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Modelling and Simulation of a Fuzzy System for Site-Specific Nitrogen Fertilization

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Abstract: Increasing environmental concerns are a driving force in the search for ways to improve the efficiency of mineral nitrogen (N) fertilization. Spectral sensors to determine the crop's supply status are among the most mature precision agriculture technologies to adapt the N dose site-specifically to the crop's need. By using artificial intelligence techniques like expert systems based on fuzzy set theory, the algorithms of such sensor systems could be adapted by the farmer to the highly varying conditions among the specific fertilization dates. This paper is dealing with the development of a fuzzy logic based model of the commercial Yara N-Sensor's dosing algorithms. Simulations for several sets of input-output data acquired in field experiments showed high accordance with the behaviour of the N-Sensor system with good adaptability to different calibrations.

Keywords: Artificial intelligence, bio control, fuzzy modelling, fuzzy expert systems, precision agriculture

1. INTRODUCTION

Mineral nitrogen (N) fertilization is one of the main drivers for biomass production in conventional farming. Yet, mean recovery rates of around 50% on a worldwide scale are causing enormous N excess. In turn, this is causing greenhouse gas emissions and pollution of air and water resources (Lassaletta, Billen, Grizzetti, Anglade, & Garnier, 2014). For several decades, researchers have been working on the topic of precision agriculture with a main focus on how to adequately respond to in-field heterogeneities by variable rate N application (VRNA). VRNA is considered as a promising mean to avoid N excess (Balafoutis et al., 2017; Griepentrog & Kyhn, 2000; Snyder, Bruulsema, Jensen, & Fixen, 2009).

Many sensor systems for controlling mineral N fertilization based on the spatial variability of the crop have been developed up to a commercial product. The Yara N-Sensor is one of them and like most of the competing systems, it is determining the local N need based on the crop's spectral reflectance at specific wavelengths. Even if several research works could prove the advantageousness of the N-Sensor, many farmers still do not use VRNA due to different reasons, like e.g. higher costs, extra work, doubts of the credibility or cost-benefit (Lindblom, Lundström, Ljung, & Jonsson, 2017). The algorithms behind the systems for VRNA are usually deterministic and not flexible enough to adapt to the strong variability of conditions prevailing at each specific application.

With the N fertilization, and thus, the plant growth, the farmer is controlling a natural process, which is characterized by high vagueness and dynamic, non-linear interactions between different influencing parameters. Knowledge-based and artificial intelligence techniques are increasingly used to model environmental systems (Chen, Jakeman, & Norton, 2008). Recent research proved their superiority to conventional descriptive statistics, analytical methods and multiple regression in modelling complex interrelationships between multiple factors (Abbaspour-Gilandeh & Abbaspour-Gilandeh, 2019; Jahangiri, Solukloei, & Kamalinia, 2019).

Fuzzy systems present an effective and structural way of dealing with decisions involving the inherent uncertainties and non-linearities of environmental processes and parameters (Mendes, Araújo, Dutta, & Heeren, 2019; Papadopoulos, Kalivas, & Hatzichristos, 2011). Beyond that, fuzzy logic is much closer in spirit to human thinking and natural language than traditional logical systems and thereby it provides a means to integrate expert knowledge via linguistic terms into an automatic control strategy (Lee, 2005). Fuzzy control enables a convenient man-machine conversation, as well as a non-linear control which is easy to control and operate. Furthermore, it has relatively good robustness and fault tolerance (Sun, Ma, Li, & Wang, 2018). Fuzzy systems are flexible, because the membership functions for the single parameters can be changed dynamically according to the situation. What's more, an adaption can be implemented to modify the membership functions automatically according to changing situations (Sivanandam, Sumathi, & Deepa, 2007).

Several research works are dealing with the control of plant production processes using fuzzy logic and the use of fuzzy systems in spatial problems is increasing (Ashraf, Akram, & Sarwar, 2014). A comprehensive fuzzy logic based system was developed by Badr et al. (2018) to aid in the selection of suitable areas for grapevine cultivation by using several bioclimatic indices, soil and topographical data. An irrigation system based on fuzzy logic is presented by Mendes, Araújo, Dutta, & Heeren (2019). It is considered attractive to farmers since there is no need for precise measurement or a precise model, which may be very complicated and require considerable funds, resources and development time.

A decision support system based on knowledge elicitation and fuzzy logic methodologies for site-specific N fertilization is presented by Papadopoulos, Kalivas and Hatzichristos (2011). Prabakaran, Vaithiyanathan, & Ganesan (2018) developed a fuzzy system respecting soil, water and agronomy parameters, as well as expert knowledge, to reduce fertilizer consumption and improving crop productivity. Lavanya, Rani, & Ganeshkumar (2018) used fuzzy logic to detect nutrient deficiency from soil data. Tremblay et al. (2010) included expert knowledge in a FIS to give recommendations for a VRNA. The system used several input parameters like spectral crop information or site properties. Yet, it cannot easily be transferred to different conditions.

Due to their lifelong work on one complex farm experiment, a tacit body of knowledge is inherent to farmers (Hoffmann, Probst, & Christinck, 2007). Using a fuzzy system, their deep recognition of the plant production process could be transferred to an automated VRNA in a straightforward manner. The present study aims to describe, how the agronomic algorithms of the commercial Yara N-Sensor system can be imitated with a model based on fuzzy set theory. This would allow the operator to intuitively adapt the algorithm to the current needs of a specific application based on their expertise. Furthermore, a VRNA system based on the fuzzy model could easily be extended by further input parameters. The first main step for the development of the fuzzy logic based N-Sensor model encompasses the identification using input-output data acquired with the commercial sensor system. Then the fuzzy model should be simulated and optimised for one specific data set. Simulation and validation with further data sets should allow assessing the transferability to different calibrations.

2. MATERIALS AND METHODS

2.1 Instrumentation and field measurements

A commercial Yara N-Sensor ALS2, which was operated with the N-Sensor 4.5 software, was used for field measurements (Yara GmbH & Co. KG, Dülmen, Germany). Mounted on the tractor roof, this system is measuring the canopy reflectance at specific wavelengths (Fig. 1). Based on a crop-specific calibration, a normalized sensor value (SN) is calculated, which corresponds to the N-Uptake of the crop in kg ha^{-1}. In order to calibrate the system for a VRNA within a field, a reference strip of around 30 m is measured at a low speed. The system is determining the average SN for that strip, and the target N-rate (TR) is assigned to that reference value (SN_{ref}).

Based on that calibration, the adequate N dose rate (DR_{YNS}) for a specific spot is deduced during the application process and forwarded in real-time to the fertiliser spreader control. The algorithms behind the calculation of DR_{YNS} have been developed by Yara over many years and they are not open to the public. In order to limit the DR_{YNS}, the operator can set a minimum and maximum value, beyond which it is kept constant. For documentation and mapping purposes, the N-Sensor software is logging a variety of parameters with a frequency of 1 Hz. The SN value, as well as the DR_{YNS}, were of interest for the present study. Furthermore, the TR, the SN_{ref}, as well as the cutoff SN (SN_{cut}) were considered. The latter is defining a biomass threshold, below which the system is strongly decreasing the DR_{YNS}. The measurements took place on three fields with winter wheat (*Triticum aestivum* L.) during the N fertilizing season 2019 (Fig. 2). The fields were

Fig. 1: Yara N-Sensor ALS2 mounted on the tractor roof.

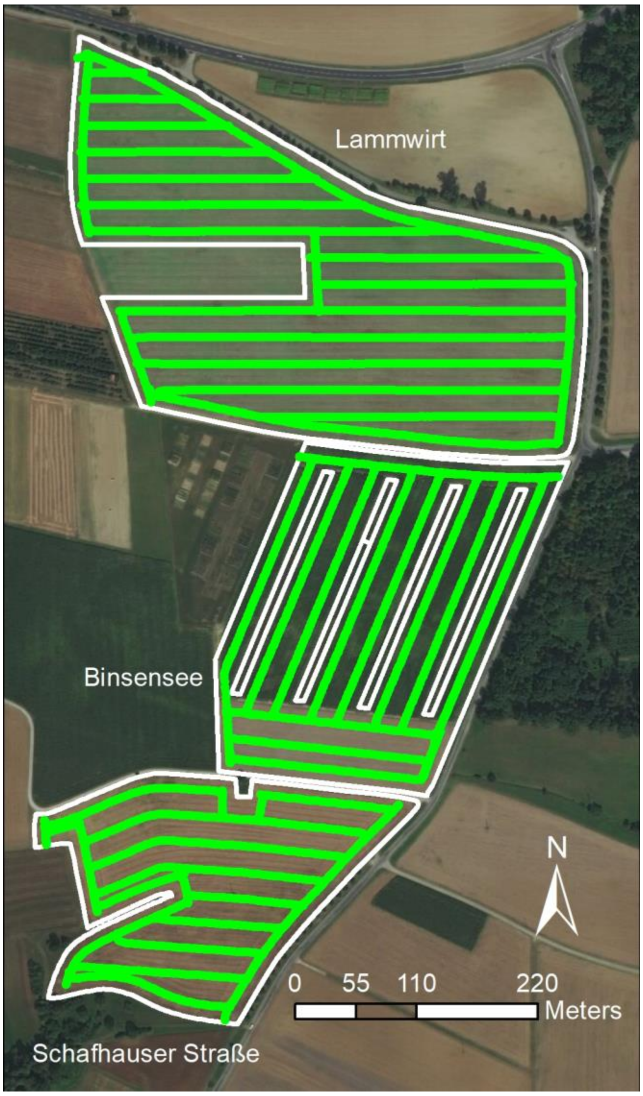

Fig. 2*:* Satellite view with the georeferenced measuring points (green) of the second N application (ESRI Inc., 2020).

Table 1. Key data of the measurements

Acronym	Field/Subarea	Date	GS	SN_{ref} [kg ha^{-1}]	SN_{cut} [kg ha^{-1}]	TR [kg ha^{-1}]	Range SN [kg ha^{-1}]
N2							
$N2_L$	Lammwirt	01 May 2019	31	54.3	20	30	21.7-75.2
$N2_B$	Binsensee	25 April 2019	31	80.4	20	40	26.9-103.7
$N2_S$	Schafhauser Straße	01 May 2019	31	83.5	20	40	27.7-103
N3							
$N3_L$	Lammwirt	31 May 2019	39	122.2	54	72	45.5-144
$N3_{BNW}$	Binsensee North+West	31 May 2019	49	142.9	54	47	6.7-194.3
$N3_{BSE}$	Binsensee South+East	31 May 2019	39	135.2	54	47	85.2-157.1
$N3_{SN}$	Schafhauser Straße North	31 May 2019	39	134.7	54	87	51.9-153.2
$N3_{SS}$	Schafhauser Straße South	31 May 2019	39	118.5	54	37	104-157

located at the research farm 'Ihinger Hof' of the University of Hohenheim (48°44'41.61"N, 8°55'26.42"E). N fertilization was split into three applications at different crop growth stages, which is common practice. For each application, specific TRs were defined for a whole field or subareas based on a crop assessment. For the present study, measurements were considered that were made within the scope of the second (N2) and third (N3) application, because they represent the most common use cases for the N-Sensor. For N3, the yield-oriented strategy was chosen, which is behaving in a similar way to the N2 strategy. For all measurements, the minimum and maximum DR_{YNS} was set to 0 and 120 kg ha^{-1}, respectively. In order to eliminate implausible values and avoid repetitions at the same site, values that were recorded at zero speed, as well as measuring points that were located outside the field boundaries, were deleted in the recordings. Key data from the measurements are given in Table 1, whereby GS is indicating the Zadoks growth stage of the crop (Zadoks, Chang, & Konzak, 1974).

2.2 Identification of the fuzzy logic based N-Sensor model

It is known from the technical documentation of the used N-Sensor, that for N2 and the yield-oriented strategy for N3, the calculated DR_{YNS} is indirectly proportional to the SN for values above the SN_{cut}. Below, it is reduced with a decreasing SN. In general, the relation between SN and DR_{YNS} is known to be piecewise linear. Using the numerical computing environment MATLAB R2019a (The Mathworks Inc., Natick, Massachusetts, USA), an algorithm was developed that created for each field and subarea, respectively, a Takagi-Sugeno FIS with constant output values. Compared to the Mamdani method, it is not that much adapted to human intuition and offers less freedom in terms of applying principles of fuzzy logic. Yet, it was chosen because of its advantages in terms of working with linear, as well as optimization and adaptive techniques (Sivanandam, Sumathi, & Deepa, 2007). The formation of the FIS was based on parameters of the calibration. In particular, those were the SN_{ref} and SN_{cut}, as well as the TR. For the input SN, the algorithm was configured to always create four fuzzy sets with triangular membership functions ('*cutoff*', '*low*', '*medium*' and '*high*'). The overall considered input range was always [0 (2×SN_{ref}-SN_{cut})]. The parameters for the membership functions of every FIS were set as follows (parameters *a* and *c* of [*a b c*] define the feet of the membership function, and *b* defines its peak):

Cutoff: [0 0 SN_{cut}]

Low: [0 SN_{cut} SN_{ref}]

Medium: [SN_{cut} SN_{ref} (2×SN_{ref}-SN_{cut})]

High: [SN_{ref} (2×SN_{ref}-SN_{cut}) (2×SN_{ref}-SN_{cut})]

In Fig. 3, the membership functions for $N2_B$ are presented as an example. For the DR outputted from the FIS (DR_{FIS}), four constant values were defined ('*cutoff*', '*low*', '*medium*' and '*high*'). For *cutoff*, the value was always zero, whereas *medium* was TR. *Low* and *high* were calculated based on the range of the *medium* membership function of the input SN, as well as a constant range factor (RF). In particular, their calculation was as follows:

Low: TR-((SN_{ref}-SN_{cut})/RF)

High: TR+((SN_{ref}-SN_{cut})/RF)

The following rules were defined to imitate the behaviour of the N-Sensor:

IF SN is *cutoff* THEN DR_{FIS} is *cutoff*.

IF SN is *low* THEN DR_{FIS} is *high*.

IF SN is *medium* THEN DR_{FIS} is *medium*.

IF SN is *high* THEN DR_{FIS} is *low*.

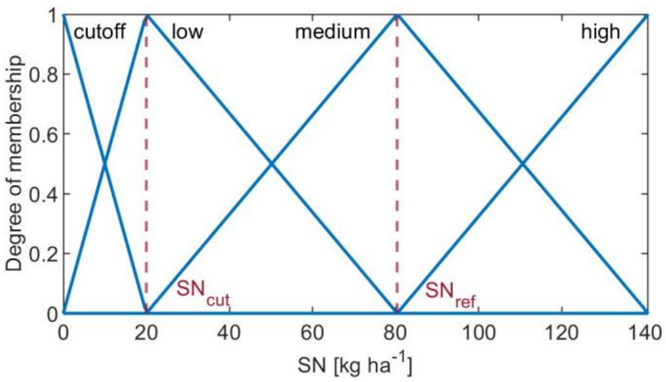

Fig. 3: Input membership function plot for $N2_B$.

To limit the range of the DR_{FIS} in the same way as the N-Sensor software, a minimum and maximum threshold of 0 and 120 kg ha^{-1}, respectively, were implemented that limited the DR_{FIS} in case it was necessary.

2.3 Simulation, optimisation and validation of the model

For simulations using the fuzzy logic based N-Sensor model, the recordings of the field measurements were used. For each recorded SN value, a DR_{FIS} was calculated using the automatically created FIS for the affected field or subarea. To evaluate the performance of the single FISs in terms of imitating the N-Sensor algorithm, the initial DR_{YNS} was compared to DR_{FIS}. The Pearson correlation coefficient r was calculated to assess the strength of the linear correlation between DR_{YNS} and DR_{FIS}, respectively:

$$r = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{y_m(i)-\overline{y_m}}{\sigma_{y_m}}\right)\left(\frac{y_s(i)-\overline{y_s}}{\sigma_{y_s}}\right) \tag{1}$$

where y_m and y_s correspond to the DR_{YNS} and DR_{FIS} respectively, at i-th measurement. N corresponds to the total number of measurements. The notations $\overline{y_m}$ and σ_{y_m} are the arithmetic mean and the standard deviation of $y_m(i)$, and $\overline{y_s}$ and σ_{y_s} are the arithmetic mean and the standard deviation of $y_s(i)$. A very common practice to compare measured and simulated data series is the root mean square error (RMSE), which was calculated according to:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_m(i)-y_s(i)\right)^2}{N}} \tag{2}$$

In order to enable a relative assessment of the RMSE, it was also calculated as a percentage of the mean DR_{YNS}:

$$RMSE_p = \frac{RMSE}{\overline{y_m}} \tag{3}$$

The RF for determining the *low* and *high* DR_{FIS} was adapted in a trial and error procedure with the aim to minimize the RMSE for $N2_B$. Trial and error is a common method to design and tune FISs (Jahangiri, Solukloei, & Kamalinia, 2019; Mehran, 2008; Sivanandam, Sumathi, & Deepa, 2007). Then, the factor was kept constant for all the other simulations, in order to keep the generation of the FISs as generic as possible. For the presented results, it had a value of 0.769.

3. RESULTS AND DISCUSSION

3.1 Characteristic curve of the modelled FISs

For every FIS, the relation between the input SN and the output DR_{FIS} can be described by a characteristic curve, whereby the basic shape is always the same. As an example, the curve for $N2_B$ is shown in Fig. 4. In general, the course of the DR_{FIS} over the SN has a piecewise linear character. Below the SN_{cut}, the DR_{FIS} is decreasing abruptly. Above, it is slightly decreasing, until it is limited by the minimum value. For this specific FIS,

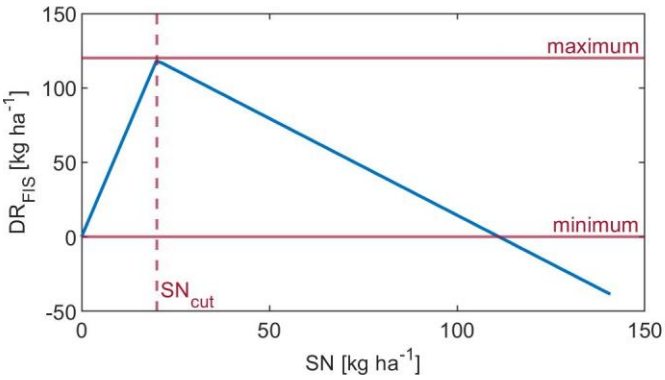

Fig. 4: Characteristic curve for $N2_B$.

the maximum has no function, because it is slightly above the peak of the DR_{FIS}. It is noticeable that the FIS would output negative DR_{FIS} values beyond a certain SN value, which would be implausible. Yet, this is due to the fact that for the input SN, a generous surplus was given in terms of its overall range. This was supposed to ensure that the characteristic curve is not limited at a certain SN value that would correspond to a DR_{FIS} above the minimum threshold. Theoretically, negative DR_{FIS} values were automatically set to 0 by the algorithm.

3.2 Simulation results

Statistics for the identification and validation of the fuzzy logic based N-Sensor model are presented in Table 2. The lowest value of r was 0.982455 for $N3_{BNW}$, which is indicating the overall strong linear correlation between DR_{YNS} and DR_{FIS}. All the RMSE values for N2 are below 40 g ha^{-1}. From a practical agronomical perspective, this difference is too small to have any measurable effect on the crop, because there are several sources within the spreading process that are likely to cause more error. Also, the very low $RMSE_p$ values indicate that the setup for the self-configuring FISs worked well for N2. Yet, it has to be noted that it was optimized for $N2_B$ and that SN_{ref} and the range of the SN for $N2_B$ and $N2_S$, which are indicated in Table 1, are very similar. So, the most objective results for N2 are the ones of $N2_L$. Unfortunately, the behaviour for values below the SN_{cut} could not be tested for N2, because there were none. Also, the thresholds for the minimum and maximum were neither touched by DR_{FIS} nor by DR_{YNS}, which can be seen in Table 2.

In Table 1, it is obvious that for N3, the testing conditions were more variable and the algorithm was partly tested also at the borders of the pieces of the characteristic curve. It appears suspicious that the minimum SN value of 6.7 for $N3_{BNW}$ is smaller than the one for $N2_B$ (i.e. 26.9). In general, an increasing value can be expected with advancing GSs. However, the smaller minimum SN value for $N3_{BNW}$ originated from the north-western corner of field Binsensee, where the sensor partially measured an area outside the field during a turn. Furthermore, the crop was damaged at this spot because of preceding turns and due to field entries.

It is apparent from the range of the SN in Table 1 and the DR_{YNS} range in Table 2, that data set $N3_{BNW}$ offered the best prerequisites to test the algorithm at border conditions. In Table 2, it is indicated that there were the biggest errors.

Table 2: Statistics for the identification and validation of the fuzzy logic based N-Sensor model

Data set	Range DR_{YNS} [kg ha^{-1}]	Mean DR_{YNS} [kg ha^{-1}]	Range DR_{FIS} [kg ha^{-1}]	Mean DR_{FIS} [kg ha^{-1}]	r	RMSE [kg ha^{-1}]	$RMSE_p$ [%]
Identification							
$N2_B$	9.75-109.52	55.26	9.70-109.57	55.26	0.999997	0.0384	0.0695
Validation – N2							
$N2_L$	2.78-72.39	32.36	2.82-72.39	32.36	0.999995	0.0377	0.1165
$N2_S$	14.59-112.50	56.84	14.64-112.56	56.85	0.999998	0.0378	0.0664
Validation – N3							
$N3_L$	43.60-120	79.77	43.65-120	79.78	0.999640	0.4746	0.5949
$N3_{BNW}$	0-120	34.74	0-120	35.44	0.982455	5.2974	15.2483
$N3_{BSE}$	18.59-112.00	44.10	18.52-112.02	44.10	0.999996	0.0381	0.0864
$N3_{SN}$	63.01-120	93.86	62.94-120	93.86	0.999926	0.1916	0.2041
$N3_{SS}$	0-55.90	25.08	0-55.86	25.08	0.999997	0.0359	0.1430

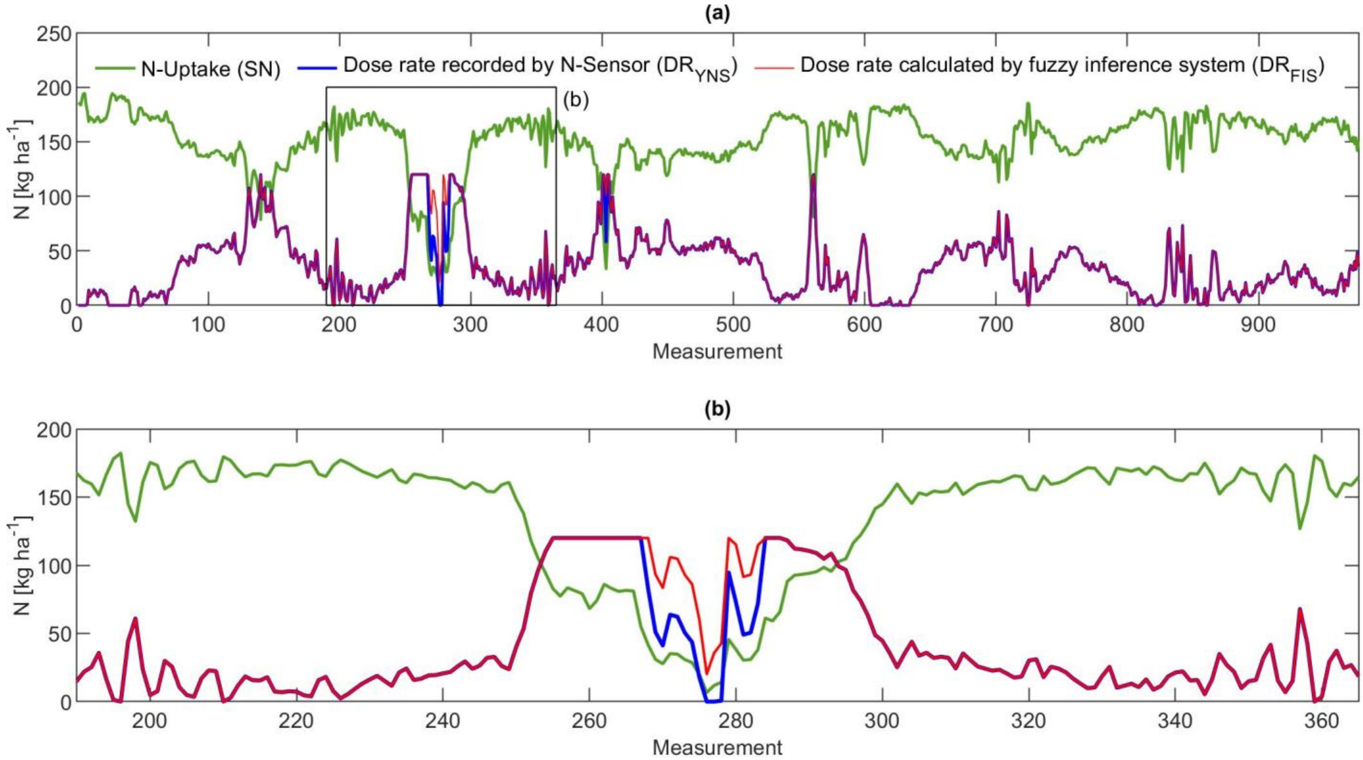

Fig. 5: Simulation results for $N3_{BNW}$ (a) showing whole data set and (b) showing a section with high variations.

In Fig. 5., the simulation results for $N3_{BNW}$ are presented as a data series. On the x-axis of each subplot, the chronologic sequence of the measurement, the SN, the DR_{YNS} and the DR_{FIS} that was calculated from the corresponding SN are plotted. It is apparent in Fig. 5a that, for large parts, the fuzzy logic-based algorithm performed well in terms of imitating the behaviour of the N-Sensor. Around the minimum SN value, the DR_{FIS} does not follow the DR_{YNS} very well, which is indicated in Fig. 5b. The most probable explanation for that pattern is that the characteristic curve was supposed to fall more sharply to 0 below the SN_{cut} than it actually did.

Also for $N3_L$ and $N3_{SN}$ one can observe a deterioration of RMSE and $RMSE_p$. After examining these simulation data, it became clear that this was also due to outliers, where the slope of the cutoff was not imitated properly by the FIS. Yet, for all of the three critical data sets, it seems that the DR_{FIS} could follow the DR_{YNS} very well even at areas where the DR was limited by the maximum value. $N3_{BSE}$ and $N3_{SS}$ show similarly good results like N2, which is an indication for the good transferability of the algorithm. For $N3_{SS}$, many values with a minimum DR are existing for high SN values. This shows that the corresponding FIS was able to cover also these border conditions.

4. CONCLUSIONS

An algorithm was developed that created a Takagi-Sugeno FIS, which was configured to imitate the agronomic algorithms of the commercial Yara N-Sensor ALS2. Even though it was optimized for one field at N2, it could be transferred to other fields or subareas by an automated adaption of the input and output parameters based on new calibration values. A validation for different fields and subareas in N2 and N3 has shown that for SN values beyond the SN_{cut}, the commercial system could be imitated very well by the fuzzy logic-based model. For values below the SN_{cut}, however, the corresponding piece of the characteristic curve should have fallen steeper to 0. In an iterative process, the algorithm could be further optimized to cover a wider range of different field conditions. Based on the presented algorithm, an expert can situationally modify the input membership functions, the output values or the rules depending on the circumstances of a specific application date. Furthermore, the algorithm can be extended by further input parameters like e.g. soil information. Using Mamdani FISs, a lower accuracy in terms of imitating the N-Sensor algorithm, but more intuitive adaptability of the output can be expected.

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