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Advances in NIR spectroscopy applied to process analytical technology in food industries

Silvia Grassi and Cristina Alamprese

Process analytical technology (PAT) in food industries can improve process efficiency and final product quality by enhancing understanding and control of the manufacturing processes. Near infrared spectroscopy (NIRS) is one of the predominant e-sensing technologies used in PAT, thanks to its ability in fingerprinting materials and simultaneously analyzing different food-related phenomena. Recent advances have shown good potentials of NIRS in real-time monitoring and modeling of different food processes. However, most studies have been carried out at a lab scale, while applications at industrial levels are still few. To bridge the gap between NIRS potentials and its actual implementation in PAT, more efforts are requested to both researchers and industries in order to close the control loop for an efficient and automated processing management.

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Current Opinion in Food Science 2018, **22**:xx–yy

This review comes from a themed issue on **Innovations in food science**

Edited by **Adriano Cruz**

[doi:10.1016/j.cofs.2017.12.008](https://doi.org/10.1016/j.cofs.2017.12.008)

2214-7993/© 2018 Published by Elsevier Ltd.

Introduction

This paper discusses recent advances (published in 2015–2017) in near infrared spectroscopy (NIRS) applied to process analytical technology (PAT) in food industries. Prominent applications at lab and industrial scale are reported.

Real-time evaluation and assurance of the process efficiency and final product quality based on real-time process data can represent a great benefit for food industries and PAT implementation can facilitate this approach. The advantages for the company's business, meant as growth in profit margins and production efficiency, are a clear key driver of PAT application in food industries together with consumers' demand for high and consistent

quality of the final products, as well as requirements by control bodies for food safety and traceability [1]. Recently, the attention for a higher environmental sustainability of food processes has been individuated as the fourth driver involved in PAT application; PAT can actually be recognized as a green production strategy, optimizing the efficient use of resources [2].

PAT approach was firstly introduced by FDA for pharmaceutical industries, as 'a system for designing, analyzing, and controlling manufacturing through timely measurements (i.e., during processing) of critical quality and performance attributes of raw and in-process materials and processes, with the goal of ensuring final product quality. The goal of PAT is to enhance understanding and control the manufacturing process' [3]. As reported in the interesting review by van den Berg *et al.* [4], PAT can be considered 'a silent revolution in industrial quality control in food processing'. Within PAT, quality control turns from a feedback approach to a model-predictive approach based on real-time process adjustment during manufacturing. Besides the clear advantages in product quality assurance and process management, a successful implementation of PAT enables also a deep understanding and a continuous learning about food materials and process dynamics, paving the way for innovations through a Quality by Design (QbD) approach. QbD can be considered a systematic way of food development based on the pre-definition of critical quality characteristics that can be designed by an accurate and sound process understanding and control. Taking into account the strict regulatory environment in which the food industry acts as well as the consumers' requirements, the effective use of modeling and control strategies can also help in ensuring food safety, authenticity, and quality, while lowering production costs and increasing energy efficiency. However, the extremely heterogeneous and varying properties of raw materials, the complex transformations that can occur during the processing chain, and the perishable nature of the products increase the challenges in this scenario.

The PAT system has four main components (Figure 1): initial understanding of relevant factors affecting the process dynamics and the final product quality, process analysis, multivariate data analysis, and process control. This review will focus on recent NIRS applications for the monitoring of critical process parameters and quality attributes, moving progress in multivariate data analysis to the background. Chemometrics is of course of

Figure 1

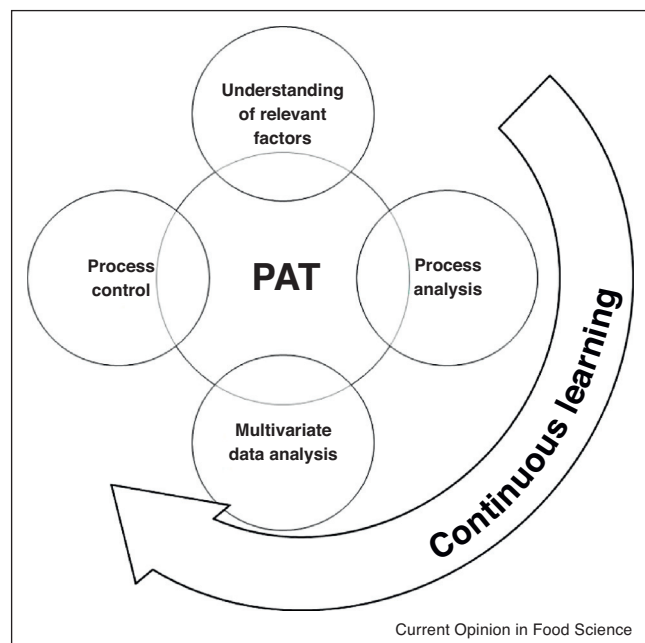


Illustration of the four main components of process analytical technology, aimed at enabling a deep understanding and a continuous learning of food materials and process dynamics.

90 fundamental importance for PAT, but a detailed survey of
 91 the advances in data analysis science is out of the scope of
 92 this review. Some of the most important univariate and
 93 bivariate parametric and non-parametric statistical tech-
 94 niques are reviewed by Granato *et al.* [5], whereas useful
 95 qualitative and quantitative multivariate approaches are
 96 reported in several recent reviews [6–10]. Chemometrics
 97 has improved the whole control process by reducing the
 98 time of analysis and providing more informative results
 99 [11]. It can be applied to PAT at different levels: for the
 100 design of experiments in order to screen and optimize the
 101 critical parameters to be considered in the process control
 102 [8,12,13]; for process control [14–16]; for both regression
 103 and classification modeling in order to predict simulta-
 104 neously several critical quality attributes from the real-
 105 time collected data [8,13]; for handling data structures
 106 from multiple analytical platforms [8,11,17].

107 Spectroscopic sensors are optimal instruments for real
 108 time analysis during manufacturing, being rapid, non-
 109 invasive, very flexible, and rugged. NIRS, in particular,
 110 with its ability to fingerprint food materials and to simul-
 111 taneously analyze different phenomena, is one of the
 112 predominant e-sensing technologies used in PAT. Its
 113 spreading is also favored by the possibility to transport
 114 radiation through optical fiber probes and by the growing
 115 availability of low-cost portable devices, which can be
 116 more easily implemented into the processing line.

Process analysis

117 Most of the published researches deal with the use of
 118 NIRS in process analysis, including characterization of
 119 raw materials, as well as intermediate and final products.
 120 The complexity and high variability of food systems and
 121 the dynamic nature of food processing together with the
 122 large number of interconnected factors affecting the out-
 123 comes are main challenges for PAT implementation in
 124 food industries. 125

126 Recent developments of NIRS in the field of liquid foods
 127 are covered by Wang *et al.* review [18^{*}], focusing on the
 128 detection of quality attributes and adulterations of alco-
 129 holic beverages (red wines, rice wines, and beer), nonal-
 130 coholic beverages (juice, fruit vinegars, coffee beverages,
 131 and cola beverages), oils (vegetable, camellia, peanut, and
 132 virgin olive oils and frying oil), and dairy products (milk
 133 and yogurt). Dairy industry is the object also of the review
 134 by Munir *et al.* [19^{**}], with a focus on milk powder, for
 135 which not only composition is important, but also tech-
 136 nological performance (e.g., particle size and dispersibil-
 137 ity), sensory and microbiological attributes. A more com-
 138 prehensive review about QbD for food processing has
 139 been published by Rathore and Kapoor [20], considering
 140 case studies in the field of both vegetable and animal
 141 products.

142 As regards the dairy products, a representative work has
 143 been published by Melenteva *et al.* [21], who proposed a
 144 global model for the spectrophotometric (400–1100 nm)
 145 determination of fat and total protein content in raw
 146 cow milk. A very large set of milk samples (>1000)
 147 collected during a whole year were analyzed, taking into
 148 account also geographical, genetic, and breeding manage-
 149 ment factors, as well as a milk storage period up to 24 h (at
 150 5 ± 1 °C). Moreover, the authors proposed some
 151 approaches for the model transfer between two different
 152 instruments.

153 At a lab scale, NIRS has been largely used for the
 154 monitoring of fermentation processes, because it can give
 155 simultaneously information about chemical composition,
 156 textural properties and microbial growth. Some good
 157 recently published reviews report results about the appli-
 158 cation of NIRS in wine and brewing industries [22^{*},23^{**}].
 159 In these fields, the control of raw material quality (e.g.,
 160 compositional, phytosanitary, genetic), processing opera-
 161 tions (e.g., mashing and fermentation) and final product
 162 quality can be successfully achieved by NIRS and multi-
 163 variate data analysis. A recent paper by Svendsen *et al.*
 164 [24] applied a NIR fiber optic reflectance probe for in-line
 165 control of yoghurt fermentation in a large lab scale (15 L
 166 fermenter). By means of principal component analysis
 167 (PCA) and kinetic modeling, they were able to model
 168 both texture changes due to the gel formation and chem-
 169 ical information related to the sugar conversion into lactic
 170 acid performed by microbial starters.

171 The usefulness of PAT in process optimization has been
172 proved also for fruits and vegetables drying, one of the
173 most energy consuming unit operation in postharvest
174 processing. Raponi *et al.* [25] reviewed literature from
175 1999 onwards exploring NIRS, multi-spectral and hyper-
176 spectral vision systems application in quality control of
177 fruit and vegetable drying processes. Recently, Moscetti
178 *et al.* [26] reported the benefits of NIRS applied to carrot
179 drying process monitoring. They focused on physico-
180 chemical changes of carrot slices during hot-air drying
181 forerun by hot-water blanching. They demonstrated the
182 efficacy of the spectroscopic system (1100–2300 nm) in
183 predicting water activity, moisture content, soluble solid
184 content, total carotenoids and color changes during drying
185 through partial least squares (PLS) regression models
186 optimized by variable selection through an interval
187 PLS (iPLS) algorithm. Furthermore they applied PLS-
188 Discriminant Analysis (PLS-DA) for the classification of
189 carrot slices according to the drying phases, obtaining
190 models with good accuracy in prediction (>75%). How-
191 ever, the industrial transfer of the presented approach
192 requires a more robust validation together with the incre-
193 ment of the instrumentation performances in terms of
light-beam intensity and wavelength range covered.

194 Some interesting applications have been suggested also
195 for coffee roasting [27], honey refining [28], dispersed
196 ground oilseed concentration in diluted solid–liquid dis-
197 persions [29], and meat composition and grading [30,31].
198 However, it is worth noting that the majority of the cited
199 works were carried out at a lab scale, and, even if they
200 show a great potential of NIRS applied to PAT for food
201 processing, a real implementation in food industries can
202 present additional challenges.

203 From process analysis to process control

204 Despite the abundant scientific literature demonstrating
205 the great potential of NIRS applied to process analysis in
206 view of PAT implementation, real case study reports
207 about on-line/at-line process analysis at industrial scale
208 are still few. It should be considered that the require-
209 ments for on-line technology application in industrial
210 production differ from laboratory-based analysis. Indeed,
211 the NIR instruments should ensure not only the ability in
212 measuring the parameter(s) of interest, but should also
213 enable an appropriate feedback speed, a non-invasive
214 character and a cleaning-in-place compatibility.

215 Porep *et al.* [32] and Beghi *et al.* [33] described the
216 application of visible/near infrared spectroscopy for an
217 on-line evaluation of crushed grapes and phytosanitary
218 status at the receipt station of wineries. Calibration PLS-
219 DA and PLS models for different relevant parameters (e.g
220 ., diseased bunches, density, fructose, glucose, and
221 organic acid content, acidity, pH) were developed, which
222 may improve payment systems and quality management.
223 However, due to the coarse qualitative or semi-

quantitative prediction achieved, further studies are nec- 224
essary in order to optimize and validate the models. 225
Moreover, in view of a final on-line application, the best 226
operating conditions and the engineering phases to per- 227
form the measurements directly at the grape receipt 228
should have been assessed. 229

An industrial scale-up of NIRS applications is more evi- 230
dent in the monitoring of fermentation processes. Among 231
the published papers, Vann *et al.* [34**] evaluated the 232
potential of NIRS for on-line monitoring of beer fermenta- 233
tion firstly at lab scale (26.5 L fermenter) and then in a 234
300 L pilot-scale plant for validation. The models devel- 235
oped for sugar consumption rate, ethanol production rate, 236
yield of ethanol on total sugars and fermentation lag-time 237
were then incorporated into a feed-forward control strat- 238
egy for yeast management. This strategy was able to early 239
detect shifts in fermentation performances and conse- 240
quently adjust yeast re-pitching rates in order to improve 241
batch-to-batch consistency. 242

A large-scale (approximately 1000 kg) experimental mill 243
was used by Allouche *et al.* [35] for monitoring olive 244
malaxation by an Acousto-Optic Tunable Filter 245
(AOTF)-NIR equipment. In particular, real-time charac- 246
terization of olives (pulp/stone ratio, extractability index, 247
moisture and oil contents) and the potential character- 248
istics of the extracted oil (free fatty acids, peroxide value, 249
UV parameters, pigments and polyphenols) were evalu- 250
ated, considering different months and years of olive 251
harvesting, as well as different processing conditions 252
(i.e., types of hammer mill, sieve diameter, hammer 253
rotation speed, and temperatures). The use of an artificial 254
neural network (SS-ANN) allowed reaching good predic- 255
tive capability, showing the possibility to obtain almost 256
instantaneously the information needed to optimize pro- 257
cess conditions in terms of both productivity and oil 258
quality, despite the high variability of the raw material 259
and the dynamic conditions of the spectra collection. The 260
acquired knowledge can be used for the implementation 261
of a process-automation system able to regulate different 262
processing variables with minimal loss of time and costs. 263

The advantages of real-time measurements, modeling 264
and control in food processing are well illustrated by 265
Glasse *et al.* [36] through the discussion of different 266
industrial case studies. In particular, the authors demon- 267
strated that NIRS might be used to improve the consis- 268
tency of dry ingredient mixing in food industries. Con- 269
sidering bread and confectionery powder mixtures with 270
different particle size distributions, experiments were 271
performed using two conical screw mixers of 4000 L 272
capacity, each equipped with a NIR diffuse reflectance 273
fiber-optic probe. Both powder homogeneity and compo- 274
sition were successfully predicted by applying a suitable 275
NIR data elaboration. The obtained results were then 276
validated using a tumble blender with a nominal capacity 277

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278 of 2000 L. Being the plant in motion, a Wi-Fi and battery
 279 powered portable device (MicroNIR) was used for spectra
 280 acquisition. The validation produced good results, allow-
 281 ing the identification of the homogeneity point. A further
 282 experiment was carried out for caramel and custard pro-
 283 cessing, where mixing of mainly water and sugar at high
 284 temperatures leads to high density and high viscosity
 285 products. A 2000 L mixing and cooking vessel was used,
 286 applying to the recirculation pipe a NIR probe connected
 287 to a MicroNIR. Good PLS calibration models with high
 288 coefficients of determination and low errors were
 289 obtained for color, moisture, and water activity. However,
 290 the predictions for an unknown batch were not very
 291 accurate. In any case, since only three batches were used
 292 for calibration, the models can be improved by analyzing
 293 more production batches.

294 Conclusions

295 Process-automation systems can really help food indus-
 296 tries in improving process efficiency, meanwhile satisfy-
 297 ing law requirements and consumers' needs. The com-
 298 plexity of a food process represents a challenge for PAT
 299 implementation, but NIRS can be successfully exploited
 300 in this field. However, the recent scientific literature is
 301 still too much focused on studies carried out at a labora-
 302 tory level, just demonstrating the potential of NIRS in
 303 understanding, modeling and monitoring food-related
 304 phenomena. Some manufacturers are integrating spectro-
 305 scopic sensors into processes, but only as substitutes for

306 traditional off-line analytical procedures. This can lead to
 307 a confused perception of PAT.

To bridge the gap between NIRS potentials and its actual
 308 implementation in PAT tools, more efforts are requested
 309 to both researchers and industries. A good dissemination
 310 and a closer collaboration are needed in order to transfer
 311 the process analysis carried out at a lab-scale into an
 312 industrial process control, closing the loop for an efficient
 313 and automated processing management (Figure 2). Resis-
 314 tance to change must be overcome by food industries, as
 315 well as deeper statistical knowledges and management
 316 skills must be transferred to the future generation of food
 317 technologists. Only in this way the 'PAT silent
 318 revolution' might be accomplished, with important impli-
 319 cations for food producers and consumers. 320

Funding

321 This review did not receive any specific grant from funding
 322 agencies in the public, commercial, or not-for-profit sectors. 323

Conflict of interest

324 The authors declare no conflict of interest. 325

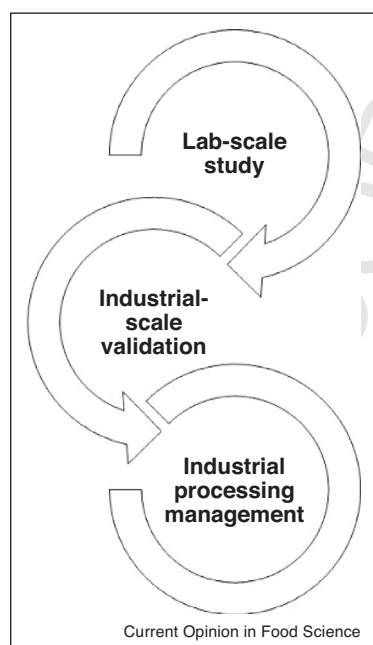
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Figure 2



Scheme for the development of an efficient and automated processing management tool.

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