Matthias Plöchl, Potsdam-Bornim

Optimising the slurry spreading operation

Using neural networks for modelling NH_3 emissions

A model is presented here which utilises the neural network to calculate ammonia emissions following slurry application. Using the model enables optimising of both timing and method of the operation. Hereby, two parameters are applied in description of the ammonia emissions and these are related to the total emissions and their dynamic. The variables and thus ammonia emissions are analysed and modelled according to their dependency on slurry-specific, application and external parameters.

Dr. Matthias Plöchl is a member of the scientific staff at the Institute for Agricultural Engineering Bornim e.V. (ATB), Department of Technical Evaluation and Material Circulation, Max-Eyth-Allee 100, 14469 Potsdam (science director: Prof. Dr-Ing. J. Zaske); e-mail: *mploechl@atb-potsdam.de*

Keywords

Model, ammonia emission, slurry application, emission reduction

Literature

Literature information is available under LT 02513 via Internet at http:llwww.landwirtschafts-verlag.com/ landtech/local/fliteratur.htm

Influencing N-losses through emissions during slurry operations offers a twofold advantage for the environment: a direct one in that too much ammonia leads to acidification, and an indirect one through less damaging emissions from manufacture of artificial manure. The advantage to the farmer lies in improved estimation capability of Nr. contents in farm manure and reduced costs through thus avoiding superfluous mineral manure applications.

Ammonia emissions are influenced by slurry-specific factors such as dry matter content, pH and ammonia concentration as well as external factors (air temperature, wind speed, precipitation and radiation) [2 to 6]. Generally there are two methods of modelling these dependencies. A good overview of the mechanistic applications is given in [7]. This model is suitable for large volume applications such as slurry stores or underground systems [8]. The other model application is based on statistical regression of the emission data in relationship to one or several influence parameters [3 to 6]. Up until now, however, no regression function has been presented which can be satisfactorily applied on other experiments.

For the following observations a model (AEM – ammonia emission from manure) is considered which links the large number of input parameters on the basis of a neural network for predicting ammonia emissions. A comprehensive presentation of the method can be found in [9]. Additionally, sensitivity analyses of the model are used to estimate the extent of influence of the different parameters on total emissions and their dynamics. This then allows calculation of the most suitable conditions for slurry spreading.

Model description

It was assumed that the period of accumulated ammonia emissions E(t) followed a hyperbolic function, analogue to the Michaelis-Menten kinetic of the protein catalysis:

$$E(t) = E_{max} \cdot t / (K_M + t)$$

Whereby E_{max} is the accumulated total emissions (analogue for maximum reaction speed), K_M the time interval in which half of the total emissions are emitted and t the time since the slurry was applied (analogue for substrate concentration).

The analysis of the dependencies of E_{max} and K_M leads to the introduction of two independent neural networks. The input vectors of both networks are the same and comprise 15 parameters (*table 1*). A principle

Table 1: Input parameters of the neural networks with their extremes and median values.

Parameter	Minimum	Maximum	Median
Dry matter [% total substance]	07	22	5.8
pH-value	6.4	8.6	7.7
Ammonia concentration [kg N/m³]	1.1	6.1	2.7
Ammonia applied [g N/m²]	2.8	33.3	8.9
Crop	1=soil 2=grassland	3=growing plants 4=stubble	2[1]
Minimum air temperature [°C] day 1 / day 2	-4.3[2] / -2.4[2]	15.5 / 13.9	5.1 / 10.8
Maximum air temperature [°C] day 1 / day 2	2.5 / -0.2[2]	21.9 / 25.9	5.4 / 11.5
Precipitation [mm] day 1 / day 2	0 / 0	10 / 20	0[3] / 0[3]
Wind speed [m/s] day 1 / day 2	0.5 / 0.5	6.3 / 6.3	4.3 / 4.3
Radiation/day total [Wh/m²] day 1 / day 2	592 / 549	6395 / 5782	2001 / 2073

1. Crop is a classification rather than a continuum. For analysis, this classification was given a number whereby grassland (2) is easily the most prevalent class.
2. In many countries applying slurry at temperatures under 0 °C is forbidden but this was carried out for scientific reasons in the trials reported.
3. Most precipitation values were 0 mm, some were at 1.2 mm and 10 and 20 mm were extreme exceptions.

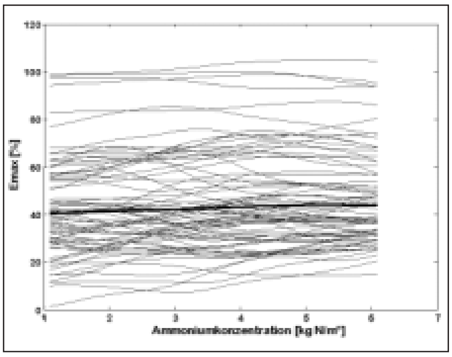

Fig 1: Example of insignificant sensitivity

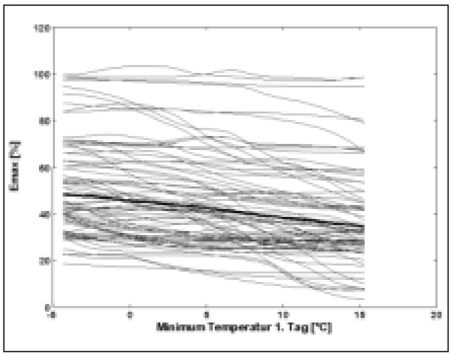

Fig. 2: Example of a slightly decreasing trend

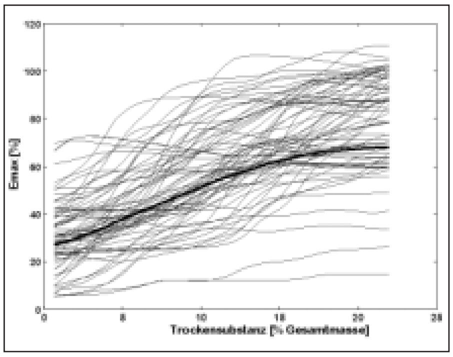

Fig. 3: Example of a significantly increasing trend

component analysis (PCA) was applied to these and this reduced the 15 input vectors to 13 independent variables.

Sensitivity of the neural networks

The neural networks can be used for investigating the sensitivity of ammonia emissions to individual influencing variables.

In the *figures 1 to 3* three typical results are shown:

- Where no clear trend can be recognised. The average progression of the curves is insignificant to the influencing variable (*fig. 1*).
- Where most simulations show a clear but less significant trend, either decreasing or increasing with the influencing variables. The average progression of all curves varies by less than 20% (*fig. 2*).
- Where nearly all simulations show the same significant trend. The average progression for all curves varies by more than 20% (*fig. 3*).

In *table 2* the sensitivity trends are shown for every parameter, according to the classification in figure 1 to 3.

Discussion

Technical options for ammonia emission reduction in slurry application include using other machinery (trailing hose, trailing shoe application, slurry injection) as well as additional operations such as ploughing-under or incorporating the slurry by harrowing or grubbing.

While applying injection technology can in most cases reduce ammonia emissions by more than 90% [11, 12, 13], this operation is associated with considerable inputs of cost and power which are associated with additional emissions of climate relevant gases from the conversion of required extra energy input and which, in overall estimation in the sense of a life-cycle assessment, substantially reduces the advantages of slurry injection. The same applies to the application technique of trailing hoses and trailing shoe both of which offer a substantially less decrease in ammonia emission of from 40 to 70% [13, 14].

With the additional actions of working-in the slurry as soon as possible after application an emission reduction of from 80 to 90% can be achieved, regardless of the technology applied [15, 16] i.e., the least power demanding operation (harrowing-in) can be applied without loss in reduction potential. Decisive for the efficacy of these operations is the time between slurry application and subsequent harrowing or ploughing and the associated amount of ammonia which is emitted between the actions. In the model [16] a constant K_M of 5.4 h is assumed. The analysis presented here shows, however, that values between 1 h and 118 h are possible, all dependent on slurry-specific parameters (dry matter, pH, ammonia concentration), external parameters (temperature, precipitation, solar radiation, wind speed), amount of slurry applied and the character of the area to which it is applied (soil, pasture, stubble or growing plants).

Table 2: Trends in sensitivity of neural networks to individual parameters

Parameter	K_M	E_{max}
Dry matter	-	++
ph-value	--	+
Ammonia concentration	-	+
Ammonia applied	++	--
Crop	4,3,2,1[1]	±
Minimum temperature day 1/day 2	± / -	- / -
Maximum temperature day 1/day 2	+ / --	+ / +
Precipitation day 1/day 2	+ / +	-- / --
Wind speed day 1/day 2	+ / +	+ / +
Radiation daily total day 1/day 2	± / -	++ /-

- lightly decreasing; – significantly decreasing; (insignificant; + lightly increasing; ++ significantly increasing

- 1 Increasing in succession K_M

If the analysis presented here was used in the form of a decision aid model, two targets could be thus aimed for:

- Selection of conditions where the smallest possible total emissions can be expected without having to work the slurry into the soil.
- Selection of conditions where the greatest KM can be expected, leaving as much time as possible for working-in the applied slurry.

The results of the sensitivity analysis (*table 2*) can, however, even now help with a rough orientation for the decision on which simple combinations of condition changes can help achieve the intended effect. Where, i.e., there can be little influence on application dates and the thus the weather, something can be done at least regarding the slurry-specific parameters:

- Through reducing slurry dry matter the total emission and K_M is reduced whilst the time required for working-in increases.
- A similar effect can be achieved through reducing the pH of the slurry, i.e. acidification, whereby here the effect on the dynamic is greater than that on the total emission.

The greatest effect on total emission and dynamic certainly comes from precipitation whereby here too the sensible combination of reducing total emission and slowing down the emission dynamic can be observed. In the other cases, with exception of the maximum temperature on day 2, only one of the two parameters can be practically influenced when taking account of the appropriate parameters. If one takes reduction of total emissions as target one should at least try to make sure that conditions are cloudy and not too warm during the day so that wind speeds are as low as possible. But where the emission dynamic is being focussed on exactly the opposite is the case. Alongside wind speed, positive influences can be expected from high temperatures in the second night and day 2, although these conditions are linked to high solar radiation.