A Neural Network Tool for Brewery Fermentations

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ABSTRACT

Fermentation is an important, if not the most important process step in the production of beer. It is subject to alterations stemming from the variation in the yeast, a living organism, and due to the complex raw materials of biological origin. The variability may manifest in changes in the fermentation speed or cause off-flavors in beer. Thus, there is a need for tools, both analytical and computational, to help in monitoring the process and keeping it in a desired course. In this paper we describe a prediction tool to assist production management in the brewery. The system relies on a neural network that predicts the course of the fermentation based on yeast history, fermentation recipe and raw material variables. The system is able to predict the fermentation time with an average error of 10 percent of the remaining fermentation time, which enables the brewery to spot problematic batches days in advance and plan the correct yeast harvesting time with an increased accuracy. The system has been in daily trial use in Hartwall's brewery in Lahti since March 2000 and the user experiences have been positive.

1 INTRODUCTION

Food and biological processes are among the more challenging ones to control, due to the complexity of the biological raw materials and the use of microbes – living organisms – such as yeast as processing agents (Linko, 1998). Brewing is among the most well studied processes in the food sector. Nevertheless, the process still provides challenges to the brewers. From the production management point of view, the ability to predict the duration of the fermentations would be a useful one (Gopal et al. 1993; Johnson, 1998). In practice, the fermentation times in seemingly equivalent settings can vary considerably which, firstly, hinders efficient scheduling in the plants. Secondly, an early warning of a slow fermentation gives the operators time to make corrective actions. Thirdly, the breweries are forced to make daily measurements to observe the course of the fermentations, in order to make the decision when to switch to secondary fermentation. With a reliable predictor for the fermentation speed, one could manage with fewer measurements.

Many proposals for the modeling of beer fermentation speed exists in the literature, perhaps due to the strong link to the models of alcoholic fermentation (see Marin, 1999, for a review) and biotechnical processes (Montague & Morris, 1994; Linko et al., 1995; te Braake, 1997). Kinetic models have been presented by Gopal et al. (1993) and Johnson et al. (1998), fuzzy modeling by Vassileva et al. (1994) and Cummins et al. (1998), and a rule-based system by Kashihara et al. (1993). Such models are typically developed and tuned by hand, which is a considerable burden.

The potential of neural nets for monitoring and control dynamical systems was discovered a decade ago (Narendra & Parthasarathy, 1990; Becraft et al., 1991) and many applications in industrial processes exist. Informative measurements are critical for the success of predictive modeling of such processes. Austin et al. (1992) present an early neural approach and Beil et al. (1992) describe a hybrid system of an Extended Kalman Filter, a fuzzy model and a neural network. Both models, however, rely on parameters not typically available in industrial-scale breweries. In this paper we describe a neural net application for the prediction of the beer fermentation speed. The system predicts the progress of the fermentation based on raw material properties, yeast

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condition and history, tank filling procedure, fermentation temperature and the observed speed of the process so far. The system has been in use since March 2000 at Hartwall brewery in Lahti.

2 BREWERY FERMENTATIONS

The main ingredients of beer are malt, water and hops. The main phases of the brewing process are wort production and fermentation. The wort production starts with crushing the malt into coarse flour, which is then mixed with water. The resulting porridge-like mash is heated according to a carefully selected temperature program that encourages 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 adding yeast to it. The yeast starts to consume the nutrients contained in wort, in order to stay alive and grow. At the same time, the yeast produces alcohols and esters. The sugar content of the wort is the primary measurement by which the course of the fermentation is followed; the main fermentation is deemed to be ended when the sugar content falls below a predefined concentration level, so that only a small amount of fermentable sugars remain. The sugar content of the wort is expressed by the *specific gravity* of the wort; the wort gets lighter as sugar is converted to alcohol and other compounds.

The traditional batch main fermentation phase takes around a week, although faster processes have been developed (c.f. Virkajärvi, 2001; Kronlöf, 1994). It is followed by a secondary fermentation, or lagering phase, where some undesirable compounds are further converted. Depending on the production line the secondary fermentation takes place in the same of a different tank as the main fermentation. Either way, most of the yeast is recovered once the main fermentation ends, and is re-used in another batch.

Fermentation is controlled by regulating the temperature, oxygen content, and the pitch rate; i.e., the amount of yeast put into the fermentation tank. Temperature has a great effect on both the speed of fermentation and the flavor of beer. The growth of yeast can be controlled by the oxygen content. The pitch rate affects the fermentation speed but not as much as the temperature. In addition, the course of fermentation is affected by other factors, such as the wort composition and the yeast condition. Ideally, these factors should be constant, so that the predictability of fermentation is maintained. In practice, neither the wort composition or yeast condition is static. The natural variation of malt induces some variation to the wort composition, although such variations can be diminished by re-planning the mashing recipes (Aarts & Rousu, 1996).

The condition of the yeast is a more complicated issue. Traditionally, the breweries have observed the *viability*, i.e. the percentage of live cells in the batch by laboratory analyses. However, these methods do not tell anything about the *vitality* of the yeast, i.e. the fermentation rate of the cells (Londesborough, 1998). The yeast used in brewing is grown by the brewery and recycled many times before disposal. The ability of the yeast to ferment is greatly dependent on the history of the yeast. For example, new yeast typically behaves differently from yeast that has been recycled many times. Also, yeast that has been stored long periods between fermentation is often less vital.

Ideally, the brewery should be able to modify the fermentation recipes so that the variability of the yeast and wort would be canceled out. So, if the vitality of the yeast is low, the brewery could increase the pitch rate or elevate the temperature or oxygen content slightly. A fermentation recipe planner, such as the Sophist system (Rousu & Aarts, 2001) is well suited to this task. A reliable estimate of the yeast vitality is needed for such an approach, though. However, as one can expect from the above introduction, no single analysis exists that would permit predicting the time of fermentations to any reasonable degree.

3 MONITORING FERMENTATIONS WITH NEURAL NETWORKS

The modeling and control of biotechnical fermentations using neural networks is a well-studied problem (Linko et al. 1995; te Braake; 1997; Linko, 1998). However, the models from the biotechnical literature cannot be directly transferred to brewing, as many measurements in the models are not available in the brewery. For example, carbon dioxide of exhaust gas is rarely measured, neither is biomass during fermentations. In practice the set of analyses at the modeler's disposal is very limited, including mostly amounts and timing of transfers of raw materials and yeast, process temperatures and the manually taken gravity (sugar content) measurement. These restrictions also rule out the previous adaptive models developed specifically for brewing fermentations: The model by Austin et al. (1992) requires wort free amino nitrogen measurement (FAN) that is not a routine analysis in Finnish breweries. The model by Beil et al. (1992), on the other hand, requires the CO_2 evolution rate as input. Hence, we opted for developing a model from scratch.

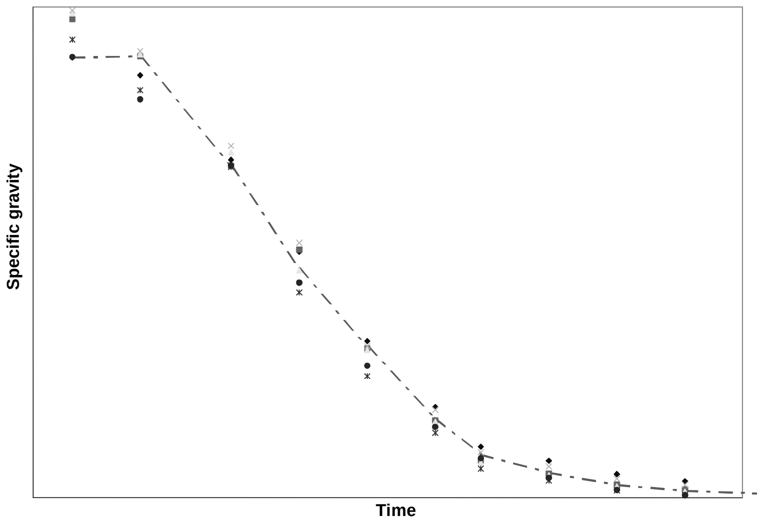

Figure 1. The group of ‘daily’ fermentation curves (markers) predicted by the neural net is composed to a single curve (dashed line) using locally weighted regression.

The development begun in 1997 when a set of 100 laboratory scale fermentations (Kataja, 1997) were used to assess the viability of machine learning methods in the prediction of fermentations speed. In the first studies, a neural net and a decision tree learner (Quinlan, 1993) were used to predict the fermentation speed based on raw material and yeast properties. In those studies the concept was found feasible and the importance of the fermentation history of yeast (the speed of the yeast in the previous batch) as a predictor was shown. In the next phase, during winter 1998-1999, the neural net approach was tested with industrial scale data. These test confirmed the findings from the laboratory: the prediction was indeed possible and the fermentation history of the yeast was a significant factor (Rousu et al., 1999). The results convinced us to develop the technology further, industrial use in mind. Neural network was chosen over the decision tree learner since continuous prediction was more desirable than classification into problematic and non-problematic batches.

The fermentation speed predictor was given two design criteria:

1. The fermentation curve was to be predicted as a whole and not just the time to the desired gravity.
2. Gaps in the fermentation curve needed to be tolerated since samples were not always taken every day.

These criteria in mind, the following structure was designed. Since we cannot know a priori which gravity measurements will be there, we required the neural net to predict the whole curve based on one gravity measurement that could be taken in any point of the process. Thus the neural net needed to predict the curve both forward and backward.

We used a feed-forward neural network architecture (Rumelhart et al., 1986). The structure of the neural net was the following: in the input layer 12 unit were used. Of these seven were batch-specific, that is, they remained constant during the batch. These included raw material properties, yeast condition and history and tank fill-up procedure. The remaining five variables changed daily during the fermentation. These included time from batch start (t), observed average fermentation speed ($(sg(0)-sg(t))/t$), specific gravity ($sg(t)$) and the time difference between the sample time and query time (Δt). The hidden layer included six units and the output layer one unit, the gravity at query time ($sg(t+\Delta t)$). Training and testing examples were generated by going through all t and Δt combinations arising from the time series data of the fermentations.

The added bonus from the design was the amount of training examples that were obtained: from a fermentation curve of six gravity measurements we got 36 training examples, all gravity measurements predicting all others including the measurement itself. In total, over 5000 training examples were obtained from the fermentation curves. The neural network was trained using the backpropagation algorithm provided by the Neuro Office tool (Alpha Systems, Inc.).

In the general case, we had anywhere from one to seven daily gravity measurements and a predicted fermentation curve from each of them. To optimize the fit of the predicted curve to observed data, we employed locally weighted regression (Atkeson et al., 1997) to combine the curves: each curve was weighted heaviest a time points near to the pivot point of the curve, i.e. the time point of the gravity measurement that was used to predict the curve (Figure 1). In the figure, the samples (and hence also the predicted curves) from days one and two were missing. Note that the significance of the local weighting is two-fold. First, the points predict their immediate neighborhood the strongest, which makes the ‘effective Δt’ small and, consequently makes the curve to follow observations closely. Second, the predicted curve can resist the effect of outliers: the contribution of the other curves makes the predicted curve deviate from the outlier.

We tested the accuracy of the predictor by letting it estimate the fermentation time of 20 previously unseen fermentation batches, giving 106 separate testing examples. The average error of prediction was around 9 hours, or 9.9% of the remaining fermentation time (Pöllänen, 2001). The result could have been even better, had the fermentable sugar content of wort been available to the network; this would have made it easier to predict the final stages of fermentation.

4 TOOL DEVELOPMENT AND INTEGRATION

The prediction application (Pöllänen, 2001) was implemented as a Microsoft Excel spreadsheet, since the operators were already familiar with the software. The layout of the user interface was designed to mimic the previously used screens (Figure 2).

An ActiveX component ‘Neuro Office’ implemented by Alpha systems, Inc., St. Petersburg, was used as the neural net implementation. The easy integrability to Excel was the primary choice for selecting the tool. The interface to the production database of the brewery was implemented using Open Database Connectivity (ODBC). The functionality of the user interface was implemented using the Visual Basic for Applications macro language embedded into Excel.

The data flow between the production database and the application was two-way. Most of the data relating to the fermentation batch, including the raw materials, fermentation temperatures, pitching volumes and the yeast history, was retrieved from the production database. However, the yeast cell count and daily gravity measurements were entered to the application by hand and written to the production database by the application. The reason for this was to make sure that operators follow the production closely enough.

The application has been in daily use since March 2000 at Hartwall brewery in Lahti. The experiences with the system have been positive, although it is difficult to assess the impact that the prediction ability has had to the routines of the operators. The fact that the new user interfaces bring automatically relevant data to the screens may have an equally large effect as the neural nets predictions. Moreover, the fact that all relevant data to the fermentation is now stored in the production database in a centralized manner has its value to the brewery.

5 DISCUSSION

The application presented shows that machine learning approaches can be used to predict the speed of an

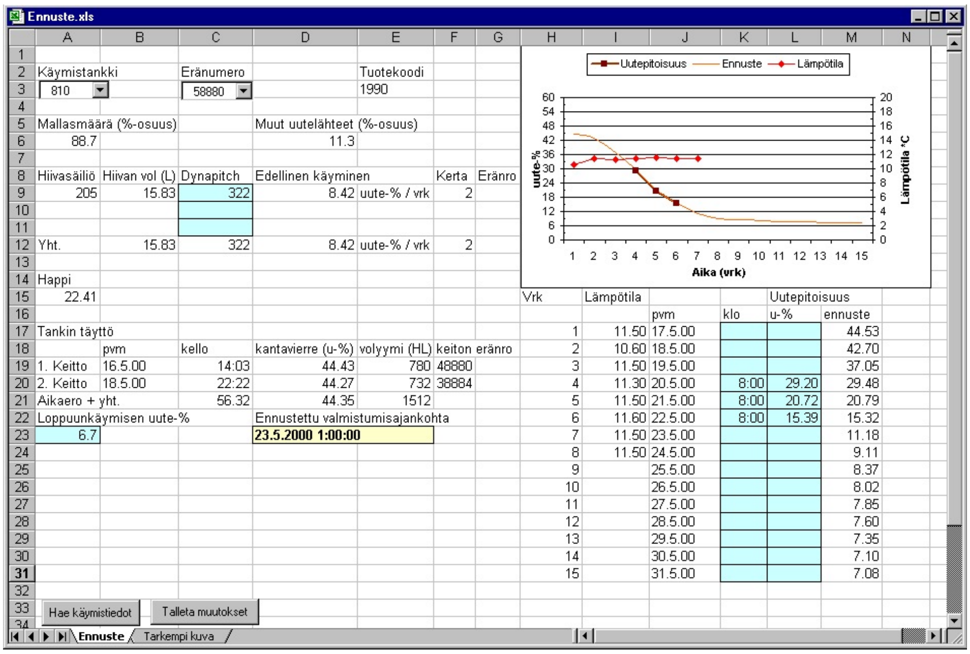

Figure 2. The main screen of the fermentation monitoring application. The figures have been changed in order to maintain confidentiality.

industrial-scale beer fermentation process. The accuracy of prediction is around 10 percent of the remaining fermentation time. It gives the operators a possibility to plan the production more accurately and an early warning of possible problematic batches. The accuracy could have been still improved had there been a measurement of the fermentable sugar content of wort at the system's disposal. The prediction tool was integrated to existing production management systems to enable automatic retrieval of data needed by the neural net. Moreover, the user interface of the application was designed to mimic the application previously used to monitor the fermentations. As the result, the transition to the new system was seamless.

The success of the prediction application leads to a question how far can the approach extended. For example, is it possible to use the tool to suggest corrective actions when a slow fermentation is predicted? The available data seems to limit this kind of an approach. Unless some corrective action has been tried out before, the neural net cannot reliably predict the outcome of such an action. However, if the brewery routinely employs some corrective strategies the training data will contain information on the success of the action.

Perhaps a better direction to extend the approach is to tie it to the production scheduling. The uncertainty of bioprocesses makes traditional scheduling algorithms fail since they require the time taken by unit processes to be exactly known. The uncertainty can be taken into account by using some upper limits of unit process time in the schedule but this easily leads to sub-optimal schedules. Utilizing the prediction applications like our fermentation predictor as 'experts' estimating the process times needed by the unit processes could be a viable choice in the design of an optimal scheduler.

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