Prediction of Evaporation Rate in a Solar Dryer for Sewage Sludge

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ABSTRACT

Efficient solar drying requires that the drying rate, as a function of the environment and the control, is quantitatively known. A solar drying installation for waste-water sludge in Füssen, Germany, designed by Thermo-System® and the University of Hohenheim, has been used to collect data for the establishment of a drying-rate function. In this solar dryer, wet sludge is uniformly spread over a concrete floor under a greenhouse-like transparent cover. The sludge is intermittently mixed by means of a autonomous robot (electric mole®), while the air under the cover is ventilated (horizontally) and mixed (vertically) by electric fans. Data of evaporation rate, environmental conditions and control operations were collected over three drying cycles. Evaporation rate via sludge sampling and via vapour balance across the structure compared favourably, justifying the use of the hourly vapour-balance data to develop linear regression and non-linear neural network (NN) models to predict the evaporation rate. The most important predictors of evaporation turn out to be (1) outdoor solar radiation (2) outdoor air temperature, and (3) the ventilation flux. The dry solids content of the sludge is next in importance, but could not be quantified with confidence over the domain, for lack of sufficient data. Air-mixing is an order of magnitude less effective than ventilation. The experimental design did not include different rates of sludge mixing.

Keywords: *sludge, solar, drying, evaporation rate, ventilation, modelling.*

1 INTRODUCTION

Sludge processing, handling and dumping is a significant cost factor of a sewage treatment plant. Increasing awareness regarding the possible impact of sludge management on the environment is expected to further increase the existing legal restrictions on bio-solids use (Anonymous, 2002), resulting in increased dumping costs. Many attempts have been made to reduce the amount of sludge remaining at the end of the treatment process and to improve its quality, resulting in a wide range of methods (Metcalf & Eddy, 2003; fig. 14-2). Besides anaerobic stabilization and mechanical dewatering, drying is an often considered option, since it reduces the amount of end material to a minimum, while eliminating most odour and pathogen problems. Conventional heat-drying is, however, technically complex, requiring high investment and consuming large quantities of energy (Melsa et al. 1999, Bux et al. 2003a). Often, therefore, solar drying of sludge turns out to be a better solution, especially for small to middle-sized sewage plants (Bux et al. 2001, Bux et al. 2002, Bux & Baumann 2003a, b).

Despite the increasing importance of solar drying of sludge, models to predict the drying rate are still not available. Therefore, an existing drying installation, designed by Thermo-System® and the University of Hohenheim, and situated at Füssen, Germany, has been used to collect data for the development of a drying-rate model (function). In this solar dryer, centrifuged sludge at dry solids content (DSC) of 0.2 to 0.3 kg[solids]/kg[sludge], is

uniformly spread over a concrete floor under a greenhouse-like transparent cover. The sludge is intermittently mixed by means of a autonomous robot ('electric mole®'). The air in the dryer is ventilated (horizontally) and mixed (vertically) by electric fans. The dried sludge is removed for transportation to a thermal power plant at a DSC of 0.6 to 0.8 kg[solids]/kg[sludge]. A more detailed description of the plant can be found in Literature (Bux & Baumann 2003b).
The main objective of this study is to develop a prediction model for the evaporation rate of sludge, as a function of the outdoor environment and the control (sludge-mixing, air-mixing and ventilation).

2 DRYING INSTALLATION AND DATA ACQUISITION

One of the four drying chambers in Füssen has been used for the drying experiments. The chamber has a concrete floor and is 10 m wide and 50 m long from air inlet to exhaust fans (air outlet). The installed capacity of the mixing and the exhaust fans is 150 m^3[air]/(m^2[floor]h). In the experiments, the mixing fans were operated at two rates: 0 or 150 $m^3/(m^2h)$, and the ventilation fans were operated at three rates: 30, 100 and 150 $m^3/(m^2h)$. The fans were operated continuously at the designated rates for periods which are multiples of 24 hours, starting at 08:00 a.m. The rates of air-mixing and ventilation were fixed in advance and hence were unrelated to (decoupled from) the weather. Sludge was mixed either 4 or 6 times each day on a constant daily schedule within each experiment.
Two methods were used to measure the loss of water: (1) sludge sampling and (2) vapour balance. The sludge sampling method consists of (a) determining the amount of solids from the volume, bulk density and DSC of the sludge, and (b) sampling the sludge every few days to determine its DSC. The rate of change of the DSC is an estimate of the evaporation rate.
The vapour balance method consists of (a) measuring the humidity ratio, w, of the ventilating air at inlet and outlet, and (b) multiplying the difference, $w_{out} - w_{in}$, by the density of the air, ρ, and the discharge of the ventilation fans, Q_v. The result is an estimate of the evaporation rate, and may be expressed as

$$E = \rho(w_{out} - w_{in})Q_v \equiv \rho \Delta w Q_v \quad . \qquad [1]$$

In addition to these measurements, weather conditions and environmental variables in the structure were monitored continuously and averaged on an hourly basis. Some of these were later used as predictors of the drying rate. Three drying experiments were carried out, as summarized in table 1.

3 THE EVAPORATION FUNCTION

The controllable variables (ventilation, air mixing and sludge mixing), together with the state of the sludge (its moisture, temperature) and the environmental variables (weather), determine together the rate of evaporation. In general, the evaporation function is written as

$$E = E\{e, s, c\} \qquad [2]$$

where E is the sludge evaporation rate, e is the outdoor environment (weather), s is the state of the sludge, and c is the control.

Table 1. Time span, weather and dry solids content (DSC) of drying experiments 1, 2 and 3 at Füssen.

Experi-ment number	Initial sludge sampling	Final sludge sampling	Mean solar radiation	Mean tempe-rature	Amount of solids	Initial DSC	Final DSC
			W/m^2	^oC	kg/m^2	%	%
1	09.10.03	30.11.03	67	5.1	58	26	43
2	14.07.04	26.07.04	111	26.1	45	28	55
3	03.08.04	06.09.04	144	18.3	74*	28	80

*Amount of solids reconstructed from vapour-balance and DSC measurements

The weather vector, e, consists of all relevant and available outdoor conditions, which here are R_o – solar radiation, T_o – air temperature, T_{do} – dew-point temperature and U – wind speed. Three measures of the state were available: σ – DSC, T_s – sludge surface temperature, and T_f – floor (or sludge bottom) temperature. The control vector, c, consists of three variables: The ventilation rate, Q_v, the air-mixing rate, Q_m, and the operation of the 'electric mole', M (on-off).
For the modelling work the hourly data sets (about 2400 in total) were distributed in groups containing similar information concerning weather, state of the sludge and control. 50 % of the data of each group were randomly selected for training of the model, the other 50 % for testing.

4 RESULTS

4.1 Drying Rate

The amounts of sludge-water, as determined by the sludge-sampling and the vapour-balance methods, are compared in figure 1. The change of the evaporation rate (slope) with season is evident. Comparison of Experiments 2 and 3, with a similar rate of evaporation, suggests that both solar radiation and temperature have a significant influence on the evaporation rate, since in Experiment 2 solar radiation is lower and temperature is higher than in Experiment 3 (table 1).

4.2 Correlated Predictors of Evaporation Rate

The first step in the development of an evaporation model is to select the proper individual predictors of the evaporation rate (Equation [2]). This depends, to some extent, on the purpose of the prediction model. If it is to be used on-line for control purposes, any easily measurable quantity may be relevant. However, if the purpose is off-line simulation, the only state variable that can be determined from the simulation via Equation [2] is W (namely σ). All other indoor variables cannot be used as predictors. Since generally both purposes are of interest, both, the quality of the prediction, described in this paper by the determination coefficient R^2 an the residual error and the used predictors of a model have to be considered.
The next consideration is to retain only one of several correlated predictors which provide the same information. Initially, 10 predictors where considered: Weather: R_o, T_o, T_{do} and U.

State of sludge: σ, T_s, and T_f. Control: Q_v, Q_m and M. Since T_{do} and T_s turned out to be well correlated with T_o, they were omitted from the list of predictors at this stage. The remaining 8 variables need to be tested for relevance.

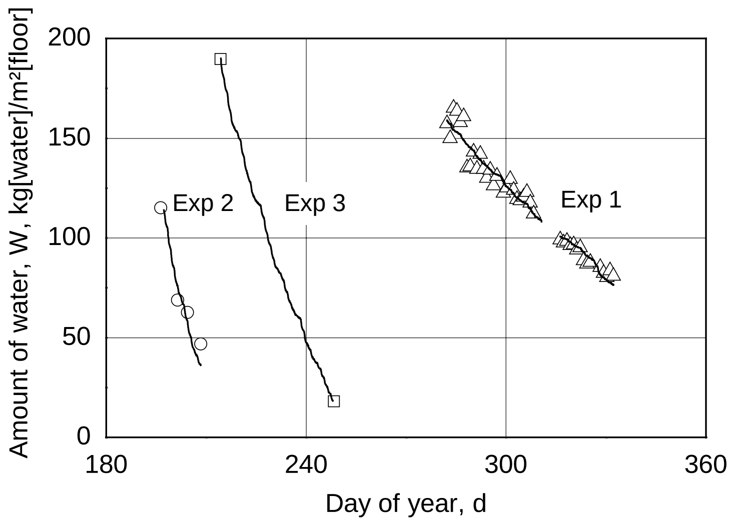

Figure 1. Water content of sludge, determined by sludge-sampling (points) and by the vapour-balance method (lines).

4.3 Linear Regressions

Two simple linear evaporation models may be contemplated: (1) Direct prediction of the evaporation rate, E, and (2) prediction of Δw and using Equation [1] to calculate E (which is, then, non-linear in Q_v). Equation [1] forces the evaporation rate to be zero when there is no ventilation, while a direct prediction of E does not do that. It is possible to force the direct prediction of E to be close to zero when $Q_v = 0$, by adding to the data-set fictitious data where $E = 0$ when $Q_v = 0$.

Several regression analyses were carried out with Δw and E as the dependent variables (outputs, predictions), and various combinations of R_o, T_o, U, σ, T_f, Q_v, Q_m and M, as independent variables (potential predictors). The results are summarized in the first four columns of table 2. The determination coefficient, R^2, increases and the residual error decreases as predictors are added. Outdoor solar radiation, R_o, ventilation rate, Q_v, and air temperature, T_o, turn out to significantly affect both the humidity ratio, Δw, and the evaporation rate, E. Air mixing, Q_m, and the DSC of the sludge, σ, seem to have a smaller effect, and the effects of the 'electric mole', M, wind speed, U, and floor temperature, T_f, are negligible, at least for the available set of data. Table 2 shows that the prediction of E^* via linear regression is significantly less accurate overall than the prediction of E.

Table 2. Coefficient of Determination and Residual error of various linear regression and neural network (NN) models (feed forward, 5 hidden nodes) using different predictors to predict Δw and E from hourly data sets (50 % of data used for training, 50 % for testing). The grey-high-lighted model is used to plot figure 3.

Prediction	Predictors	Linear regression R^2	Linear regression Residual error	NN model R^2	NN model Residual error
			g[water] /kg[air]		g[water] /kg[air]
Δw	R_o	0.463	1.21	0.468	1.21
Δw	R_o, Q_v	0.542	1.12	0.810	0.72
Δw	R_o, Q_v, T_o	0.709	0.89	0.876	0.58
Δw	R_o, Q_v, T_o, Q_m	0.719	0.88	0.887	0.55
Δw	$R_o, Q_v, T_o, Q_m, \sigma$	0.723	0.87	0.900	0.52
			mm/h		mm/h
E	R_o	0.575	0.100	0.590	0.098
E	R_o, Q_v	0.740	0.078	0.834	0.062
E	R_o, Q_v, T_o	0.808	0.067	0.887	0.051
E	R_o, Q_v, T_o, σ	0.838	0.062	0.923	0.042
E	$R_o, Q_v, T_o, \sigma, Q_m$	0.840	0.061	0.937	0.038
			mm/h		mm/h
E *	R_o	0.482	0.109	0.487	0.110
E *	R_o, Q_v	0.720	0.080	0.806	0.067
E *	R_o, Q_v, T_o	0.768	0.073	0.889	0.050
E *	R_o, Q_v, T_o, σ	0.795	0.069	0.915	0.044
E *	$R_o, Q_v, T_o, \sigma, Q_m$	0.797	0.068	0.931	0.040

E*: Including 10 % of artificial data points to force the model through $E = 0$ when $Q_v = 0$.

The regression equation to predict Δw, based on the five predictors of table 2, is

$$\underset{(76)}{\Delta w = 1447} + \underset{(0.14)}{4.57R_o} - \underset{(0.44)}{15.62Q_v} + \underset{(3.0)}{109.1T_o} + \underset{(0.27)}{2.02Q_m} - \underset{(173)}{997\sigma} \qquad [3]$$

while the prediction equation for E is

$$E = \underset{(0.000009)}{0.000461R_o} + \underset{(0.000029)}{0.001010Q_v} + \underset{(0.00021)}{0.00744T_o} - \underset{(0.008)}{0.220\sigma} + \underset{(0.000017)}{0.000114Q_m} \qquad [4]$$

where R_o is in W/m^2, T_o is in ^{o}C, Q_v and Q_m are in m^3/(m^{2}h), σ is in kg[solids]/kg[sludge], Δw is in mg[water]/kg[air] and E is in mm/h. The numbers in parentheses are the standard errors of the corresponding regression coefficients. The first four coefficients are highly significant. Note that in Equation [3] the coefficients of R_o, T_o and Q_m are positive, and those of Q_v and σ are negative, while in Equation [4] only the coefficient of σ is negative, all in qualitative agreement with the physics of the system.

4.4 Neural Network Models

Non-linear prediction models generally produce better fits than linear models, this being the result of incorporating more parameters (flexibility) in the model. The non-linear models pose, however, the risk of wild extrapolations in sparse regions of the predictor (input) domain. Our data-set is dense only around

$$T_o = R_o / 20 \qquad [5]$$

(where T_o is in ^oC and R_o is in W/m^2) and only for some of the ventilation rates.
Modelling with standard forward neural network (NN) models, (Matlab® NN toolbox) produced the last two columns of table 2. The most significant predictors appear in the same order as in the linear analysis, but there is a significantly larger contribution from the ventilation rate, Q_v, especially in the model to predict Δw, meaning that the response to ventilation is strongly non linear. The effect of σ is also more significant in the NN models than in the linear models. In general, the non-linear NN models produce considerably better fits than the linear regression models.
Averaging over a range of 0 to 600 W/m^2 for R_o, 0 to 30 ^oC for T_o, and 0 to 150 m^3/(m^{2}h) for Q_v, the ***reduction*** in NN-predicted E between typical initial and final DSC levels of 0.3 and 0.8 kg[solids]/kg[sludge], is about 30%. This is significant and can be illustrated by measured values at certain sub-regions of the domain, as is shown in figure 2.

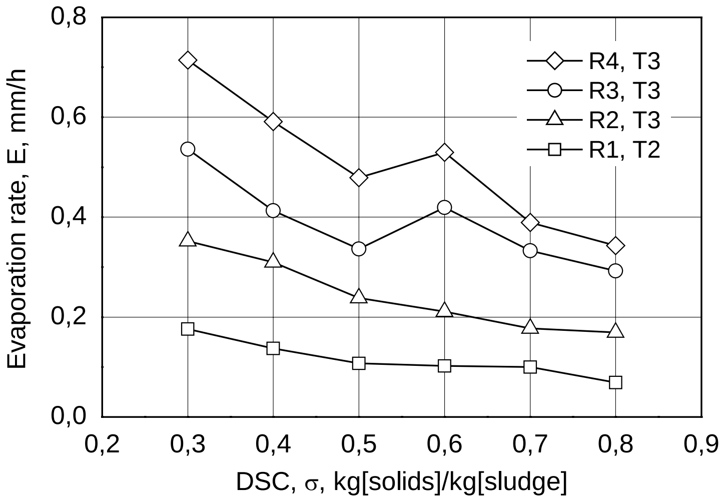

Figure 2. The decrease in observed evaporation rate with increasing DSC. The domain sub-regions Rn, Tn correspond to solar radiation and air temperature, respectively. Higher numbers (n) indicate higher values.

The data show that the reduction in evaporation rate is gradual and that already at a DSC of 0.3 kg[solids]/kg[sludge] there is some ‘internal control’ (internal resistance to vapour diffusion) of the evaporation process.
The effect of air mixing is considerably smaller than that of the DSC (table 2). Averaging over the range indicated above (for the DSC), E is predicted to ***increase*** by about 10% on average, by turning on the mixing fans at a rate of Q_m =150 m^3/(m^{2}h).
Figure 3 compares, for the neighbourhood of Equation [5], measured evaporation rates with the corresponding NN predictions of E^*, based on R_o, Q_v and T_o. Using Equation [1] is an alternative method, although marginally less accurate than E^*, as seen from table 2. Its advantage is that it does not require the artificial data (at the origin) included in the data set for E^*.

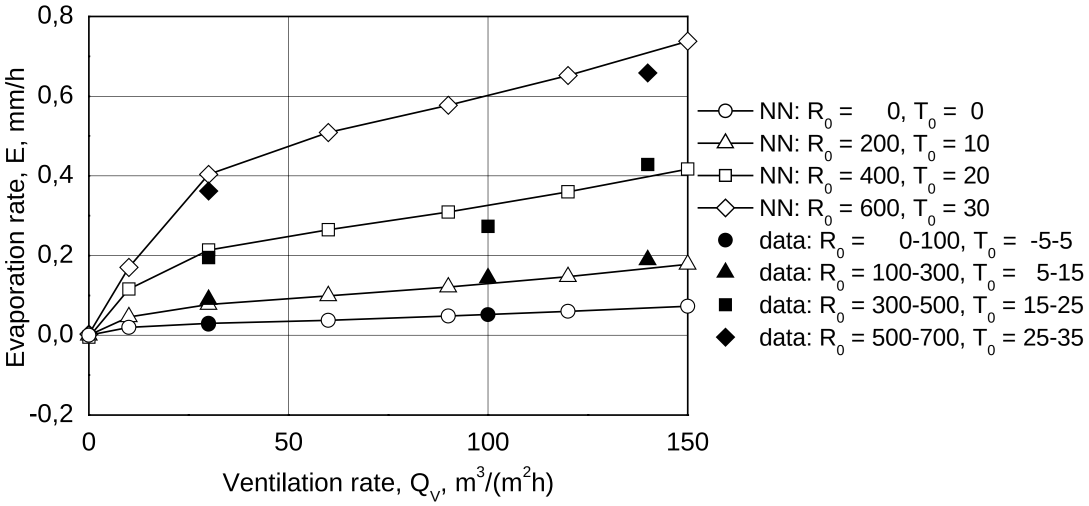

Figure 3. Neural network (NN) model predictions of the evaporation rate, based on the augmented data set $E*$, compared with mean measured evaporation rates for domain subregions around Equation [5].

Figure 3 shows (1) a fair agreement between measured and predicted values, (2) that the effects of all predictors are non-linear (curved response to Q_V and unequal spacing of the curves), and (3) that the evaporation rate is increasing approximately linear in the upper range. However, the slope is expected to decrease with higher ventilation rates since the mass transfer coefficient increases at a rate that is less than linear.

5 DISCUSSION AND CONCLUSION

Control of drying installations exposed to weather variations, requires model-based predictions of evaporation rates. Sludge sampling techniques cannot produce the short-term data for such models, and must be supplemented with, or replaced by, faster responding methods, such as the vapour balance method. This is considerably more convenient. As it turns out, the long-term evaporation rates obtained by the sludge and the vapour-balance methods were in fair agreement (fig. 1).

Figure 3 shows $E*$ as a well-behaved, non-linear function of R_o, T_o and Q_V. The effect of DSC is ignored for the time being, but must be added when more data become available. In reality, the first unit of water is more easily evaporated than the last one. On the other hand, the current pricing system rewards equally for all water. This means that an upper limit could be set on the DSC, beyond which further drying is not beneficial. An evaporation model with σ as an additional argument would be required to find, via simulation, the optimal size of the drying installation and the limiting DSC.

The evaporation curves of figure 3 are approximately linear in the upper range, but the slope is expected to decrease with ventilation rate. For while, as in a wet-bulb thermometer, the vapour-pressure difference between surface and air approaches a constant with increasing ventilation rate, the corresponding transfer coefficient increases at a rate that is less than linear (power of 0.8 for forced convection; ASHRAE, 1981 Fundamentals Handbook, p 2.14).

For the prices currently prevailing at Füssen, the optimal ventilation rate is, most of the time, at the installed capacity. This suggests that a higher installed ventilation capacity may be justified.

In summary:

1 The vapour-balance method is a promising technique to determine, on-line, the evaporation rate of sludge.

2 Black-box non-linear data-based models, such as neural networks, are convenient tools to be included in model-based control schemes. They can be adapted on-line to individual installations and local conditions.

3 The Model $E = E\{R_o, T_o, Q_v\}$, as shown in figure 3, is a good practical starting point for control applications. Solar radiation, air temperature and ventilation rate are the three most important predictors of evaporation rate. Next in line is the dry solids content of the sludge, which has a significant effect (fig. 3), but requires more data to be properly quantified. Air mixing seems to have a minor effect and the contribution of sludge mixing could not be quantified at this time.

6. ACKNOWLEDGEMENT

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