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Process modelling and sensitivity analysis of roller mill and lauter tun subsystem operation

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Abstract

Industrial beer production faces many technical as well as economic challenges, with increased competition and trends towards craft beers and non-alcoholic beverages posing new challenges to brewers, who strive to minimise production costs and processing times whilst improving product quality. Milling, mashing and lautering are a major bottleneck in sweet wort production; however, mathematical models describing these unit operations remain elusive. This study focuses on modelling these unit operations as a subsystem, using a dataset compiled from a brewhouse pilot plant. A first-principles model using batch filtration theory is conceived for the lauter tun, with another statistical model based on Partial Least Squares (PLS) regression describes the milling and mashing operations. The first-principles model describes reasonably well lautering data; the PLS model offers reasonable accuracy for batch time prediction. A holistic view on the brewhouse is then emphasised through a sensitivity analysis, in which variables such as mashing agitation speed and pre-mashing, resting and mash-out temperatures have been found to have the greatest influence on subsystem batch time. Strategies for improved operating protocols are also presented, highlighting the strengths and limitations of the models proposed.

Keywords: Process modelling; Partial Least Squares (PLS); roller mill; lauter tun; beer.

1. Introduction

Beer is one of the most globally consumed alcoholic beverages, accounting for 74% of alcohol consumption in 2016. However, consumption per capita has decreased over the past 50 years in traditionally beer-drinking (mainly European) countries while consumption in the US has plateaued. These trends may be due to increased globalisation and competition, the rise of microbreweries and craft beer and the emergence of health-oriented drinks, which has shifted consumer preferences (Conen and Swinnen, 2016).

Milling, mashing and lautering operations in beer brewing are strongly linked due to the complex interactions and trade-offs arising between them. A very fine grist will increase starch conversion and sugar extraction rates, but at the cost of undesirable flavours such as bitterness in the finished beer. Moreover, it could lead to a “stuck mash” condition in the separation vessel, where the mash filter becomes clogged and cannot filter the wort and thus hindering its collection rate. On the other hand, coarser grists increase wort flowrates and reduce filtration times but with lower extraction yields. A balance must be struck between grist particle size and the obtained extraction efficiency (Crescenzi, 1987).

This study aims to analyse the milling-mashing-lautering operations in an industrial UK brewery, and improve their performance by means of formulating a mathematical model describing the subsystem and the main drivers behind wort separation. To this end,

operational parameters and process variables contained in datasets collected from a pilot plant are used to develop a validated model for the subsystem. The ultimate goal is to improve brewhouse efficiency via superior operating protocols towards minimising batch time whilst not compromising high product quality (Rodman and Gerogiorgis, 2019).

2. Roller Mill and Lauter Tun Subsystem Modelling

Model formulation for brewhouse subsystems must be pursued in accordance with plant size, sensor availability and process variables obtained or inferred from industrial data. The experimental data in this study is acquired from a pilot plant consisting of a roller mill, a mash conversion vessel and a lauter tun. Process variables are recorded at one-second (1 s) intervals over the entire subsystem batch duration. The experimental data has been compiled over 12 different days, with one batch produced per day. Process variables associated with the mashing and lautering operations (and raw material weights used) have also been recorded over the batch duration for each batch. The subsystem is therefore considered as two connected sub-processes, presented in Fig. 1; milling and mashing are described via the statistical (PLS) model and the lautering via a physics-based model.

Figure 1: Modelling strategy for the sweet wort subsystem.

For the milling and mashing sub-process PLS model, 14 variables were chosen in order to develop the statistical model. The general linear regression model can be written in a compact form as Eq. 1, where $\mathbf{y}$ is the response vector, $\mathbf{X}$ is the process matrix, β is the regression coefficient vector and ε the residuals vector. PLS regression is based on the idea that while many predictor variables could be present, only a few variables, i.e., components or latent variables, account for most of the variation in the response, measured by the coefficient of determination, R^2 . By projecting the information present to low-dimensional spaces as delineated by the number of PLS variables (n_{comp}), data redundancy is eliminated, giving structure to the process matrix formulated. To obtain the PLS components, initially the variables in $\mathbf{X}$ and $\mathbf{y}$ are normalised. Afterwards, a linear transformation for the original variables is performed, using an appropriate weight matrix $\mathbf{W}$, such that the covariance between the PLS components from the $\mathbf{T}$ matrix and the response variable $\mathbf{y}$ is maximised. Using the new latent variables obtained, OLS regression is performed to solve for the vector $\mathbf{Q}$ (Eq. 3), which represents the loading vector for the response variable. The original coefficients β are then determined (Eq. 4).

$$y = X\beta + \varepsilon \quad (1) \quad y = TQ + \varepsilon \quad (3)$$

$$T = XW \quad (2) \quad \beta = WQ \quad (4)$$

The PLS model (MacGregor et al., 1994) was implemented in MATLAB using a modified version of the SIMPLS algorithm (de Jong, 1993). To assess the PLS model, the cumulative R^2 vs. the number of PLS components was plotted to determine the range of optimal latent variables. Then, a detailed PLS regression was performed for the selected components, making use of the cross-validation technique, to test its capability against future observations. Following best practice and prior experience, the ‘leave-one-out’ cross-validation method has been selected. Along with the R^2 coefficient, the Root Mean Squared Error of Prediction (RMSEP) was also considered as a performance indicator.

Lauter tun vessels can be described by Darcy’s law (Eq. 5), where Q : the volumetric flowrate, k the permeability constant, A : the filter area, ΔP the pressure differential, μ : the wort viscosity, and L : the filter bed thickness. The resulting differential form of the filtration equation is given by Eq. 6, defining α_{av} : average specific resistance accounting for compressible cake filtration, c : the corrected dry solids concentration in the filter cake, V : the cumulative filtrate volume, R : the medium resistance. To ensure optimal flowrate and to avoid filter blocking in a lauter tun, the differential pressure through the filter cake is often selected as the controlled variable. When ΔP is kept constant during filtration, Eq. 6 can be integrated analytically, assuming constant α_{av} , c and R to obtain Eq. 7: K_1 and K_2 are the cake and medium resistance factors, respectively. For the sake of filter size scaling, the cake resistance factor K_1 is converted to a filterability coefficient F_k (Eq. 8). A plot of t/V vs. V yields a linear trend if the Darcy model adequately fits industrial data.

$$Q = \frac{kA\Delta P}{\mu L} \quad (5)$$

$$\frac{1}{A} \frac{dV}{dt} = \frac{A\Delta P}{\mu(\alpha_{av}cV + AR)} \quad (6)$$

$$\frac{t}{V} = \frac{K_1}{2} V + K_2 \quad (7)$$

$$F_k = K_1 A^2 \quad (8)$$

3. Subsystem Model Validation

The PLS model results for the mashing-milling sub-process vs. industrial data for different numbers of PLS variables (n_{comp}) are shown in Fig. 2. With 6 or 7 PLS components, the PLS model does not accurately represent the data; however, when 9 components are used, the model represents the data accurately but may exhibit significant deviation when fitted to new data. Generally, one should avoid having too many variables (MacGregor et al., 1994; Shen et al., 2019). Thus, a selection of $n_{comp} = 8$ is used here, in order to ensure an adequately descriptive but not overly complex statistical formulation.

Figure 2: PLS components (n_{comp}) predictive assessment.

Lautering modelling results from the first-principles model are presented in Fig. 3. Experimental points from individual days follow a linear trend, as per the $R^2 = 0.654$ – 0.993 in this work, indicating reasonable fit. The variation may be attributed to equipment design or gradual filter blocking due to insufficient wort recirculation time. The resulting model coefficients K_1 , K_2 and F_k and their standard deviations are listed in Table 1.

Figure 3: Lautering time vs. normalised volume for various operation days, and average.

4. Sensitivity Analysis

To detect the main drivers for the overall subsystem, a sensitivity analysis was performed, under a $\pm 10\%$ scenario. Following the method of Jørgensen and Fath (2011), sensitivity indices S were calculated. The values of S -indices remain constant regardless of the parameter relative perturbation if the model is linear. The perturbed subsystem variables, x_i , are listed in Table 2. Sensitivity analysis results are presented in Fig. 4 by illustration of S -values (Fig. 4a) and the effect of a $\pm 10\%$ variable deviation on the overall subsystem batchtime. The subsystem batch time is highly sensitive towards changes in the pre-mashing temperature (x_8), third resting temperature (x_{11}), mash-out temperature (x_{13}),

mashing agitation speed (x_{14}) and moderately sensitive to the amount of malted grain weight (x_1 – x_4) and the wort volume collected (x_{15}), providing valuable hints for operation.

Table 1: Lautering model statistics summary.

Stats	K_1		K_2		F_k
Units	$10^{-7} \text{ hr L}^{-2}$	$10^{-4} \text{ hr m}^{-6}$	hr L^{-1}	hr m^{-3}	hr m^{-2}
Average	8.24	3.79	0.824	0.379	2.57
Std. dev.	3.26	1.84	0.326	0.184	1.02
Variation (%)	85.1	92.9	85.1	92.9	85.1

Fig. 4b shows an increase mash-out temperature (x_{13}), agitation speed (x_{14}) and wort volume (x_{15}) also increases the batch processing time. On the lower end of the tornado plots, increasing the malted grain weight (x_1), the pre-mashing temperature (x_8) and the third resting temperature (x_{11}) decrease the subsystem batch time significantly. Implementing a speed control system would improve mash filterability, because excessive stirring leads to increased batch times because of the increased shear forces exerted on the mash, in agreement with brewing theory (de Rouck et al., 2013). The wort volume can thus be controlled via a composition loop system so as to stop its collection and reduce batch times, once the sweet wort has achieved a desired sugar composition.

Table 2: Milling, mashing and lautering: subsystem process variables.

Variable	Name	Units	Unit Op.	Variable	Name	Units	Unit Op.
x_1	Material Weight 1	kg	Milling	x_9	Resting T_1	°C	Mashing
x_2	Material Weight 2	kg	Milling	x_{10}	Resting T_2	°C	Mashing
x_3	Material Weight 3	kg	Milling	x_{11}	Resting T_3	°C	Mashing
x_4	Material Weight 4	kg	Milling	x_{12}	Resting T_4	°C	Mashing
x_5	Initial tank T	°C	Mashing	x_{13}	Mash-out T	°C	Mashing
x_6	Pre-mash water volume	L	Mashing	x_{14}	Agitation speed	rpm	Mashing
x_7	Strike water volume	L	Mashing	x_{15}	Wort volume	L	Lautering
x_8	Pre-mash T	°C	Mashing				

Not all sensitive variables mentioned can be used as manipulations for process control. The mass of malted grain (MW1) and the wort volume are defined as design parameters for a specific brewing recipe and cannot change under normal conditions. The rest of the sensitive variables (x_3 , x_8 , x_{11} , x_{14}) can be conveniently used for batch process regulation.

Figure 4: (a) Parameter sensitivity indices, (b) Batch times vs. $\pm 10\%$ parameter variation.

5. Conclusion

The modelling strategy conceived in this study resulted in the formulation of two mathematical models capable of capturing mashing and lautering behaviour, giving rise to operational protocols aimed at reducing batch times and increasing plant productivity. To gain mechanistic understanding of the wort separation processes, a first-principles model based on filtration theory has been formulated to describe lauter tun operation. Correlation of the coefficients K_1 and K_2 to other process parameters may further increase the fidelity of the presented model and the accuracy of the modelling results vs. the considered industrial datasets which can be analysed. This model can be used to predict lautering times as a function of the wort volume only, which is a key operating parameter. The optimal number of PLS latent variables for mashing-milling modelling is a compromise between model accuracy and reliability for future predictions. This model predicts milling-plus-mashing times with adequate accuracy for performance monitoring. The sensitivity analysis clearly indicates that significant reductions in batch time can be achieved by increasing the malted grain weight, pre-mashing temperature, resting temperature and decreasing the mash-out temperature, agitation speed and wort volume.

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