Data Logging for Fermentation Duration Prediction

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Introduction

In order to remain competitive in an expanding market, the importance of predicting beer fermentation duration can be regarded as extremely useful to craft microbreweries, for the purposes of optimising production scheduling.

Unlike their large-scale counterparts, microbreweries do not hold the capital nor expertise to install, operate and maintain high specification process equipment.

Previous predictive models for fermentation duration have included kinetic modelling (Andrés-Toro *et al., 1998),* multivariate linear regression (Montague *et al.,* 2008) and artificial neural networks (ANNs) (Rousu *et al., 1999).* However most models either require 48 hours of initial batch data, have several hundred datasets or would otherwise be impracticable to implement on a commercial scale.

Recent technological advances have led to the development of the Tilt™ Hydrometer, an on-line hydrometer and thermometer designed and priced originally for the homebrew market. It is proposed that, if the readings remain valid, that this affordable device may prove useful for craft microbreweries aiming to develop, fermentation duration predictive models.

Aims

- Evaluate the performance of an online hydrometer and thermometer, designed for homebrew scale, on a 400 L brewing kit.
- Develop a model to predict the fermentation duration of a beer recipe using only initial conditions.

Data Collection

For every batch, a Tilt™ is cleaned, sanitised and placed into the fermenter. The tilt of the device relative to gravity is found by an accelerometer, the software then calculates the present gravity of the wort (± 0.002). These readings, along with the current temperature are transmitted via Bluetooth to a local Raspberry Pi 3, which then writes the data to an online spreadsheet.

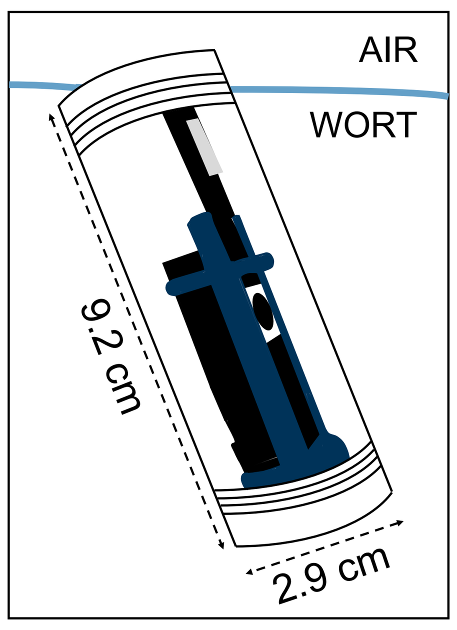

Figure 1 - Diagram of Tilt™ Hydrometer.

The other initial variables used in model development are obtained from the Gyle (batch) records and are known, or can be estimated, prior to fermentation.

Model Development

The model generated uses initial conditions of original gravity (OG), final gravity (FG), expected temperature profile (°C) and yeast pitch rate (g/L).

For each batch, an hourly fermentation rate (FR) is calculated using linear approximation.

A shallow artificial neural network (ANN) with one hidden layer and nine nodes is trained using eleven (20 L and 400 L) fermentation sets. The initial parameters, along with the present gravity, at each hourly sample are used as the ANN's inputs and the FR is the target / output.

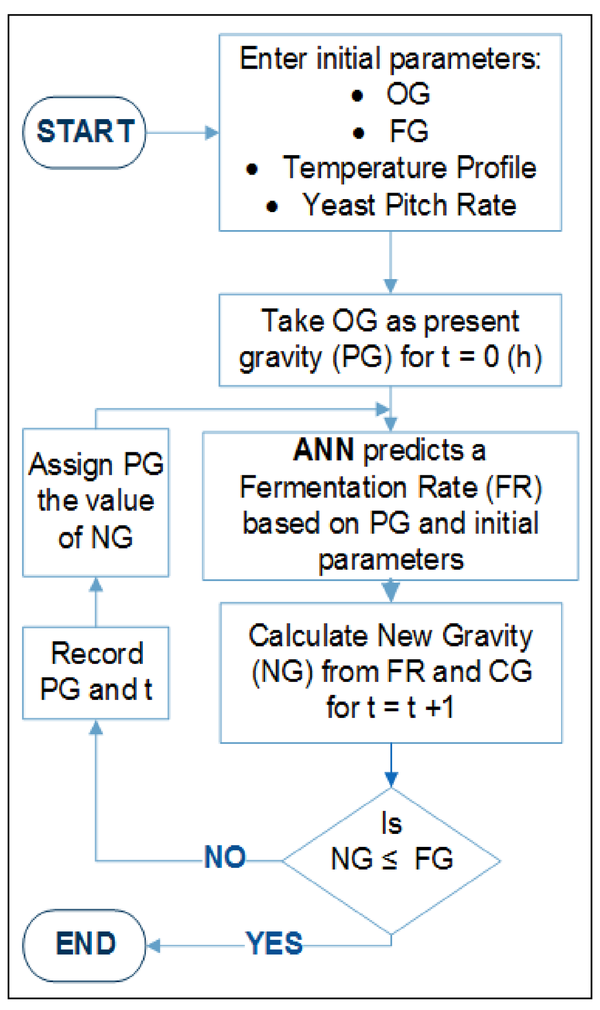

Figure 2 - Flowchart of overall modelling objective.

The overall model then calculates the new PG based on the fermentation rate. The process iterates until the NG reaches the FG as shown in Figure 2.

Tilt™ Hydrometer Performance

Due to the operating principle of the Tilt™, greater process noise occurs in the 400 L batches compared to the 20 L batches as shown in Figures 3 and 4. However, the data in both cases is pre-treated with outlier removal, noise removal using a local weighted linear least squares regression over a five hour window.

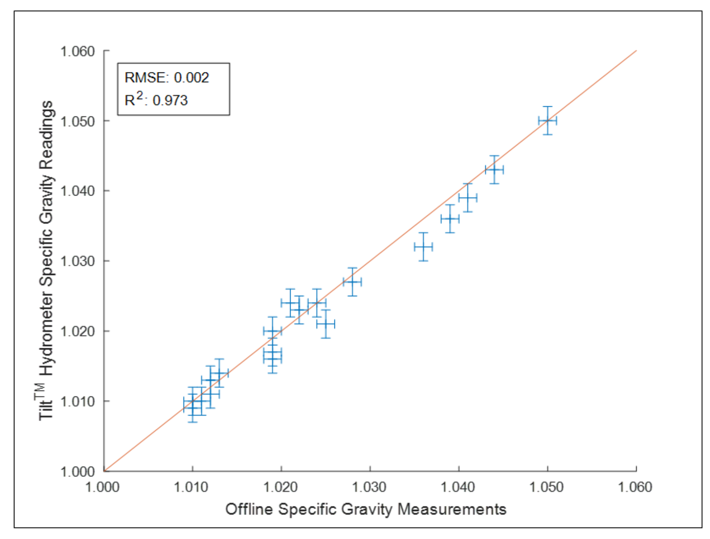

Figure 5 — Online and offline comparisons of specific gravity.

Figure 5 shows the comparison between PG readings from the Tilt™ and an offline density meter. Agreement is good between the two meters with an RMSE of 0.002, indicating the Tilt™ could be used in large scale fermenters with appropriate pre-treatment.

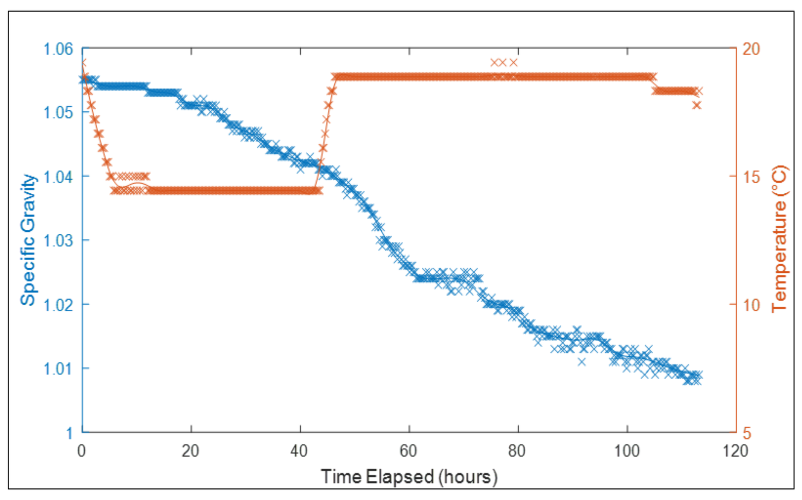

Figure 3— 20 L Fermentation profile for same recipe as that in Figure 4.

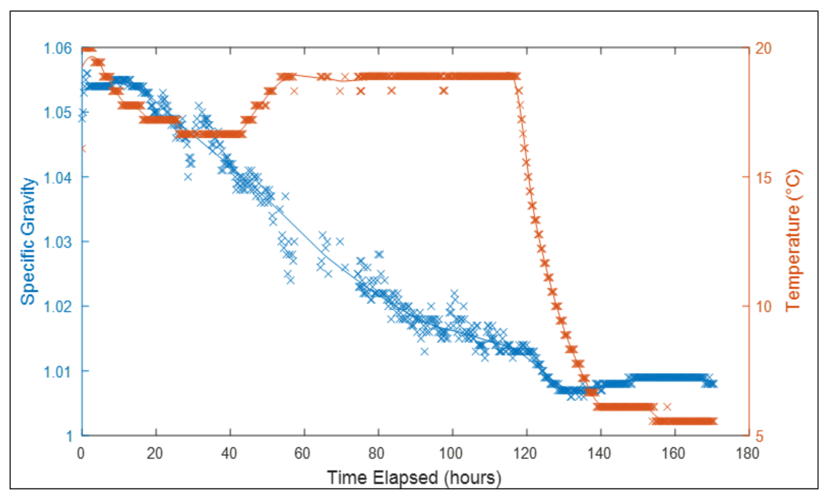

Figure 4— 400 L Fermentation profile for same recipe as that in Figure 3.

Predictive Model Performance

It was noted during validation that the model performs better when separating 400L and 20L batch data into individual models.

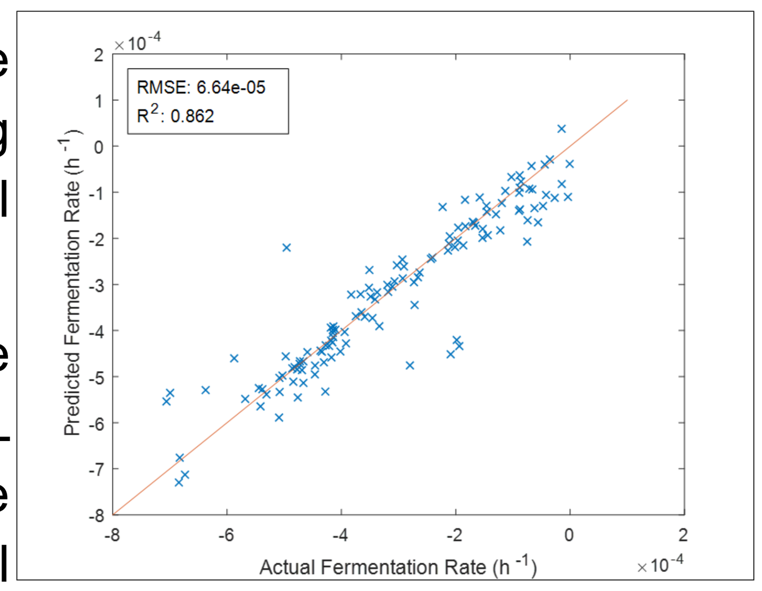

Figure 6— Predicted vs. Actual FR on 400 L only model (validation dataset).

Figure 6 shows good predictive capabilities of the model on 400 L validation data. Figure 7 shows the predictive performance of overall fermentation duration on the same validation set. Although the model consistently under predicts fermentation, the RMSE is found to be 9.8h, comparable to that in literature. However, the model does not perform well on unseen test data, indicating that the training sets may be too small or batches too varied.

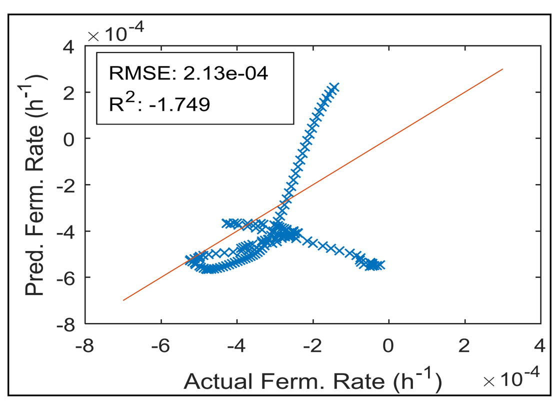

Figure 8—Performance of ANN on unseen test data.

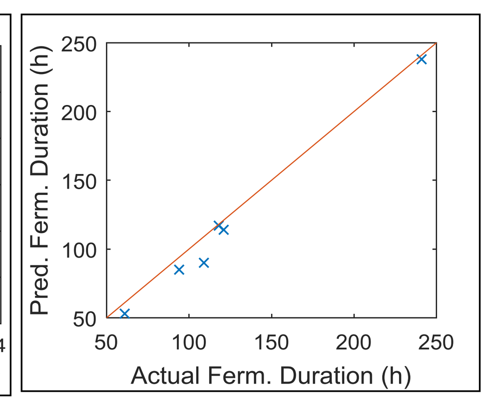

Figure 7— Predicted vs. Actual Fermentation duration on 400 L only model (val. dataset).

Conclusions and Recommendations

It is shown that the Tilt™ Hydrometer appears to perform well as measuring the specific gravity of 400 L tanks, provided appropriate pre-treatment techniques are applied. The performance on larger fermenters should be further investigated to see how the signal-to-noise ratio is affected.

It is also shown that there is potential to use ANNs to iteratively estimate a fermentation rate in order to predict fermentation duration using only variables known or estimated prior. However, it is suggested that the variability amongst batches may be too high and so a greater number of batches should be obtained in order to develop more reliable models.

References

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