calculated separately by their corresponding measurements. Both concentration and leachate volume are considered by overall weights to estimate the mass states.

Resampling step: same as weights calculation, effective ensemble sizes are computed respectively in coupled assimilation. Then the corresponding particles will be resampled when effective ensemble size is smaller than *N/2.* The mass states are recalculated by resampled volume and concentration states.

Iteration: the former steps will be repeated until the last assimilation step.

3. Results

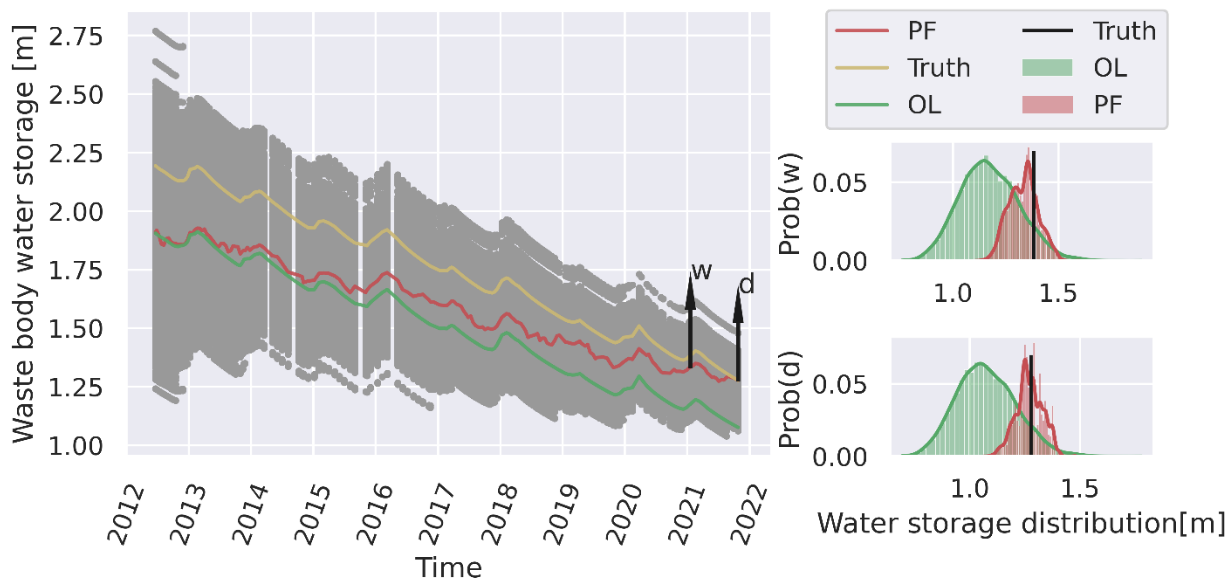

Figure 2. Water storage in the waste body. The red line represents the mean estimation of the particle filter. The green and yellow lines represent the open loop results and synthetic truth, respectively. The individual particles are shown as grey points. The two black arrows point to the wet and dry period during the assimilation process, with corresponding probabilities plotted. The black vertical lines in the probability histograms are the truth at specific time steps.

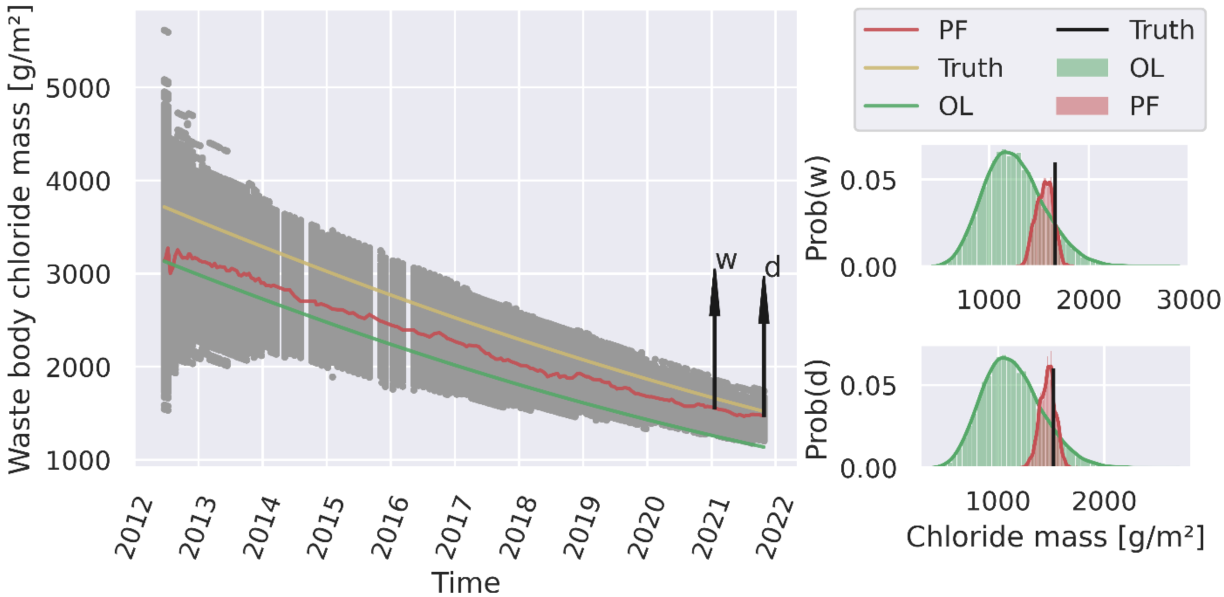

Figure 3. The evolution of total chloride mass in waste body over time.

4. CONCLUSIONS AND OUTLOOK

This work presents a weakly coupled particle filter framework to assimilate leachate production rates and chloride concentrations. A concentration-coupled travel time distribution model was used as a forward model for data assimilation. Overall, the results of this study indicate that the proposed coupled assimilation procedure can be used to estimate total water storage and chloride mass in the waste body. The assimilation of leachate production rates helped improve the accuracy of total water content estimation compared to assimilating concentrations solely. The gap between volume states and mass states is filled by concentration assimilation. Future studies will focus on quantifying the uncertainty caused by model parameters, which, for example, determine baseflow sensitivity.

ACKNOWLEDGEMENTS

This research is part of the CURE project supported by the Dutch National Science Foundation (NWO) under project no. OCENW.GROOT.2O19.O92. The research is also supported by the Dutch Sustainable Landfill Foundation via the iDS project. The authors also express appreciation to the support from Chinese Scholarship Council (No. 201906090271).

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