

# On-line Recalibration of FTIR Measurements Using Metabolite Spiking and Dynamic Orthogonal Projection



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## Introduction

### Fourier-transform infrared (FTIR) spectroscopy

- increasingly used in bioprocess monitoring and control applications
- characteristic absorbance peaks in the *fingerprint* region (1800-800  $\text{cm}^{-1}$ )
- non-invasiveness, *in-situ* sterilizability
- ability to provide real-time concentration profiles for several metabolites simultaneously

### Stochastic drift of the measured spectra in time

- The FTIR signal is sensitive to short-term fluctuations and long-term drift
- Using dual-beam instruments, the drift effect can be eliminated by taking a background spectrum before each measurement
- Using single-beam instruments, mathematical model correction methods can be applied

### Methodology for single-beam instruments

- To maintain the online robustness of the calibration model and to reduce the effect of signal drift,
- planned pulse additions of known amounts of monitored analytes are injected into the culture medium
- a novel model adaptation method known as Dynamic Orthogonal Projection (DOP) [1] is used to fine-tune the calibration model on-line

## Experimental Setup and Calibration

Application: anaerobic batch culture of *Saccharomyces cerevisiae* CBS 426 on glucose in a 2L laboratory RC1 calorimeter

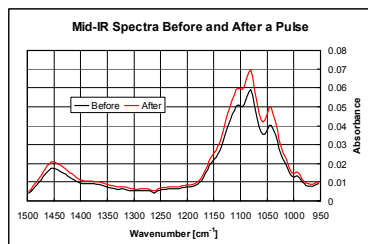
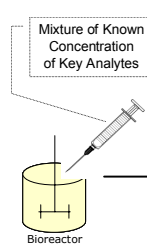
Monitoring: single-beam FTIR (ReactIR 4000 from Mettler-Toledo) equipped with a flow-through cell. Single water background spectrum collected at beginning of experiment



- A calibration model for five analytes was developed using mean-centered data, Partial Least Squares (PLS) and a 7-level multivariate design [2]
- The choice of the number of PLS factors was based on Predictive Residual Error Sum of Squares (PRESS) plots of leave-one-out cross-validation

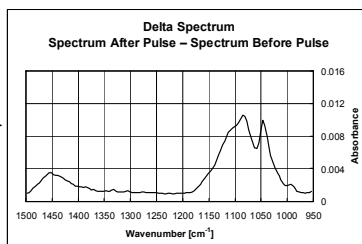
Analyte	Concentration Range [g/L]	Spectral Range [ $\text{cm}^{-1}$ ]	PLS Factors	Standard Error of Calibration (SEC) [g/L]
Glucose	0 - 25	1500 - 950	12	0.347
Ethanol	0 - 25	1300 - 950	8	0.327
Ammonium	0 - 2	1500 - 950	4	0.037
Phosphate	0 - 4	1500 - 950	13	0.042
Glycerol	0 - 4	1150 - 950	7	0.222

## A novel on-line model adaptation approach



### Delta spectrum

- corresponds to the pulse-injected mixture
- serves as an on-line reference measurement



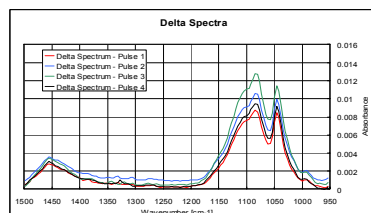
### DOP Algorithm [1] using Metabolite Spiking

- Scale each pulse composition to fall into the calibration design (linearity between analyte concentration and absorbance to be checked)
- Estimate the delta spectrum that should have been obtained in the absence of signal drift from the calibration set using a Gaussian kernel function of the scaled pulse composition
- Compute the orthogonal correction from the difference between the augmenting set of estimated and on-line delta spectra (additive drift assumed)
- Recalibrate the model based on the orthogonally corrected calibration data sets

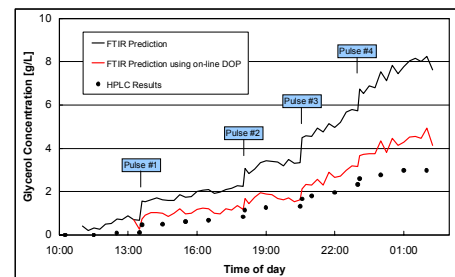
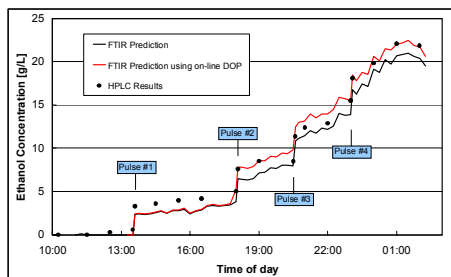
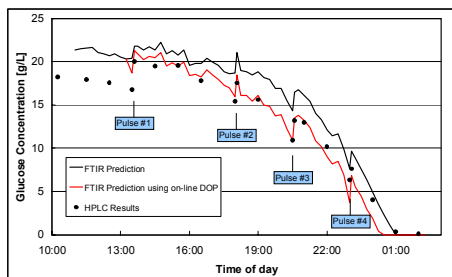
## Experimental Results

Four mixture pulses were injected with a composition corresponding to a multiple (1/5) of the calibration design centre:

- 2.5 g/L of Glucose,
- 2.5 g/L of Ethanol,
- 0.2 g/L of Ammonium,
- 0.4 g/L of Phosphate,
- 0.4 g/L of Glycerol



- Signal drift was observed in the resulting delta spectra (see figure to the left)
- Linearity between mixed analyte concentration and absorbance was verified by Principal Component Analysis (PCA) of 8 mixtures with linearly dependent compositions (1 significant factor observed)
- Each pulse composition and delta spectrum were multiplied by a factor of 5 to scale it to the mean of the calibration data set
- Following each pulse, the calibration model was corrected by DOP in real-time to reduce the effect of signal drift
- Improved prediction performance was achieved for glucose, ethanol and glycerol (see figures and table below)



- The application of DOP lead to a significant reduction in the standard error of prediction (SEP) for each analyte
- The results were compared to the commonly used In-Process Standard (IPS) method [3], where the calibration matrix is augmented by on-line reference standards

Analyte	SEP without DOP [g/L]	SEP with DOP [g/L]	Improvement with DOP	Improvement with IPS
Glucose	2.600	1.662	36.1%	17.1%
Ethanol	1.149	0.833	27.5%	9.1%
Ammonium	0.187	0.144	23.1%	1.3%
Phosphate	0.646	0.456	29.4%	35.9%
Glycerol	2.717	0.783	71.2%	33.4%

## Conclusions and Future Work

- On-line reduction of SEP has been achieved by spiking the culture with known amounts of analytes and using DOP to correct the calibration model.
- The main advantage of this novel approach is that the reference samples did not need to be analyzed by off-line methods; thus, the model adaptation is performed in real-time.
- Future work will include applying the DOP approach to a fed-batch culture where continuous feeding is replaced by substrate pulses.

[1] Zeiter, M., J. M. Roger, et al. (2005). "Dynamic Orthogonal Projection. A new method to maintain the on-line robustness of multivariate calibrations. Application to NIR based monitoring of wine fermentations." Preprint submitted to Elsevier Preprint.

[2] Brereton, R. (1997). "Multilevel multifactor designs for multivariate calibration." *The Analyst*, 122, p. 1521-1529.

[3] Kommann, H. (2003). Monitoring and control of exopolysaccharides production by *Gluconacetobacter xylinus* 1-2281 using *in-situ* mid-infrared spectroscopy. PhD thesis, Swiss Federal Institute of Technology, Lausanne.