

Application of Fuzzy Logic and Near Infrared Spectroscopy for Malt Quality Evaluation

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ABSTRACT

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An increasing number of quality criteria are involved in the evaluation of the final malt. This implies a comprehensive quality evaluation, normally based on experience and prior knowledge by the maltster/brewer/breeder. This paper describes the principle in, and use of, fuzzy logic for the translation of a complex malt quality profile into a simple univariate overall quality index (OQI). The approach was tested on a data set of 50 malt samples including eleven quality parameters according to the European Brewery Convention.

The presented fuzzy logic approach involves three steps: i) an appropriate definition of how good a certain quality parameter level is, ii) a sound way to combine several quality parameters and iii) a way to express the overall quality based on all these individual parameters, taking their individual relative importance into account. The fuzzy logic based OQI presented here turned out to be a sound index for the overall quality of the tested malt samples, and thus provides a way of reducing and automating the quality data evaluation.

It is furthermore shown that near infrared transmittance spectra of the malt samples showed reasonable ability to predict the calculated OQI. Hereby, both analysis and evaluation efforts in malting barley breeding can be reduced considerably.

Key words: Fuzzy logic, malt quality, overall quality index, Near Infrared Transmittance spectroscopy.

INTRODUCTION

Malting is basically a controlled germination of barley in which the starchy endosperm is modified into friable malt, ready for enzymatic degradation into fermentable sugars and amino acids to be used by the brewer's yeast. An increasing number of quality criteria are involved in the evaluation of the final malt. A complete quality analysis might contain 10–15 physical and chemical analyses, which makes the malt analysis costly and time consuming. Near infrared (NIR) spectroscopy has been used extensively for the prediction of a range of these malt quality

parameters, as reviewed by Osborne *et al.*¹⁰ and Meurens and Yan⁶, and thereby contributed to a considerable reduction in the time of analysis. However, the high number of analyses, either determined by classical reference methods or by NIR spectroscopy, implies a comprehensive quality evaluation, as a given malt lot is to be evaluated on several quality parameters simultaneously. This evaluation is normally based on experience and prior knowledge by the maltster/brewer/breeder, in which each quality parameter is evaluated according to a target or target range. The single value evaluations are then summarised in a total evaluation, to be used for final acceptance or rejection of a given malt sample.

The purpose of this investigation is to study the use of fuzzy logic for the translation of a complex malt quality profile into a simple univariate overall quality index. By using fuzzy logic it is possible to define in a simple way, i) an appropriate definition of how good a certain quality parameter level is, ii) a sound way to combine several quality parameters and iii) a way to express the total quality based on all these individual parameters taking their individual relative importance into account. At the heart of fuzzy logic is a membership function for each quality parameter. As an example of a membership function, consider the non-fuzzy logic implied when a person is asked to tell whether another person is young or old. The traditional binary logic implied requires that everyone beyond, say, 40 years is old (one), while everyone below is not (zero). It is apparent, however, that a person at 41 years is not much different with respect to age than a person at 39 years, even though the former would be considered old and the latter young. In a fuzzy system, the membership function enables age to be defined as a continuous function of age. For example, persons above 70 years may have a membership of one, meaning they belong completely to the class old. Persons at the age of 40 may have a membership of ½ meaning that these are equally young and old. Clearly, the fuzziness of the membership function is appropriate in this case and as will be shown, such fuzziness is also what is called for when quantifying the quality of malt with respect to different parameters. Fuzzy logic has found use in diverse disciplines since its formal introduction¹⁴. There are several different types of fuzzy logic based inference systems^{3,4,12} and they have been applied in virtually all branches of applied science under slightly different names. Relevant reviews on fuzzy logic can be found in the literature^{2,11}. As the fuzzy system built in this

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paper is particularly simple, only the relevant theory will be described.

Several indices combining single barley and malt quality variables have been proposed. In the framework of the European Brewery Convention, a statistical index for the overall evaluation of malting and brewing quality in barley has been proposed^{7,8}. This index is based on a weighted linear combination of extract, Kolbach Index, Apparent Final Attenuation, Viscosity and Diastatic Power. Monnez *et al.*⁹ proposed an index based on expert definition of barley groups based on their overall quality followed by linear discrimination between these groups.

The earlier approaches for calculating an overall quality index build on either a binary logic where each parameter is assessed and compared to one specific target value or a continuous approach where the actual value of the parameter is used directly as being proportional to the quality^{7,8}. These approaches are not satisfactory, since they unnaturally change the apparent expert knowledge into an overly restricted mathematical system.

For example, having one specific target value for a parameter is mostly not consistent with the a priori knowledge. For example, if a viscosity value of 1.10 is deemed optimal, then most likely a viscosity value of 1.20 or 1.40 is also optimal. Having the overall quality being linearly related to the level of a certain parameter throughout the parameter range is also not appropriate. Naturally, the relation between the level of a parameter and its evaluated effect on quality is highly nonlinear. Using the concept of fuzzy membership functions, will allow a simple way of treating the above problems. The method suggested in the following builds on membership function, and has no statistically estimated parameters. It is based on expert knowledge only, and therefore completely transparent from a user point-of-view.

MATERIALS AND METHODS

Sample collection

The samples, provided by Carlsberg Research Laboratory, originate from trials harvested in 1995, under the European Brewery Convention (EBC). Fifteen spring barley varieties and ten winter barley varieties were grown at two different locations in Denmark, Jutland and Zealand, giving 50 malting barley samples in total. The barley grain samples were screened over a standard 2.5-mm sieve and the grains above 2.5 mm were subjected to the micro-malting and mashing procedure.

Malting quality analyses

The following 11 quality analyses were performed according to the official methods from the European Brewery Convention¹: β -glucan in malt, extract, N in malt, viscosity, friability, malt modification, homogeneity, diastatic power, wort colour, soluble N in malt and β -glucan in wort. These parameters are typical for a malt quality evaluation.

Near infrared transmittance (NIT) measurements

Near infrared transmittance spectra of the 50 malt samples (whole kernels) were recorded using an Infratec 1225 Food and Feed Analyzer (Foss Tecator, Höganäs, Swe-

den). The spectrophotometer records spectra in the range from 850 to 1050 nm with data collection at every 2 nm, yielding 100 data points as reported in absorbance ($\text{Log}(1/T)$). The whole malt kernels were loaded in a large vertical sample cell with a 30 mm path length and inserted into a transport module. Each spectrum is the average of 10 sub-scans acquired along the vertical sample cell.

Data analysis

The fuzzy logic calculations were performed using MATLAB version 6.1 (The MathWorks, Inc. Natick, MA) using the associated Fuzzy Logic toolbox. Principal Component Analysis¹³ and Partial Least Squares Regression⁵ were computed using The Unscrambler 7-6 SR-1 (Camo A/S, Trondheim, Norway).

The principle of fuzzy logic

There are several steps in developing an overall quality index (OQI) using fuzzy logic. These steps are described in the following.

A simple non-binary (fuzzy) membership function is attached to each individual parameter, indicating to which degree any level of the parameter is good (with respect to malting). Thus, the membership function defines to which degree the quality parameter is acceptable and is defined on the basis of expert knowledge. Fig. 1 shows an example of the membership function of soluble N in malt. For any value of soluble N (x-axis), a corresponding membership can be read from the ordinate axis. For example, if soluble N is between 0.58 and 0.66, the membership will be one, indicating perfect malting quality (with respect to soluble N). Below 0.55, the membership, hence quality, is zero. Between 0.55 and 0.58 as well as between 0.66 and 0.69 is the interesting 'fuzzy' area, where the quality (membership) will increase or decrease. If the parameter lies within these areas, the malt is not unacceptable, though not optimal. The closer the parameter is to the optimal region, the better the malt is. This is quantified by the membership function which is a one-to-one mapping from the parameter space to membership space. The membership for any parameter is a number between zero (unacceptable) and one (optimal).

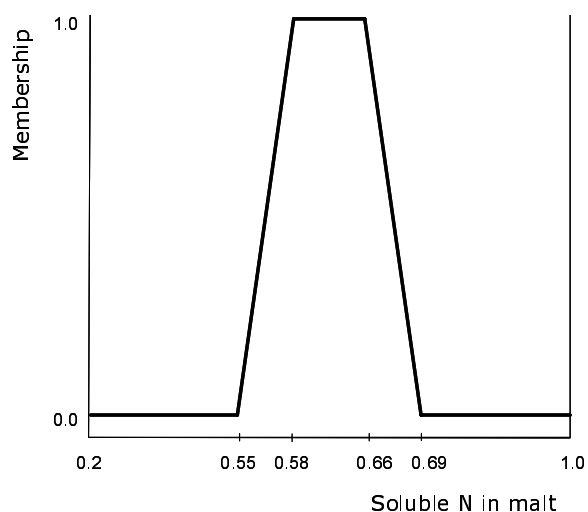


Fig. 1. Example of a membership function of soluble N in malt.

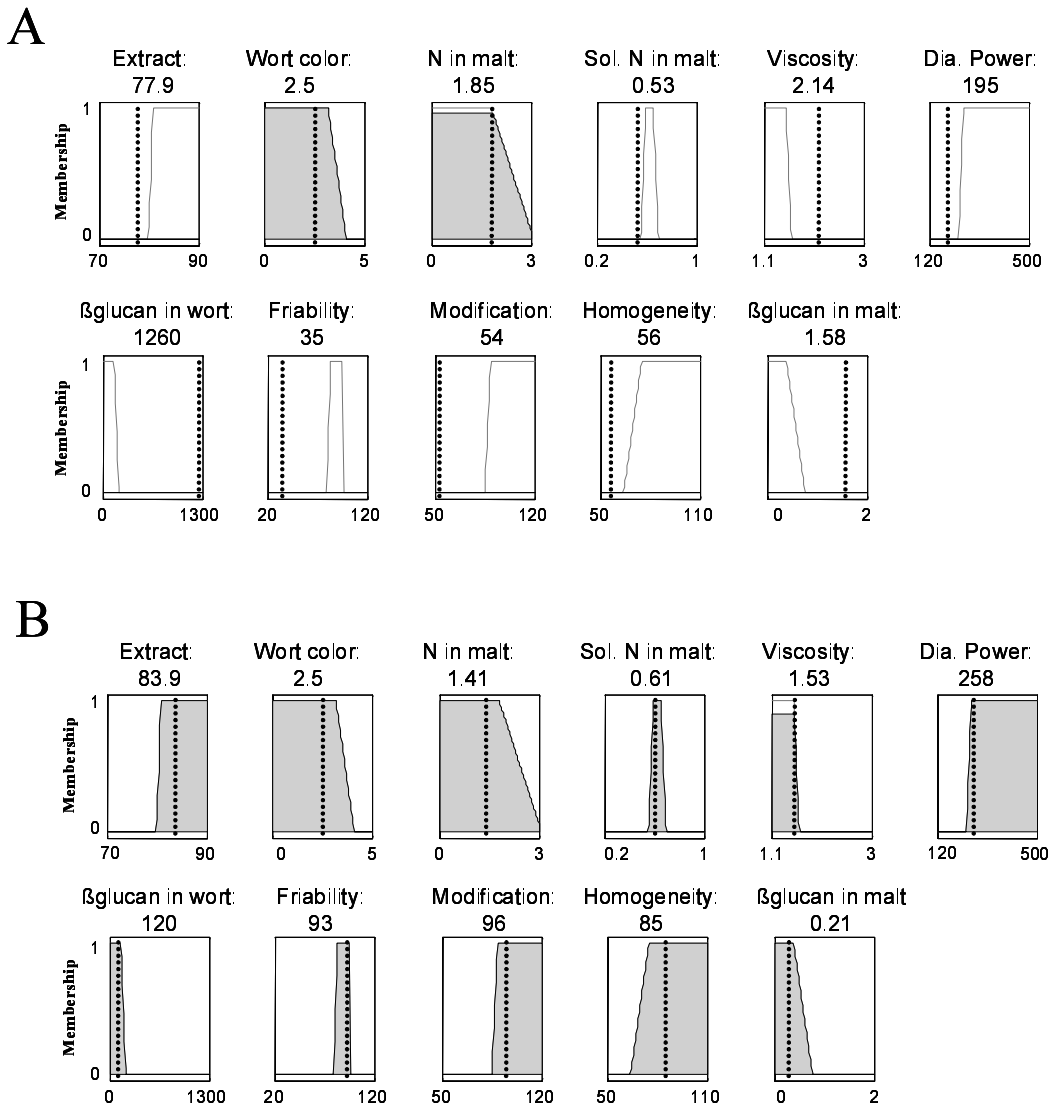


Fig. 2. The membership functions for the 11 quality parameters. Two specific malt samples are also given. The top plots (A) show the least interesting malt sample and the lower (B) shows the best quality in the current sample set. For each parameter, the level of the parameter is defined on the x-axis and the membership (between zero and one) read on the y-axis.

Table I. Importance weights of the 11 parameters.

	Extract	Wort colour	N in malt	Sol. N in malt	Viscosity	Diastatic power	β-Glucan in wort	Friability	Modification	Homogeneity	β-Glucan in malt
Weights	9	7	4	9	3	9	10	7	8	9	10

Membership functions can have virtually any shape (usually convex) but the exact shape is mostly not important. As long as the shape is in reasonable accordance with the background knowledge, reasonable results are obtained. For all 11 parameters in this investigation, the membership functions are defined on the basis of current subjective expert quality assessments and are shown in Fig. 2. As can be seen, some parameters are simply better the higher (or lower), such as extract yield, while others have an optimal target region (e.g. soluble Nitrogen). This is easily handled by setting the shapes of the membership functions accordingly. When the membership functions are

defined, any parameter can be converted into a membership degree for any malt sample. These memberships are then combined into one OQI.

The memberships (one for each quality parameter) are combined into the OQI by means of a simple weighted addition (sugeno-type). This type turned out to provide the most intuitive and directly appreciable quality measure. The weights are defined on the basis of expert evaluation of importance of each parameter where 10 is very important and 1 is less important. In Table I, the expert-defined weights are shown for the 11 parameters.

As for the definition of the membership functions, these

weights are subjectively defined by the current evaluation of importance. OQI is then simply defined as

$$OQI = \sum_{i=1}^{11} m_i w_i$$

where m_i is the membership for parameter i 1 to 11 and w_i is the corresponding weights.

This choice of aggregation method is non-trivial and it is possible to argue for other more traditional aggregation methods. For example, it is reasonable to define OQI as equal to the lowest attained membership value, such that if only *one* attribute is in a low-quality region, the overall quality is deemed low. However, it is conjectured that this

is not an appropriate weighting scheme for this type of problem. Imagine that all but one variable have perfect quality and the last one has very low quality (for example membership zero). If this variable has a low weight, hence is of inferior importance, then it is reasonable that this sample is judged to be of overall good quality. It would certainly not be reasonable to discard the sample as inferior. On the other hand, if this variable is of high importance, then it is reasonable that, through the weighting, the overall quality is affected more severely. In essence, it is argued that by choosing appropriate weights, it is possible to obtain a system which is in quite good accordance with how the quality would be assessed by a human expert.

Table II. Malt quality data of the 50 analysed samples including 15 spring barley and 10 winter barley varieties respectively grown in Jutland (number 1–25) and Zealand (number 26–50) including the calculated OQI.

Number	Variety	Extract	Wort colour	N in malt	Sol. N in malt	Viscosity	Dia-static power	β -Glucan in wort	Friability	Carlsberg modification	Homogeneity	β -Glucan in malt	OQI
1	Alexis	81.7	2.2	1.58	0.55	1.64	254	260	83	88	58	0.42	49.0
2	Triumph	81.2	2.5	1.62	0.57	1.81	231	450	74	86	79	0.79	35.6
3	Nevada	80.9	1.9	1.59	0.51	1.96	232	580	72	81	62	0.84	19.8
4	Cooper	82.0	1.9	1.56	0.57	1.59	166	210	86	93	81	0.42	56.4
5	Caminant	81.4	3.0	1.59	0.63	1.85	201	420	72	82	65	0.84	29.8
6	Miralix	81.0	2.2	1.71	0.53	1.91	257	630	65	75	59	1.27	29.0
7	Texana	82.3	2.5	1.62	0.61	1.63	167	200	87	92	77	0.32	64.3
8	Trebon	81.9	2.5	1.62	0.58	1.59	307	150	77	92	60	0.26	64.6
9	Cork	81.0	2.2	1.49	0.50	1.57	373	180	80	91	59	0.32	54.8
10	Delibes	81.2	2.2	1.56	0.49	1.69	286	290	78	81	65	0.53	34.1
11	Polygena	82.4	2.2	1.62	0.60	1.60	356	240	84	91	78	0.32	72.2
12	Mentor	81.3	2.2	1.68	0.57	1.62	379	220	73	93	76	0.27	60.5
13	Mie	81.7	2.2	1.65	0.55	1.70	239	400	73	84	68	0.69	27.4
14	Reggae	82.4	2.5	1.53	0.53	1.68	215	400	79	84	70	0.74	24.9
15	Anni	81.0	2.5	1.57	0.50	2.16	239	1200	58	71	69	1.79	28.0
16	Plaisant	78.2	2.2	1.78	0.52	2.10	333	1200	38	51	68	1.79	23.3
17	Angora	79.6	2.5	1.80	0.61	1.73	378	770	48	71	53	1.15	29.0
18	Clarine	77.9	2.5	1.85	0.53	2.14	195	1260	35	55	56	1.58	10.8
19	Puffin	78.7	2.2	1.86	0.63	1.91	277	730	53	68	54	1.00	28.8
20	Geneva	77.1	2.5	2.13	0.70	1.83	437	650	44	71	66	1.00	20.6
21	Trasco	79.1	2.5	1.86	0.60	1.75	277	830	49	66	54	1.16	28.8
22	Fanfare	80.5	2.5	1.68	0.54	1.86	204	770	49	66	64	1.31	15.9
23	Melanie	79.9	2.5	1.78	0.60	1.77	388	750	58	71	56	1.15	29.0
24	Rejane	79.5	2.5	1.83	0.57	1.90	166	680	48	76	59	1.05	15.4
25	Sunrise	78.9	2.2	1.75	0.55	2.11	270	890	42	58	63	1.26	20.0
26	Alexis	82.7	2.5	1.52	0.59	1.56	305	180	88	93	71	0.26	75.5
27	Triumph	83.1	2.5	1.47	0.60	1.64	260	280	82	90	80	0.79	60.3
28	Nevada	82.1	2.5	1.45	0.51	1.78	238	450	79	84	64	0.63	25.1
29	Cooper	83.9	2.5	1.41	0.61	1.53	258	120	93	96	85	0.21	84.7
30	Caminant	82.1	2.8	1.52	0.63	1.71	252	300	78	84	69	0.79	42.1
31	Miralix	83.4	2.8	1.50	0.61	1.60	158	180	89	94	75	0.26	68.6
32	Texana	82.7	2.5	1.49	0.55	1.57	146	500	80	87	77	0.68	35.1
33	Trebon	82.5	2.8	1.52	0.61	1.58	313	145	84	94	81	0.31	82.8
34	Cork	82.5	2.2	1.35	0.51	1.48	390	120	88	95	74	0.21	75.2
35	Delibes	82.6	2.7	1.42	0.50	1.56	287	150	89	95	82	0.21	74.8
36	Polygena	83.2	2.8	1.44	0.62	1.53	279	190	90	92	82	0.31	77.7
37	Mentor	82.6	2.8	1.55	0.63	1.57	316	150	82	92	72	0.31	78.9
38	Mie	83.1	2.8	1.47	0.58	1.56	212	220	86	90	71	0.31	58.9
39	Reggae	83.3	2.8	1.47	0.60	1.52	217	190	88	90	63	0.31	60.0
40	Anni	81.7	2.8	1.54	0.51	1.87	232	830	66	73	64	1.52	20.6
41	Plaisant	80.6	2.8	1.35	0.44	1.94	205	660	72	76	70	1.10	21.6
42	Angora	82.4	2.8	1.43	0.60	1.54	282	170	92	92	83	0.21	81.1
43	Clarine	81.0	3.1	1.49	0.47	1.87	151	700	68	73	64	0.94	20.0
44	Puffin	81.4	2.5	1.53	0.59	1.63	221	240	84	88	73	0.36	57.7
45	Geneva	80.9	2.5	1.71	0.63	1.65	384	260	81	85	72	0.42	54.2
46	Trasco	82.2	3.1	1.74	0.60	1.62	376	240	82	81	62	0.31	52.9
47	Fanfare	82.6	2.8	1.33	0.54	1.66	206	380	78	76	62	0.58	23.1
48	Melanie	82.7	3.1	1.33	0.61	1.54	314	170	92	92	76	0.21	81.1
49	Rejane	82.4	2.5	1.37	0.56	1.57	155	160	86	94	80	0.21	66.1
50	Sunrise	82.1	2.5	1.33	0.53	1.72	253	410	76	80	66	0.68	31.1

RESULTS AND DISCUSSION

As an example, the fuzzy logic function described in the previous section was applied on a limited data set comprising of 50 malt samples representing 25 genotypes grown on two Danish locations. The detailed results of the eleven EBC malt analyses of the 50 samples used for this investigation are given in Table II.

A normal evaluation of such a data table of malt quality results is based on experience and prior knowledge of the maltster/brewer, in which each quality parameter is evaluated according to a target or target range. By applying the membership functions including the specific weights on to the original data (Table II) these data are converted from parameter space to weighted membership space. Thus, the original data matrix (50 samples \times 11 variables) is converted into a new 50 \times 11 matrix, where the variables represent new weighted optimality indices, one for each parameter. For instance, the first column (extract) has a weight of nine and is hence converted from the original range of 77.1–83.9% extract yield to a weighted optimality index ranging from 0 (unacceptable) to 9 (optimal).

Exploration of this new weighted optimality matrix using PCA reveals five relatively distinct groups in a score plot of principal component (PC) 1 and PC 2 (Fig. 3). These two principal components explain 70% of the variation, where PC 1 mainly explains differences in malt modification, while PC 2 mainly explains differences in diastatic power. The clusters can roughly be grouped as follows:

A: not acceptable modification;
optimal diastatic power

B: partly acceptable modification;
optimal diastatic power

C: optimal modification;
optimal diastatic power

D: not acceptable modification;
not acceptable diastatic power

E: close to optimal modification;
not acceptable diastatic power

Performing a similar PCA analysis on the “raw” data in Table II (not shown) instead of the membership functions did not provide as clear results as the above, which is sensible considering that the two different representations provide different information. A PCA on the raw data focuses on the main directions in the original data, where the principal components are linear combinations of the original data and extreme samples will therefore have a large impact on the principal components. This is feasible for data overview, sample comparisons and interpretation of the principal components. The transformation from the raw variables to memberships can be viewed as an attempt to linearize the data according to their relevance. A monotonic continuous scale, for example such as “soluble N in malt”, does not reflect the associated quality linearly. By transforming to a suitable membership function, the variable is re-expressed in a domain which is, at least ideally, linearly related to the quality. Even though the data may not be perfectly bilinear in the sense assumed in PCA, the data are feasible in the sense that variables that reflect the same underlying type of quality are expected to be correlated by having high and low memberships in the same samples. And samples that display the same type of under-

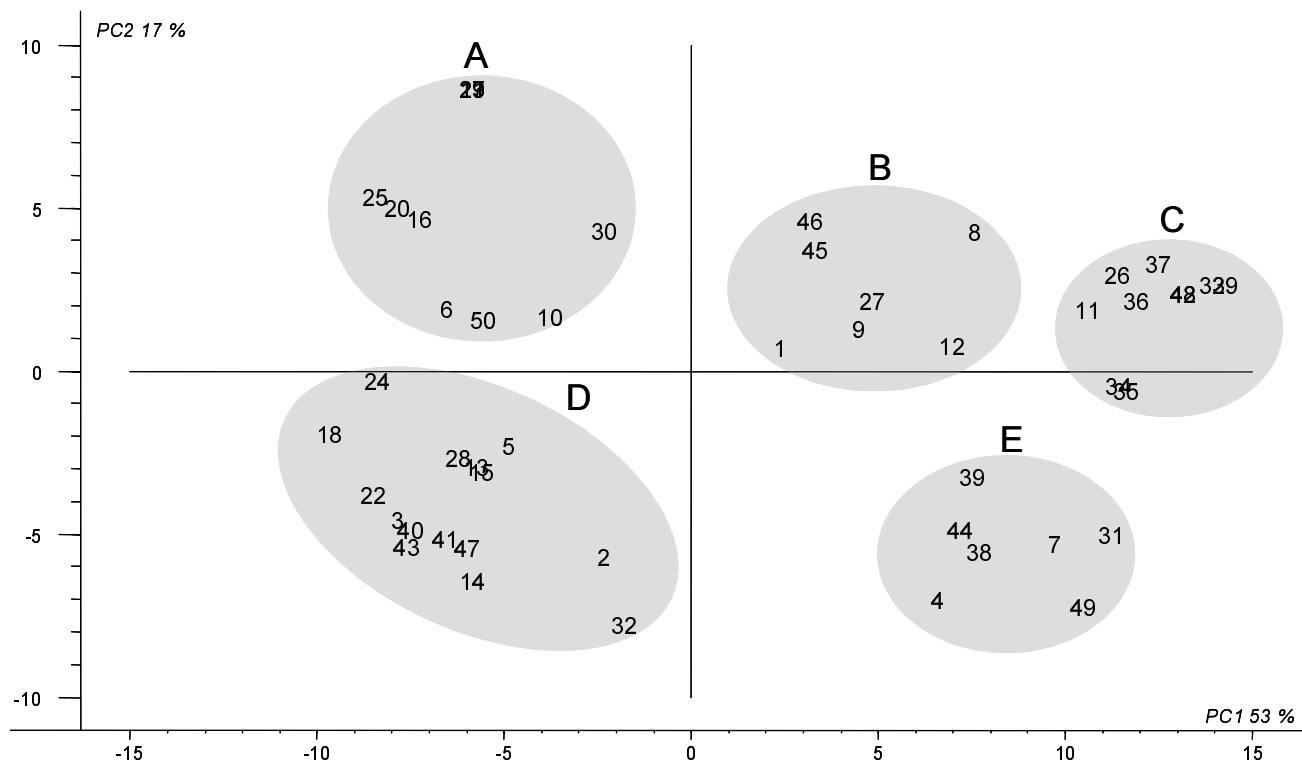


Fig. 3. PCA score plot (PC 1 versus PC 2) of the weighted optimality matrix. The variety identification is given in Table II.

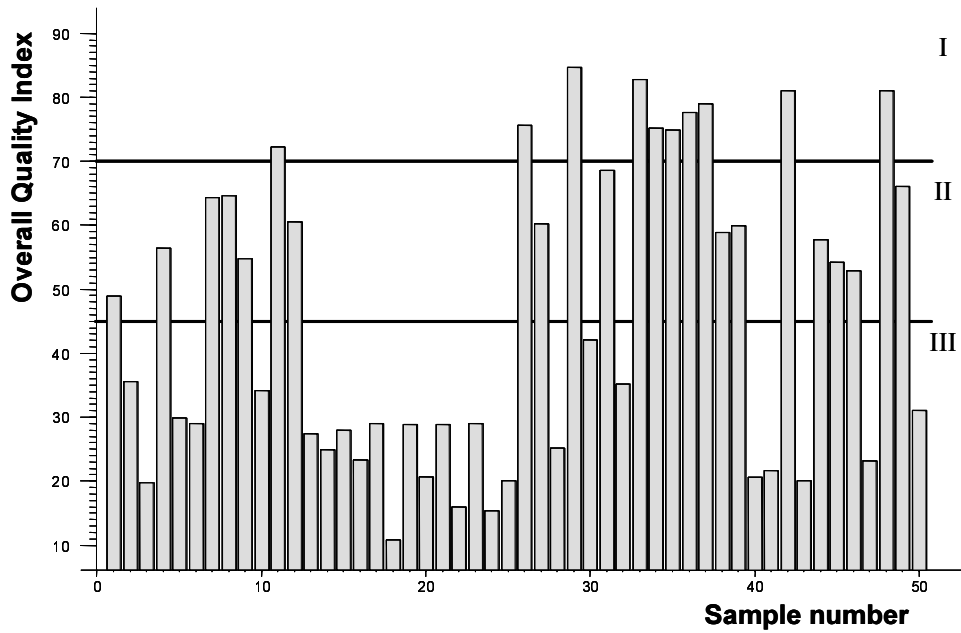


Fig. 4. Bar plot of the calculated Overall Quality Index (OQI) of the 50 analysed malt samples. The variety identification is given in Table II. High overall quality index means good malt quality and low means poor. The horizontal lines indicate tentative limits for optimal (I), medium (II) and unacceptable (III) malt quality.

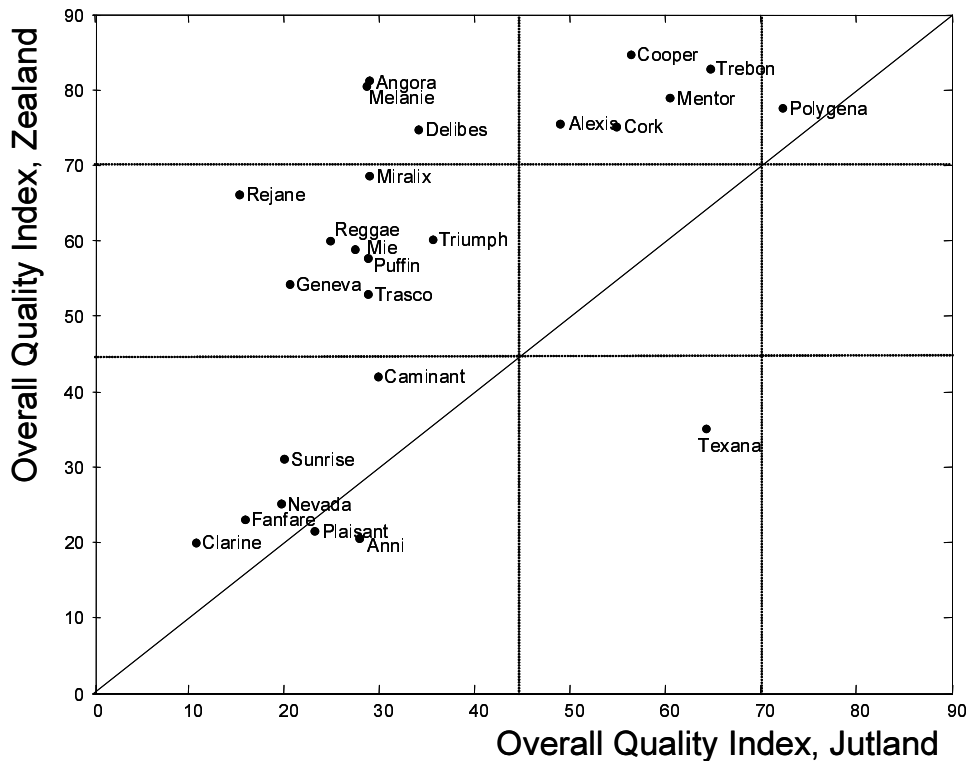


Fig. 5. Scatter plot of OQI of the 25 genotypes grown on two locations (x-axis: Jutland; y-axis: Zealand).

lying quality reflected in the variables are expected to be similar in terms of memberships. These notions are supported by the actual PCA model which explains 70% of the variation in the first two components, hence a fairly high amount of variance for a data set of this kind.

For each sample, the weighted optimality data are combined into a single overall quality index (OQI) by simple addition. An optimal sample would thus give an OQI of 85 (the sum of the weights multiplied by one), while a completely unacceptable sample would give an OQI of zero

(the sum of the weights multiplied by zero). The OQI's of the 50 samples are given in Fig. 4 (and listed in Table II), showing considerable variations. Sample number 18 (Clarine grown in Jutland) seems to be the most unacceptable sample (OQI of 10.8), while sample number 29 (Cooper grown at Zealand) seems to be the most optimal (OQI of 84.7) of the analysed samples. The calculated OQI's of all the samples were thoroughly validated by the third author and found to be a sound index reflecting prior knowledge and expectations of the tested samples. It should, however, be strongly emphasized that the membership functions as well as the importance weights in this investigation have been chosen in order to fulfil current malt requirements based on the experience of the third author, but can be changed according to other requirements.

Two tentative limits have been added to Fig. 4, indicating near optimal samples (I), medium samples (II) and not acceptable samples (III). A comparison between the PCA grouping in Fig. 3 and the OQI's shows that the OQI group I is comprised of all the C samples in Fig. 3, group II is comprised of B and E samples, while group III is comprised of A and D samples. Thus, the calculated OQI does not clearly differentiate between B and E samples or between A and D samples. This shows that the calculated OQI as such only aims to determine whether a given sample is acceptable or not.

Combining the malt quality data into one single number facilitates plotting and easy data overview of the interactions between genotype and environment. Fig. 5 shows the OQI's of the 25 genotypes grown on the two locations (x-axis Jutland and y-axis Zealand) including the tentative limits. It is evident that most of the samples perform considerably better in Zealand compared to Jutland (most genotypes located above the diagonal), while only Texana performs better in Jutland. Genotypes along the diagonal perform equally well on the two locations, while the non-diagonal samples are environmentally unstable (based on two locations only). As discussed earlier, Cooper grown in Zealand was the most optimal single sample. However, from a stability point of view, Polygena seems to perform

similarly on both locations, even though on a slightly less optimal level. In the lower end, the group comprising Sunrise, Nevada, Fanfare, Plaisant, Anni and Clarine seems to be unacceptable on either location.

The fuzzy logic based OQI presented above is a way of reducing eleven malt quality parameters and thereby reducing the data evaluation efforts in, for example, malting barley breeding. However, the eleven input parameters are based on real malt quality analyses involving micro-malting and mashing. In order to reduce the analysis efforts as well, it would be of interest to predict this OQI by near-infrared spectroscopy. NIT spectra were recorded on the 50 malt samples, and the spectra were pre-transformed by the second derivative (Fig. 6A) and used in a partial least squares regression (PLSR) model for the prediction of OQI.

Four outliers needed to be removed prior to modelling, namely the samples: 14, OQI = 24.9; 16, OQI = 23.3; 25, OQI = 20.0 and 32, OQI = 35.0 (See Table II for variety ID). These four samples were all in the lower end of the OQI scale, but the exact reason for these four being outliers remains unclear. The predicted versus measured plot of the remaining 46 samples is shown in Fig. 6B, indicating a reasonable model with a correlation coefficient (r) of 0.88 and a cross-validated prediction error (RMSECV) of 11, which corresponds to approximately 15% of the OQI range. This is not a perfect predictive model, but it is probably accurate enough for screening purposes in malting barley breeding by having the capability to classify the material into good, medium and bad categories. This will thus reduce both malt quality analyses and data evaluation.

CONCLUSIONS

This investigation has employed fuzzy logic for the translation of a complex malt quality profile into a simple univariate overall quality index. The approach was tested on a data set of 50 malt samples including eleven quality parameters. Fuzzy membership functions were constructed for each of the quality parameters. These functions define

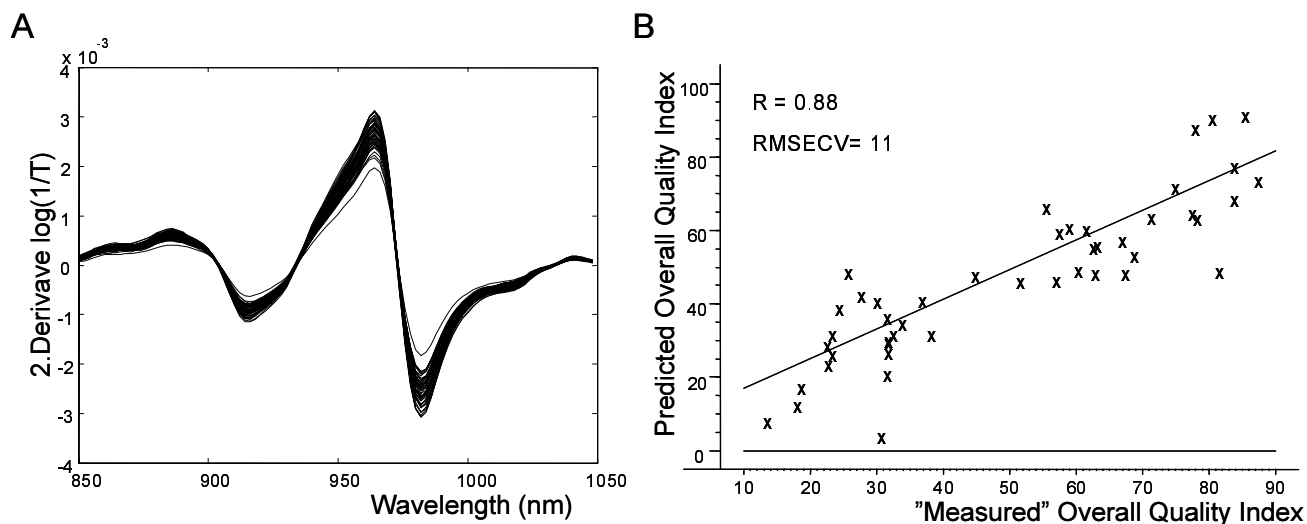


Fig. 6. A) Second derivative NIT spectra in the range 850–1050 nm of the 50 analysed malt samples. B) Predicted versus “measured” OQI of a PLSR model using the second derivative NIT spectra.

to which degree the quality parameter is acceptable on a scale from zero (unacceptable) to one (optimal), taking into account the non-binary and non-linear relationship between the level of the quality parameter and the degree of optimality. The memberships (one for each quality parameter) are combined into an overall quality index (OQI) by means of simple weighted addition. This OQI turned out to be a sound index for the overall quality. It is furthermore shown that a reasonable PLSR prediction model based on NIT spectra is obtainable. A relative prediction error of 15% was achieved, indicating a useful calibration for breeding purposes.

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REFERENCES

1. Analytica-EBC. EBC Analysis Committee. Brauerei- und Getränke-Rundschau: Zurich, 1987.
2. Center, B., Fuzzy logic for biological and agricultural systems. *Artificial Intelligence Review*, 1998, **12** (1-3), 213-225.
3. Jang, J.-S. R. and Sun, C.-T. *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice Hall: USA, 1997.
4. Mamdani, E.H. and Assilian, S., An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 1975, **7** (1), 1-13.
5. Martens H and Næs T., *Multivariate Calibration*. Wiley: New York, 1989.
6. Meurens, M. and Yan, S.H. Applications of vibrational spectroscopy in brewing. In: *Handbook of Vibrational Spectroscopy; Applications in Life, Pharmaceutical and Natural Science*; J. M. Chalmers and P.R. Griffiths, Eds., John Wiley and Sons: Chichester, UK, 2002.
7. Molina-Cano, J.L., The EBC barley and malt committee index for the evaluation of malting quality in barley and its use in breeding. *Plant breeding*, 1987, **98**, 249-256.
8. Molina-Cano, J.L., Madsen, B., Atherton, M. J., Drost, B.W., Larsen, J., Schildbach, R., Simiand, J.P. and Voglar, K., A statistical index for the overall evaluation of malting and brewing quality in barley. *Monatsschrift für Brauwissenschaft*, 1986, **9**, 328-335.
9. Monnez, J.M., Flayeux, R., Muller, P. and Moll, M., An approach to the estimation of brewing quality in barley and malt. *Journal of the Institute of Brewing*, 1987, **93**, 477-486.
10. Osborne, B., Fearn, T. and Hindle, P.H., *Practical NIR Spectroscopy with Applications in Food and Beverage Analysis*. Longman Scientific and Technical: Harlow, UK, 1993.
11. Saffiotti, A., The uses of fuzzy logic in autonomous robot navigation. *Soft Computing*, 1997, **1** (4), 180-197.
12. Sugeno, M. *Industrial applications of fuzzy control*, Elsevier Science: U.K., 1985.
13. Wold, S., K. Esbensen, and P. Geladi. Principal component analysis. *Chemometrics and Intelligent Laboratory System*, 1987, **2**, 37-52.
14. Zadeh, L. A., Fuzzy sets. *Information and Control*, 1965, **8**, 338-353.