Developing Functional Malt Specifications for Improved Brewing Performance

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Introduction

As many authors have reported, there is often little or no correlation between the current malt quality parameters and malt processing performance in the brewery (Copestake, 1998). Process changes in the brewery are rarely made based on the malt quality data supplied with each batch of malt. In some instances, particularly with new barley varieties, traditional malt quality parameters have been misleading with respect to process performance. This study evaluates the potential of neural networks (NN) to correlate current malt parameters with brewing performance and thereby develop functional malt specifications. Combining malt and wort quality data with neural networks may improve consistency in the brewhouse by linking malt parameters directly to process outputs.

Neural Networks

Neural Networks are a type of parallel processing structure that are useful for modelling non-linear relations. They were first proposed in 1943 (Sye *et al*. 1994), and their architecture is based on our understanding of the workings of the mammalian brain's cerebral cortex (Chitra *et al*. 1995) – e.g. Figure 1.

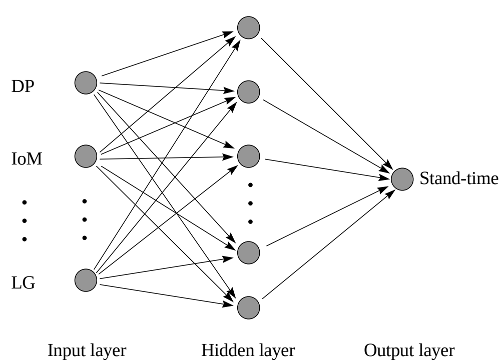

Figure 1. Typical structure of a neural network

The circles depict nodes/neurons where information processing takes place and the lines depict the connection paths between each of the neurons. In order to learn the mathematical relationships represented in a process, Neural Networks are presented with a large number of training data sets. Once trained, the input neurons of the NN are presented with the input values from unseen data sets for validation. The predicted output is then compared to the actual value in the data set to enable the accuracy of the NN to be determined. As NN's are ideal for modelling non-linear relationships and they "don't require any *a priori* knowledge on relationships of the process variables in question" (Linko, 1998) they are particularly suited for modelling biological processes (Garcia, 1995). The potential of expert system technologies such as NN’s to model and control biological process is only just being realised by the brewing industry.

Application of Neural Networks for Malt Analysis.

The apparent attenuation limit (AAL) of malt describes the maximum percentage of fermentable sugars in an EBC wort that can be metabolised by brewers yeast. It provides useful data on the likelihood of a particular malt achieving a target gravity, however it is a very time consuming test. Carbohydrate data has been used to predict malt AAL (using multiple linear regression) for Australian barley varieties (Cole, *et al*, 1992) with some success, however with the introduction of new barley varieties these predictions have deteriorated. This highlights the limitations of applying linear models to non-linear relationships. The parameters used for AAL predictions by multiple linear regression are shown in Table 1. Individually, most of these parameters correlate poorly with AAL.

Table 1. Correlation between individual malt parameters and Apparent Attenuation Limit

Parameter	Ext	Viscosity	DP	SN	G+F	M	M3	M4	TC	All parameters
Correlation coefficient (n = 424)	0.28	0.64	0.57	0.10	0.50	0.36	0.21	0.49	0.39	0.71

Ext = EBC extract, DP = diastatic power, SN = soluble nitrogen, G+F = glucose + fructose, M = maltose, M3 = maltotriose, M4 = maltotetraose, TC = total carbohydrate = G+F+M+M3+M4

A NN trained using the Back Propagation Module from the CIS Software Library (Swinburne University of Technology) was applied to commercial malt quality data (475 samples) to investigate the ability of NN’s to predict AAL from the parameters in Table 1. The training set consisted of 424 malt samples (10 different barley varieties from 6 different malting plants). Several neural networks were produced and tested on an independent validation set (51 samples). Table 2 shows the correlation coefficients and average errors for some of the networks for both the training and validation sets. The 6 inputs used for the construction of these networks were: EBC extract, viscosity, glucose + fructose, maltose, maltotriose and maltotetraose. AAL was the single output. Results have also been included for multiple linear regression applied to the same validation set.

Table 2. AAL prediction by neural networks; correlation coefficients and average errors

	Training set - 424 samples			**Validation set - 51 samples**			
	NN results			NN results			Linear regression *
NN	Franklin	Arapiles	All varieties	Franklin	Arapiles	All varieties	All varieties
n	106	89	424	13	8	51	51
r	0.95	0.98	0.86	0.48	0.68	0.86	0.62
Mean error	0.27	0.22	0.76	1.97	0.54	0.83	1.24

r = correlation coefficient, n = number of samples, * equations based on all 9 parameters shown in Table 1.

The NN results show that AAL can be predicted from wort analyses. Overall this represents an improvement over the use of linear regression equations, although the average error would need to be further reduced to around 0.5 AAL units for routine use. The Franklin network produced a high correlation coefficient for the training set but did not accurately predict the validation set. In fact the mean errors for the Franklin and Arapiles training sets (0.27 and 0.22 respectively) are smaller than the standard deviations expected for the reference AAL method (0.4 units). This suggests that the results for relatively small data sets may not be meaningful and highlights the danger in using such networks. In this particular case study more than 300 data sets were deemed necessary for meaningful prediction.

Application of Neural Networks in Mashing

Mashing is the process where enzymes in the malt convert starch to fermentable sugars and dextrins. The carbohydrate profile created during mashing has a significant effect on final beer flavour and mouth feel. It is controlled by careful manipulation of the mash stand-time and/or mash temperature. Since the quality of malt batches used for each brew can be variable it is necessary to adjust both mash stand-time and mash temperature to achieve consistent beer flavour. In the past, malt parameters such as diastatic power (DP) have been used as a guide in determining the required mashing conditions, however with some new varieties like Arapiles, DP has proven to be a poor indicator. Malts with the same DP have often produced worts with quite different carbohydrate profiles under comparable conditions. To achieve better process control, neural networks have been used to model the mashing process and to predict the stand-time required to achieve the right carbohydrate profile.

Two types of NN's including a back propagation network using the Levenberg-Marquardt algorithm (LM) and a recurrent network using the Elman algorithm were evaluated (RMIT University). The models were trained with ten input parameters, seven of which were derived from the malt delivery analysis (extract, colour, beta glucan, DP, permanently soluble nitrogen, total nitrogen and index of modification). Another two inputs accounted for the difference in malt to adjunct ratio and adjunct mix and limit gravity (which is used to estimate the desired carbohydrate profile) was the final input. Mash stand-time was the predicted output. Sets of data (314) were collected for three major brands at CUB's Abbotsford brewery and correlated with their corresponding stand time. Seventy five percent of the data was used for training and the remainder was used for validation. To ensure that the numerical value of each variable was given equal weighting and to eliminate training bias, the data was normalised between 0.1 and 0.9.

The correlation coefficients and average errors obtained for the validation set are shown in Table 3. The best result was obtained for the LM network with 50 neurons in the hidden layer (average error 3.53 minutes, correlation coefficient 0.78). This shows that NN's have the potential to predict stand time, however the average error would need to be reduced to around 2 minutes before NN's could be used for routine process control in the plant. The maximum error of 13.6 minutes is certainly unacceptable and would cause wort to be produced out of specification. Results for the Elman network were comparable to the LM network and further testing would be required to determine which type of network is better for this application.

Table 3. Results of stand time prediction by neural networks.

Network Type	LM	LM	LM	ELMAN	ELMAN
No. of Neurons in hidden layer	10	30	50	10	30
Average error (minutes)	7.80	6.06	3.53	5.25	4.41
Minimum error (minutes)	0.08	0.01	0.01	0.33	0.03
Maximum error (minutes)	34.86	21.44	13.59	15.85	15.50
Correlation Coefficient	0.06	0.54	0.78	0.61	0.66

Discussion

For both the NN applications described in this paper it may be possible to further improve accuracy by increasing the number of data sets and by investigating the sensitivity of each input parameter. Other parameters, that may better relate to the biochemistry underlying the models, could also be investigated. Neural networks are only as good as the data that they are trained on and in the long term may need to be periodically re-trained as different barley varieties and growing seasons would have an effect on their performance.

By applying NN technology to malting and brewing we may be able to gain a better understanding of the malt attributes that will serve best as functional quality parameters. We can use NN's in adopting a holistic approach to brewhouse performance improvement. There firstly needs to be a clear understanding of the critical control points in brewing where malt quality has a significant impact. Secondly, those malt characteristics found to impact most on process performance and/or beer quality need to be identified. New technologies such as Near Infra Red (NIR) may improve the efficiency of testing and provide wider coverage of the large malt tonnages produced nowadays. Finally all the relevant parameters would need to be processed using expert systems that allow the brewer to rapidly assess the performance of any malt purchase made and make adjustments to the process if necessary.

Conclusion

Although the suitability of a malt sample for a particular brewing process can be described by a large number of quality parameters, some parameters give more useful information on processing performance than others. In most cases, to optimise process performance, brewers learn from experience, judging the likely contribution of a group of malt quality parameters to actual brewing performance. The ability to improve upon this prediction process using Neural Networks offers the potential for efficiency gains and more consistent quality in the brewery. In this paper the potential of neural networks to predict mash stand-time during the mashing process and apparent attenuation limit from malt quality data has been demonstrated. A fundamental understanding of the biochemistry of malting and brewing, coupled with identification of critical analyses (normally in a specification) can be used to develop networks to provide effective and consistent processing. Neural networks will not completely replace malt specifications, however they may assist in determining the critical malt parameters of use to brewing performance.

References

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