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Industrial Brewery Modelling by Using Artificial Neural Network

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Abstract: Fermentation is a complex phenomenon well studied which still provides challenges to brewers. In this study, artificial neural network, precisely multi layer perceptron and recurrent one were utilised for modelling either static (yeast quantity to add to wort for fermentation) or dynamic (fermentation process) phenomena. In both cases, the simulated responses are very close to the observed ones with residual biases inferior to 4.5%. Thus, ANN models present good predictive ability confirming the suitability of ANN for industrial process modelling.

Key words: Fermentation, artificial neural network, modelling, brewery

INTRODUCTION

Fermentation processes are among the more challenging ones to control, due to the complexity of the biological raw materials and the use of yeast as processing agents (Linko, 1998). Brewing, that is the most well studied processes in food domain, occurs according two main phases: wort production and fermentation (Trelea *et al*., 2004).

The wort production starts with crushing the malt into coarse flour, which is then mixed with water. The resulting porridge-like mash is heated to a selected temperature that permits the malt enzymes to partially solubilize the ground malt. The resulting sugar-rich aqueous extract, wort, is then separated from the solids and boiled with hops. The wort is then clarified and cooled. The main fermentation process starts with aerating the cooled wort and inoculating yeast to it. The yeast consumes the nutrients contained in wort for growth. At the same time, the yeast produces alcohols and other compounds (CO_2, esters, acids, etc.). This first phase called primary fermentation occurs during around a week. It is followed by a secondary fermentation, or lagering phase, where some undesirable compounds are further converted. Most of the yeast is recovered once the main fermentation ends and is re-used in another batch (Marin, 1999).

Nevertheless, although well studied, the process still provides challenges to brewers, particularly for industrial scale fermentation. Thus, the ability to predict the duration of the fermentations or to detect fault would be useful (Gopal *et al*., 1993; Johnson *et al*., 1998), in order to make corrective action.

The purpose of this study is to monitor an industrial scale fermentation using artificial neural networks, that are mathematical estimator based on biological neural network functioning. Their use in increasingly complex dynamical control systems under significant uncertainty is very attractive. The main reasons are their ability to learn to approximate functions and classify patterns. During the last decade, application of artificial neural network in identification and control has been increased exponentially (Hunt *et al*., 1992; Widrow and Lehr, 1990). The wide spread of application has been due to the following attractive features:

- Artificial neural networks have the ability to approximate arbitrary nonlinear functions;
- They can be trained easily by using past data records from the system under study;
- They are readily applicable to multivariable systems;
- They do not require specification of structural relationship between input and output data.

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The artificial neural networks are often viewed as black box estimators, where there is no attempt to interpret the model structure (Ungar *et al.*, 1996).

MATERIALS AND METHODS

Two aspects of brewery; yeast inoculation and fermentation are considered. Indeed, brewery occurs correctly when the yeast added to wort are in sufficient quantity and good quality (viability and vitality). In industrial scale, this phase, badly performed can cause till 71.20% (Traore, 2002) of non conformity (cells quantity different to the admitted one), leading to time and economic disadvantages. The study firstly propose to control this phase and secondly to model the fermentation process.

Inoculation step: In order to monitor correctly inoculation, using neural network, the variables studied were:

- Yeast quantity (Y) in kg to add to wort
- Compacity C (yeast concentration for a defined volume in Cells mL^{-1})
- Wort volume (V) in hectolitre;
- Wort mean density (D).
- Initial yeast population P_0 : Two initial populations were studied (beer A: 32.10^6 cells mL^{-1} and beer B: 40.10^6 cells mL^{-1})

These variables were followed for two kinds of beers (beer A and beer B). Concerning the former, two tank volumes (i.e., 1400 and 2300 hL) were studied, while for the later only one tank of about 650 hL was used. The purpose was to find out a function linking the different variables: $Y = f(C, P_0, V, D)$. A multi layer perceptron with an architecture 4-3-1, as presented by Fig. 1, was used.

Data set, from industrial brewery (417 individuals), was divided into three subsets: Training subset (50% of records), cross-validation subset (25% of records) and the test one (25%) used for future calculations. The training subset is used for computing and updating the network weights and biases. The error on the validation set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped and the weights and biases at the minimum of the validation error are returned. This method for improving generalization is called early stopping (Widrow and Lehr, 1990; Sudheer and Jain, 2004). The test set error is not used during the training, but it is used to compare different models.

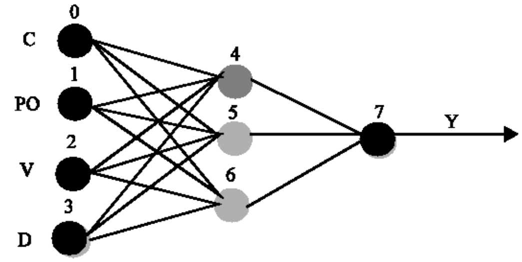

Fig. 1: Feedforward multi-layer perceptron

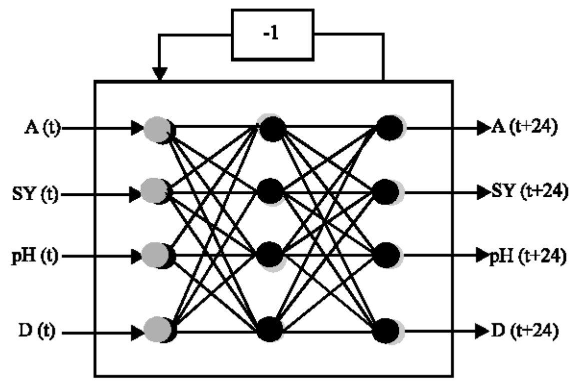

Fig. 2: Recurrent multi-layer perceptron

Fermentation control: In order to assess the learning machine method in the prediction of fermentation, a recurrent feed-forward network, whose structure was 4-4-4 (4 nodes in input layer; 4 in the hidden one and 4 in the output layer), as shown in Fig. 2, was used to control the industrial scale fermentation.

Parameters as, alcoholic production rate (%), wort density, suspended yeast quantity (cells mL^{-1}) and pH were considered.

Data used in this study, were recorded daily. Therefore, the sampling time was 24 h. Each day, 20 fermentation batches were studied. As indicated earlier, data were divided into three subsets.

The training was performed using a back propagation algorithm provided by Matlab R14 (MathWorks Inc., Natick, Massachusetts, USA) software.

In both cases (inoculation step and fermentation control), artificial neural network calculations were repeated 150 times and the best result was stored.

RESULTS AND DISCUSSION

Yeast quantity prediction: Analysing the Table 1, it appears that weights differ according to the volume of the tank concerned and the type of beer. Thus, for instance, when tank volume is 2300 hL, weights range from -1.294 to 1.972, whereas weights concerning volume of 1400 hL vary from -1.870 to 2.323 in hidden layer. In addition, biases that are a neuron prediction error are in all cases different to 0.

Table 1: ANN weights matrices

Product type and volume	Node number	Bias	Weight			
Beer A						
W T V = 1400 hL	Hidden layer					
	4	-0.5276	0.6655	-0.5296	2.3232	-0.2427
	5	-0.4727	0.9956	-0.7957	0.1241	-0.0249
	6	-1.8881	0.2577	-1.8702	-0.9623	-0.5081
	Output layer					
	7	-0.6909	0.1421	-0.3667	-0.2271	
Beer A						
W T V = 2300 hL	Hidden layer					
	4	1.4165	-0.4207	0.2693	-0.6477	0.6265
	5	0.6401	-1.2943	1.9724	1.3162	0.2777
	6	-1.8538	-1.2031	1.2977	0.0414	-0.3692
	Output layer					
	7	0.1333	-0.0983	0.7326	0.6573	
Beer B						
W T V = 650 hL	Hidden layer					
	4	-1.8204	1.5446	0.0809	-0.3203	0.5667
	5	-1.1290	1.6552	-0.9559	0.2625	0.1539
	6	-1.9810	-0.5763	0.7444	0.5352	-0.2891
	Output layer					
	7	0.9668	0.3165	0.5430	0.0170	

W T V: Wort tank volume

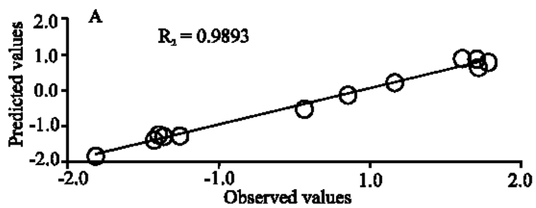

Fig. 3a : Regression plots of the models for Bear A with a tank volume of 1400 hL

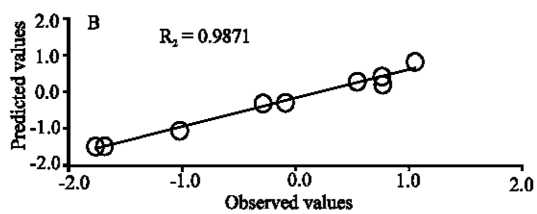

Fig. 3b: Regression plots of the models for Bear A with a tank volume of 2300 hL

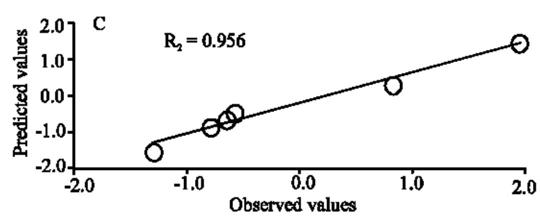

Fig. 3c: Regression plots of the models for Bear B with a tank volume of 650 hL

The weights obtained with ANN method do not represent the strength (impact) of a variable in response determination. Indeed, before training step, weights are randomly initialised. During training, they are sequentially adjusted till a minimal final prediction error. It is a reason why ANN methods are classified in the so-called black-box methods. The training error obtained ranging from $7.6.10^{-3}$ to $3.17.10^{-10}$, is very low, indicating therefore the good ability of the model to estimate accurately the quantity of yeast to add to wort. In order to confirm or infirm this assertion, predicted values are represented according to experimental ones (Fig. 3a-c). It appears that determination coefficients R^2 are superior to 0.965. This coefficient is an indicator of the less or good accuracy of prediction. Indeed, more its value is higher more the response predicted values are closer to the experimental ones. The highest R^2 value is obtained when the tank volume is 1400 hL (0.989). These results point out the relative good ability for prediction of artificial neural network (ANN) models with correlation coefficients higher than 0.982 (square root of 0.965). The mean prediction error was estimated to around 1.73%.

The processing of these same set of data by using a logarithmic model led to a prediction error higher than 20% (Traore, 2002).

Fermentation control: The validity of the model obtained is highlighted by Fig. 4a-d, respectively for alcohol, density, suspended yeast and pH evolution. On all these figures, is represented a fermentation example (randomly chosen) that was not used for training the identification of the model coefficients.

The ethanol production (Fig. 4a), lower in the first 24 h increases slowly till at 96 hours where it increases exponentially to reach a value of 3.7% at 192 h and then remains constant. This third phase is marked by a plate

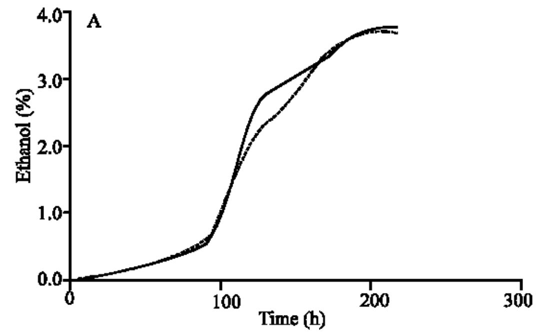

Fig. 4a: Ethanol (%) as a function of time

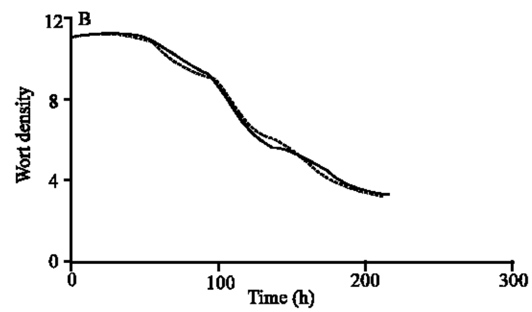

Fig. 4b: Wort density as a function of time

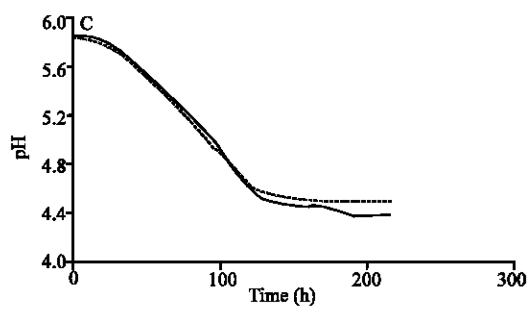

Fig. 4c: pH as a function of time

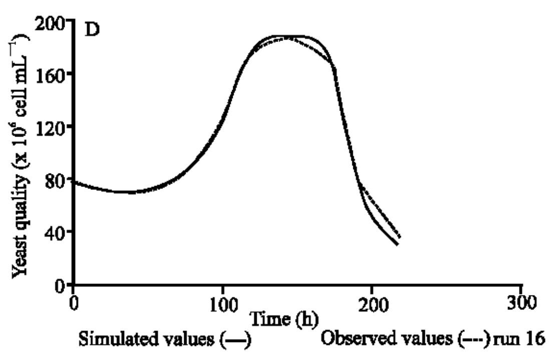

Fig. 4d: Yeast quantity as a function of time

around 3.72%. Therefore, the ethanol production appears generally as an S like curve. When comparing the predicted and observed ethanol values, it appears that the ethanol production is predicted reasonably well with a mean bias of 3.99% (Table 1). But, at 120 and 144 h, mismatch between predicted and observed values appears more clearly. These discrepancies can be explained by the fact that ANN models were developed taking account the scatter of the experimental data; several fermentation batches were used for modelling. On Fig. 4b, depicting the wort density evolution, it appears contrary to alcohol one, that when this later proportion is lower, the wort density is higher and vice-versa. Indeed, alcohol being lighter than water, its presence in the medium reduces the wort density. In addition, during fermentation, sugar is consumed by micro-organisms for alcohol and CO_2 production. The conjugated action of both phenomena (decrease of sugar and the alcohol increase) decreases the wort density. Therefore, density evolution during fermentation process appears to be a reverse S function. This parameter (wort density) is also well predicted with a mean prediction error of 3.43%.

Concerning pH values (Fig. 4c), as the wort is acidic, they start around 5.8. This acidity increases during fermentation decreasing consequently the pH till a limit value sensibly equal to 4.4. This pH decrease is related to the production of organic acids (i.e., lactic, acetic and tartaric acids) by *S. cerevisae uvarum* during fermentation process. Figure 4d analysis shows that biomass evolution can be decomposed in 4 phases, with the 3 first already found with other parameter evolution. Indeed, it is observed a first phase during which yeast number remains constant around 75.10^6 cells mL^{-1}: the lag-phase. After 72 h, the second phase is characterised by an exponential increase of suspended yeast number that reaches, at 120 h, 178.10^6 cells mL^{-1}: active phase. In the third phase, the yeast quantity remains static and fails in the fourth phase to 40.10^6 cells mL^{-1}. These different phases were already extensively described in literature: the lag-phase during where micro-organisms adapt themselves to the culture medium; the active phase or exponential phase during which the yeasts multiply in an exponential way, consuming sugar and producing alcohol. The decrease of yeast number in suspension is due to their fall down in fermentation tank confirming therefore, the lower fermentation type of *S. cerevisae uvarum*. As shown earlier, in this parameter (i.e., suspended yeast) case, the prevision obtained is also good. The residuals between observed and predicted values (from 0.003 to 4.51%), inferior to 5%, can be negligible.

The global analysis of prevision depicted in Fig. 4 a-d points out the good ability of ANN models for prevision. Indeed, the ANN models obtained give values very close to the observed ones, whatever the parameter concerned. Therefore, they permit a quite precise control of industrial scale fermentation process. Thus, one can predict, for example, the end of the process when knowing the initial conditions (wort sugar content, initial yeast population, so on and so for). In addition, if in the calculations a limit constraint is introduced, one can detect fault in fermentation process; a fact that will be very useful in non-quality reduction.

CONCLUSIONS

This study aimed to determine the quantity of yeast to add to wort for brewing purpose, respecting the beer type constraint (e.g., initial population of yeast). This determination depends also of other parameters like wort volume, yeast compacity. It was proved elsewhere that, in industrial scale, non conformity can reached 71.20%. Thus, the control of this important step prior fermentation is necessary.

The Artificial Neural Network (ANN), precisely the Multi Layer Perceptron (MLP), used for this purpose, has shown their ability to predict the quantity of yeast to inoculate with error less than 1.73%. In addition, plots between simulated values and observed ones show determination coefficients R^2 higher than 0.965, confirming the suitability of ANN for static phenomenon modelling.

In the other hand, a recurrent ANN was used to control the fermentation process. The mathematical models obtained enable the prediction of alcohol quantity, wort density, pH and suspended yeast quantity evolution with error inferior to 4.5%. Therefore, these sigmoid functions can permit the determination of end of fermentation when knowing the initial conditions. Moreover, they can enable fault detection during the process occurring.

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