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A Conceptual Approach on Downwind Optimization of Processes for Air Pollution Control

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Control of air pollutant emissions is a mean to protect air quality. In most cases, this is realized by the imposition of specific emission standards, which usually are based on national and international experience. However, in areas with intense and dense polluting activities (e.g. industrial sites, trafficked roads) these horizontal measures will most probably fail to sustain local air quality. This is mainly because they do not consider the local transport mechanisms of pollutants from the source to the receptor. High local concentration levels might be the result of specific meteorological conditions, amplification owe to neighbour sources and deficient design of the air pollution control (APC) systems. Present work describes a conceptual and holistic approach based on the downwind optimisation, which takes into consideration also the transfer mechanisms that induce the ground level concentration of pollutants. This method can be used to design efficiently and dynamically control both the APC systems and the plant processes. Thus, local air quality can be sustained and protected in all cases and also achieve a significant reduction in capital and operational costs. Nevertheless, no cost-benefit analysis has been conducted here. The approach is also demonstrated in a comprehensive case study.

1. Introduction

Air pollution is the outcome of two distinct and general processes: the pollutants production (emissions) and their transfer to the environment (dispersion). Mainly, control of air pollution focuses on the latter process via imposition of emission standards and selection of pollutants' treatment technologies. Advanced optimization methods can deal with multiple sources and achieve economically feasible emission reduction. Liu et al. (2000) introduced a hybrid inexact chance-constrained mixed-integer linear programming method, with an objective of reducing emissions under constraints of renewable energy resources availability and environmental regulations. A significant number of similar published works present how pollutants' releases are reduced while minimizing the expenses and costs. For example, Heikkinen et al. (2009) demonstrate an optimization and modelling system for fluidized bed power plants, which can be used in air pollution control and emission trading schemes. Sweetapple et al. (2014) showed how a Multi-objective optimisation of wastewater treatment plant operational parameters and controller tuning parameters enable a significant reduction in emissions without the need for plant redesign.
On the other hand, pollution concentration reflects the state of atmospheric contamination in an objective way, and it has a direct impact on human health and the state of the environment. Zelinski et al. (2004), instead of costs connected with air pollution, applied concentrations of pollutants in optimization procedures. Using a traditional empirical dispersion model explored the possibility to optimize the expenditures connected with lowering the ambient air pollution in urban industrial area. In a series of publications, a group from Canada combined different numerical methods with again an empirical (Gaussian) dispersion model in order to achieve a cost efficient selection of control strategies at the regional level. Such as, a two-phase flexible optimization model (Lu et al., 2010), an interactive fuzzy boundary interval programming approach (Wang and Huang, 2013), and interval dual stochastic-mixed integer programming (Zhen et al., 2014). Most of the similar studies are targeting air quality management at the regional level.

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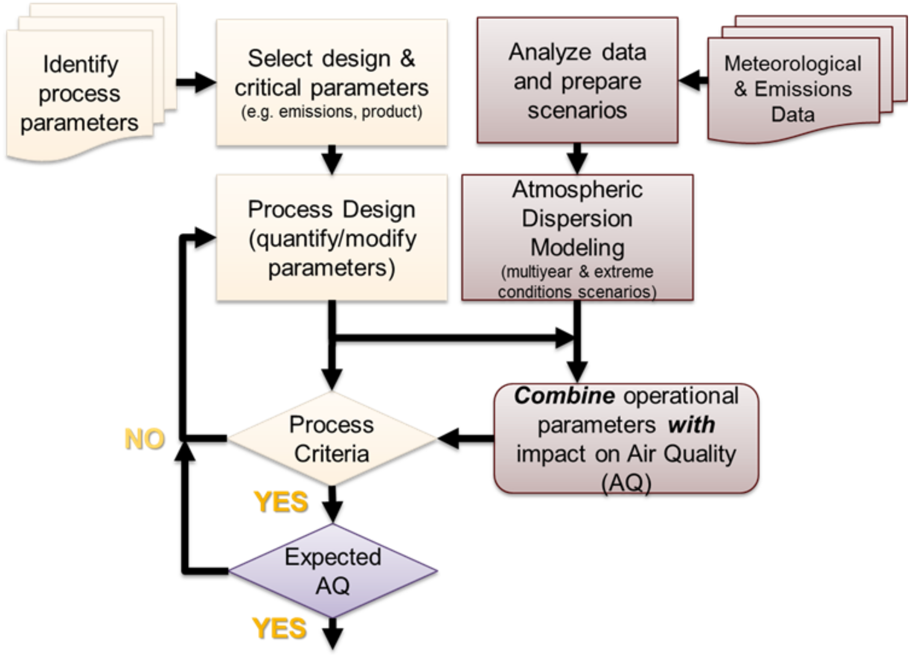

Figure 1: Main concept of the proposed methodology. Left half (light coloured blocks) presents the traditional process optimization approach, and the right half (dark coloured blocks) shows the proposed additional steps

Sule et al. (2011) developed a decision support system for the evaluation of control strategies using an advanced atmospheric chemical model (CAMx). The use of such advanced models is somewhat important when dealing with multi-pollutants as a better basis for prioritization of control strategies (Sonawane et al., 2012).

Nevertheless and to our best knowledge, so far both processes of pollutant emission (process design) and transfer (meteorology) are treated separately. There is a genuine interest to develop a framework where these are taken into consideration simultaneously. Present study explores this approach and aims at outlining the concept of reducing air quality local impact of a particular process via a dynamic optimization and control of the process itself.

2. Methodology

As an extension of the traditional process optimization steps, Figure 1 illustrates the main steps of the proposed concept. Following paragraphs present the methodology and principal components. Each of these components comprises a numerical module with a specific task.

2.1 Process description and design

For a demonstration of the concept, an appropriate case study has been selected, compositing. Turned (aerated) windrow composting (Figure 2) is a well-studied process for the biological decomposition of biodegradable solid waste. It takes place under controlled, predominantly aerobic, conditions to a state that is sufficiently stable for nuisance-free storage and handling. On the other hand, this process causes substantial emissions of malodorous compounds (5 – 500 m^3 m^{-2} min^{-1}) like sulfur and nitrogen compounds (H_2S, NH_3), fatty acids, terpenes, ketones and aldehydes.

Composting is used to treat solid waste and sludge from wastewater treatment. It is a robust process but sensitive to a number of design parameters (Haug, 1993): carbon and nutrients content (C:N ~ 25-30:1), moisture content (50 % - 60 %), oxygen (>> 5 %), pH (6.5 – 8.0) and temperature (40 °C – 60 °C). A bulking agent stabilizes the windrow and contributes to the control of the above parameters. Detailed mass and energy balances were formulated following literature recommendations, which also include the windrows turning, watering, screening, recycling and storing. The selected case study is based on a real project, initiated in 2009 for the treatment of 30,000 t of sludge in a municipal landfill southern of the city of Thessaloniki, Greece (N40.463, E23.041).

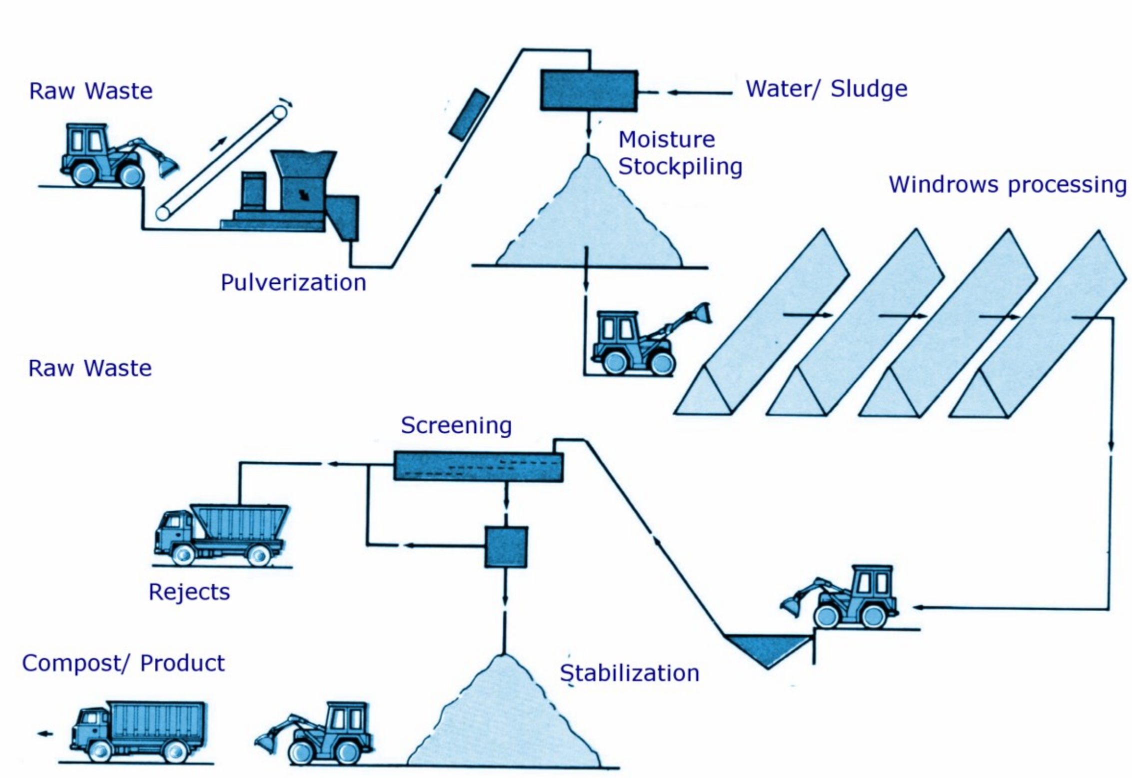

Figure 2: Flowchart of the studied open windrow composting process [reproduced from Eurowaste (Eurowaste, 2015).

2.2 Emissions modelling

Composting process releases malodorous compounds mainly during the following procedures: windrows turning, storage or resting, and handling. The emission rates, for any of these procedures, are based on the related emission inventories (E.P.A. U.S., 1995) and on the specialized composting handbooks on manual sludge treatment (E.P.A. U.S., 1979), on general solid waste management (U.N.E.P., 2005), and on the engineering design (Haug, 1993). Figure 2 illustrates the main composting steps and the emitting phases. On average, it was concluded that ~500 $m^3 m^{-2} min^{-1}$ of malodorous compounds are emitted when the compost is fresh (day 1 - 2), ~50 m^3 m^{-2} min^{-1} during the initial digestion (week 1-4), ~20 m^3 m^{-2} min^{-1} during the initial digestion (months 2 - 3) and ~5 m^3 m^{-2} min^{-1} while is resting (months 4 - 5). The dependence of the emission rate to some of the design parameters like pH, temperature and humidity, has been extracted from other sources (Gutiérrez et al., 2013).

Currently, there is only one European olfactometry standard to measure odour concentration expressed in OU_E m^{-3} (E.N.13725, 2003). A selection of panelists sniffs the sample in various dilution levels in odourless air, and they indicate if they smell the odour of the diluted sample or not. When half of the panelists can identify the odour, this concentration level is set equal to 1 OU_E m^{-3}.

2.3 Dispersion modelling

The CALPUFF model (v. 5.8), coupled with CALPUFF VIEW ™ from Lakes Environmental Software (2010) was chosen to calculate the atmospheric dispersion of malodorous compounds. CALPUFF is a non-steady-state Lagrangian Gaussian puff model, which has been developed since 1990. U.S. EPA approved and proposed it as a guideline model for regulatory applications, involving both long-range transport and near-field effect cases. As described in the manual (Scire et al., 2000) the CALPUFF modeling system consists of CALMET, CALPUFF, CALPOST and a large set of preprocessing tools. CALMET is a meteorological model that develops a three-dimensional gridded modeling domain, using extensive data, in this study, from the mesoscale meteorological model MM5 (NCAR, 1995). CALPUFF is a transport and dispersion model that advects “puffs” of material emitted from modeled sources, simulating dispersion and transformation processes along the way. CALPOST is a set of tools that process the output files from CALPUFF and produce tabulations and diagrams summarizing the result of the simulation. CALPUFF has been used successfully in the past for the prediction of odour dispersion and in comparison

with measurements (Mantovani et al., 2010). Apart from measurements, CALPUFF also showed good agreement between odour perceptions (Sironi et al., 2010) and simulated odour immissions (Busini et al., 2012). The use of the gridded wind fields (e.g. MM5, WRF) it is expected to improve the prognostic accuracy of CALPUFF (Murguia et al., 2014). However, wind tunnel modelling studies showed that more work is necessary to obtain a more accurate prediction of plume dispersion close to complex structures (Vieira de Melo et al., 2012).
The orography around the study area is relatively complex, which combined with the complex meteorological conditions (low-speed winds and many calm hours) makes the air dispersion modeling in this area, quite difficult. CALPUFF is suitable for these conditions, as it contains modules for complex terrain effects, over water transport and coast interaction effects (Chatzimichailidis et al., 2014). As recommended in other works, a multi-year MM5 wind fields dataset was used to initialize and drive the dispersion modelling system.

2.4 Downwind process optimization

The final component integrates all previous ones to achieve local air quality improvement. A sequential execution of the first three components provides the starting point, in other words, the initial conditions. Then and for every following hour (selected time step) a decision is made on how to control air pollution, based on a series of pre-calculated filters. The filters are related to the odour impact per wind direction and speed, mixing height, and ambient temperature. They are pre-calculated on an hourly basis using the dispersion modelling system and the given emissions. A decision is made following “only” two criteria. First, to maintain the composting parameters with the design specifications (e.g. temperature between 40 °C and 60 °C). Second, to reduce odour impact to less than 1 OU at three neighboring towns. When both criteria are satisfied, a decision is made, and the process goes to the next time step. At this specific case study, there was no need to implement any advanced optimization numerical algorithm (e.g. fuzzy logic, Monte-Carlo). This is because all filter calculations are pre-calculated, and all decisions could be checked in reasonable computational times.

3. Results and discussion

The implementation of the proposed methodology starts with the application of the dispersion modelling system for three consecutive years, using the formulated emission profiles.

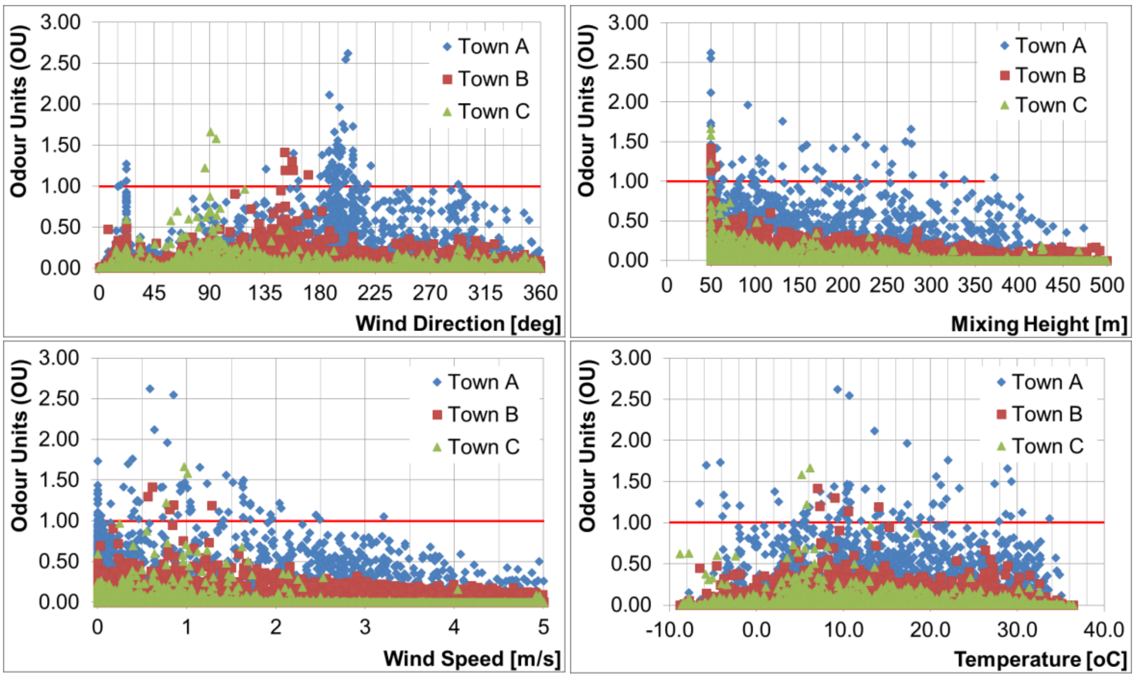

Figure 3: Sensitivity analysis for the four major meteorological parameters represented as Odour Units distribution vs. each parameter

Then a statistical analysis, of the four selected meteorology parameters (wind speed and direction, mixing height, and temperature), reveals the conditions where there is an impact to any of the selected receptors (Town A to C). Figure 3 illustrates these results, which comprise the per-calculated filters that drive the decisions. For example, we observe that a wind direction of 200 ° has a high likelihood of affecting Town A. The likelihood increases when this condition is combined e.g. with high temperatures. Consequently, the downwind optimization algorithm will limit and push for later the heavily emitting operations while such conditions are true (e.g. 200 ° wind direction and high temperature). The composting schedule is then updated, and the procedure continues.
Figure 4 presents the improvement or in other words the impact reduction. In the same figure, the odour contours in the case of the standard process (non-optimized) show a significant impact that reaches both three towns. On the other hand, the optimized process shows a significantly reduced impact. Moreover, the overall impact is extremely low and solely within the facility's perimeter.
The optimization of the composting process changes only the operation cycle. Therefore, it is not expected to affect its operational or capital cost. Nevertheless, one could assess the cost undertaken to control air pollution with other means like bio-filters to estimate the overall benefit of the proposed methodology.

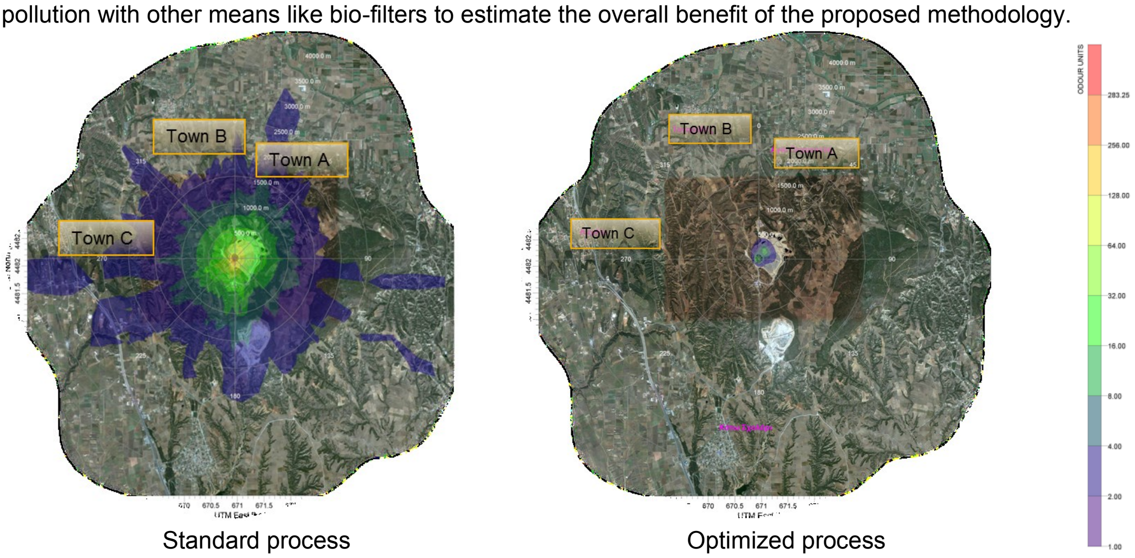

Figure 4: Impact of the standard process (left) and after optimization (right) represented with the annual average odour units

4. Conclusions

Traditional process optimization focuses on improving the design parameters and reducing its cost. In the present work, a concept was examined on whether atmospheric dispersion of pollutants can be used as an additional optimization component – downwind optimization. Aim of the new concept is to improve air quality and protect human health. The proposed methodology involves the development of an emission and a dispersion component, and both integrated into new brute-force type optimization algorithm. We selected a case study, open windrow composting, to demonstrate the methodology and evaluate the improvement. Indeed, there is a significant improvement of the local air quality by simply manipulating the operation cycle and without affecting the process performance.
Present work proves the validity of the concept, but there are a number of open issues that need to be further examined in future work. More cases need to be evaluated assess the overall improvement and identify possible issues. The optimization algorithm is based on brute-force calculations while more efficient procedures need to be checked in order to improve performance and reduce CPU requirements. Finally, a cost-benefit analysis is necessary to evaluate the overall improvement of the proposed concept.

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