

Fast Determination of 2-Ethylhexyl Nitrate Diesel/Biodiesel Blends by Distillation Curves and Chemometrics

Matías Insausti* and Beatriz Susana Fernández Band

Lab FIA, INQUISUR—CONICET, Department of Chemistry, Universidad Nacional del Sur, Avenida Alem 1253, Bahía Blanca, B8000CPB, Buenos Aires, Argentina

ABSTRACT: A new method for the quantification of 2-EHN (2-ethylhexyl nitrate) was developed and validated. In order to speed up and simplify the chemical analysis of diesel samples throughout inspection procedures, we propose a single analytical method to determine 2-ethylhexyl nitrate by using the distillation curves routine assay used to evaluate the quality of diesel (ASTM D86). This test was allied with multivariate calibration based on PLS (partial least squares) regression. The results were comparable with reference methodology. Using distillation curves of commercial diesel samples results in a prediction of the cetane improver content with relative standard deviations lower than 12% for all fuel samples. Since this correlation was established using commercial samples, the new approach is immediately applicable in the petrochemical industry, which needs an adaptation to biodiesel/diesel blends.

1. INTRODUCTION

In order to improve the fuel properties of diesel, several kinds of chemicals such as nitrates, ether nitrates, or nitroso compounds are added. It has been checked that these chemical additives produce an increasing effect on the cetane number, which is associated with burning of fuel in the engine. Commonly, the additive most used is 2-ethylhexyl nitrate (EHN), due to the improvement in the combustion characteristics, shortening ignition delay and the start of combustion. The ignition delay period is counted from the injection start to the sharp rise of in-cylinder pressure. The ignition delay period of a diesel engine is mainly influenced by physical–chemical characteristics of the fuel. A fuel with a high cetane number has a short ignition delay and starts to burn soon after it is injected into an engine.¹ The time to vaporize the fuel and mix with the air content in cylinder and the time to react through free radical processes determine the ignition delay. Under normal conditions, if the ignition delay is excessively lengthy in the diesel engine, the outcome is unburned fuel, low power, and formation of particulates that increase engine noise and wear.²

Reported mechanisms include the decomposition of cetane improvers into free radicals and gas-phase catalysts such as NO₂. These generated species are involved in the fuel–air reaction. There are also reactions which inhibit free-radical scavengers found in the fuel.^{3,4}

The fuel from petroleum distillation is obtained by mixing several fractions from the processing stages of crude oil. The ratio of these components in diesel is made so as to frame the normative specifications which enable good performance of the product, control toxic exhaust emissions, and minimize wear of engines and components.⁵ Distillation is a physicochemical assay used to measure the volatility of the sample components of a complex liquid mixture. The boiling range gives information on the composition, the properties, and the behavior of the fuel during storage and use.⁶ This assay is used to verify the right proportions of the light and heavy fractions of fuel in order to attain good performance. The assay results in a matrix with samples in rows and the temperature

reached by recovering 10, 20, 30, 40, 50, 60, 70, 80, 85, 90, and 95% of initial fuel volume in columns, allowing the use of multivariate models.

The multivariate models associated with analytical techniques are an advantageous alternative to predict physicochemical parameters, because they are easy to apply, fast, low-cost, and useful for online determinations. Recent studies have shown the great potential of distillation curves, or a few specific points, for the analysis of different parameters of petroleum products,^{7–12} specific gravity,¹³ kinematic viscosity,¹⁴ octane numbers,¹⁵ cetane index,¹⁶ flash point, ethanol content, and biodiesel content.¹⁷ Bruno and co-workers demonstrated that different additive concentrations in fuel produce modifications in distillation curves.¹⁸

The worldwide output of this nitrated additive is approximated to be about 100 000 tons/year, a large-scale commodity. For a long time it has been regarded as not involving particular risks to human health. In spite of this, the substance shows no evidence of biodegradability in water,¹⁹ is completely miscible in fat, and has potential for bioaccumulation and may form a film on water affecting the oxygen transfer.

Decomposition products of the EHN form nitric oxides (NO and NO₂), giving as a result an additional source of NO_x. Approximately the third part of the nitrogen in the cetane improver goes to the exhaust as NO_x in pure diesel combustion.²⁰ In diesel/biodiesel blends, owing to the lower cetane number (CN) of pure biodiesel (B100),²¹ the addition of EHN is necessary to increase the CN. By considering that the percentage of biodiesel in the blends was increasing in recent years, the concentrations of EHN also did. Therefore, the determination of EHN in blends is very important in order to control the presence of this contaminant, which causes pollution of air and soils dangerous to life.²²

Received: December 28, 2015

Revised: June 15, 2016

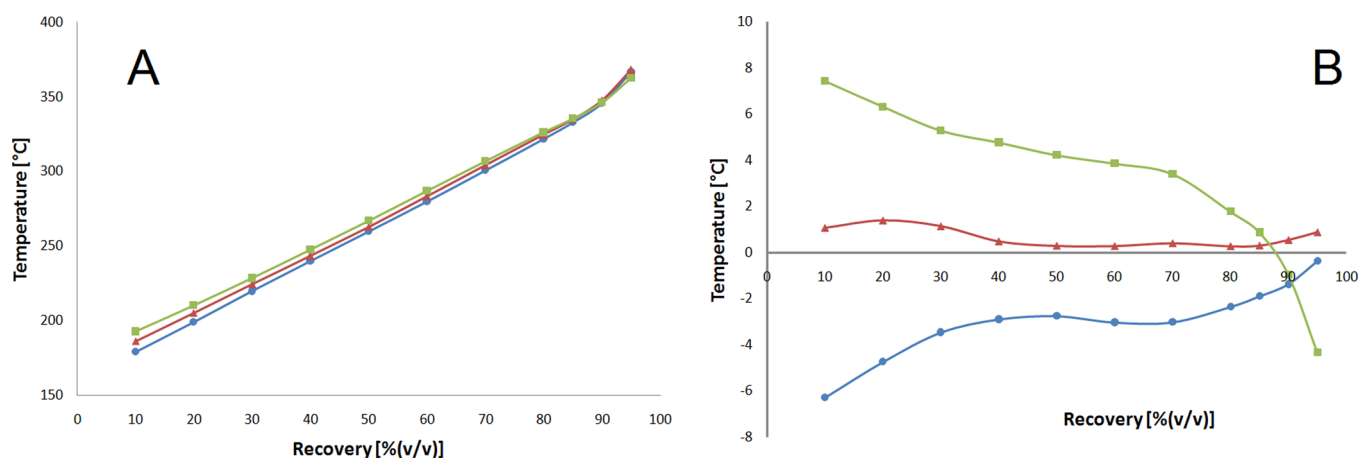


Figure 1. (A) Distillation curves data. (B) Behavior of mean centered distillation curves. (●) 0.03–0.12% EHN (v/v); (▲) 0.12–0.2% EHN (v/v); (■) 0.21–0.3% EHN (v/v).

84 The American Standard Test Method D4046 indicates the
 85 methodology to establish the alkyl nitrate quantity in fuel
 86 samples. The norm includes a wearisome liquid–liquid
 87 extraction by using organic solvents, a derivatization, and
 88 spectrophotometric measure. The procedure starts with a
 89 hydrolysis in nitric acid solution, and then reaction with 2,4-
 90 dimethylphenol. The reaction product is extracted by 2,2,4-
 91 trimethylpentane followed by addition of sodium hydroxide.
 92 The measure is done in a spectrophotometer at 452 nm. All
 93 these steps result in several methodology disadvantages, such as
 94 organic solvent consumption, large time expenditure, and
 95 relatively high values of relative standard deviations for
 96 repeatability and reproducibility. In the literature, there are
 97 some alternatives using headspace gas chromatographic/mass
 98 spectroscopy (GC/MS) assay,²³ chemiluminescence detection
 99 of a derived product,²⁴ or infrared spectrometry.²⁵ The
 100 developed GC/MS and infrared spectrometry methods,
 101 although they avoid the problems of the standardized method,
 102 require costly instruments not available in every laboratory and
 103 qualified operators.

104 The daily work of quality control in the automotive and
 105 petrochemistry industries seeks the development of new low
 106 cost and rapid methods for determining the cetane improver.
 107 Thus, the aim of this work is to propose a simple and rapid
 108 analytical method to predict the EHN concentration in blends
 109 through a chemometric model and the data obtained from the
 110 routine distillation curves.

2. EXPERIMENTAL SECTION

111 Commercial diesel samples were collected within the years 2010 and
 112 2015, when the Argentinean fuel policy was changing, so the biodiesel
 113 content of the 120 diesel samples varies between 0 and 7% (v/v). In
 114 this country the biodiesel added to blend the petroleum diesel fuel is
 115 produced from soybean oil.

116 The samples were distilled with automatic ISL AD 86 5G according
 117 to ASTM D86. Distillation curves (distillation temperature vs the
 118 recovered volume) were recorded as a daily routine at the
 119 PETROBRAS laboratory (Bahía Blanca). This test is performed in
 120 all fuel laboratories, providing very important information to establish
 121 not only the quality of fuel but its price in the market. The distillation
 122 curves data are also useful for determining the cetane index (ASTM
 123 D4737).

124 In fuel laboratories, the EHN determination is not usually done as
 125 routine analysis because the ASTM Standard Method has a lot of steps
 126 which makes it complicated, as said above.

Therefore, the EHN contents in the 120 fuel samples were
 measured with the Eraspec Diesel Fuel Analysis from Eralytics
 Company of PETROBRAS (Bahía Blanca).²⁶ This instrument is a
 NIR/mid-FTIR interferometer which permits the determination of
 different parameters showing repeatability and reproducibility values
 comparable with the ASTM Method.

All distillation curves and EHN values were acquired in the same
 day that the samples left the refinery to go to gas stations. This
 information was registered in the daily fuel quality reports.

Construction of Chemometric Model. The multivariate analysis
 was carried out using the Kennard–Stone algorithm (KS)²⁷ for sample
 selection and partial least squares (PLS)²⁸ for calibration modeling.

From data of distillation curves and EHN contents obtained for the
 120 samples, were separated into three sets: 60 for calibration, 30 for
 validation, and 30 for prediction.

The calibration set could be selected randomly from the whole set
 of 120 samples. Nevertheless, this procedure does not warrant the fair
 election of the set over the entire sampling range. To solve this
 problem, the KS algorithm ensures the representative choice of the
 prediction set and guarantees the predictive ability of the calculated
 model along the whole calibration range. The PLS model proposes
 data decomposition in score and loadings (latent variables) matrices,
 and model relationships between sets of observed data. In order to
 choose the correct number of latent variables to model the distillation
 curve data, a so-called validation process, two strategies were used:
 “test set” and “cross-validation”. In the “test set” process the
 calculation of the latent variables and scores were done using the
 calibration set of samples, and the validation was done predicting the
 validation set of samples. In the “cross-validation” process the
 calibration and validation sets were the same group of samples. In
 this work a “full cross-validation leave-one-out” was used; all
 calibration–validation samples were predicted by a model calculated
 with the remainder samples of the group.

Then, the 30 data of distillation curves selected as a prediction set
 were introduced into the calculated PLS models. Thus, the EHN
 concentrations can be obtained through the models. It is worth
 noting that the 30 samples of the prediction set were not used in any
 step of the process to calculate the chemometric models.

The predicted values of EHN concentration were compared with
 those obtained experimentally with the Eraspec instrument.

3. RESULTS AND DISCUSSION

Figure 1A shows the distillation curves for different EHN
 concentration ranges. Three curves (an average curve of each
 range) were plotted in order to show the significant
 displacement of the curves, due to the presence of EHN.
 This effect can be best seen in Figure 1B, in which were plotted

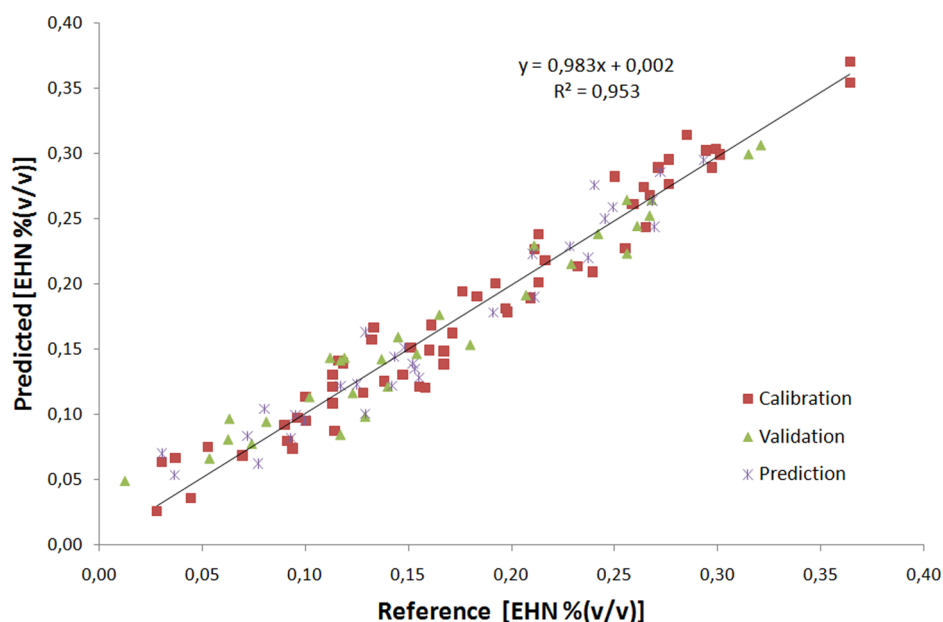


Figure 2. Cross-validation prediction versus reference value.

172 the mean centered curves (subtracting the mean temperature
173 value of each recovery point).

174 The fuel additive presence retards the vaporization of lighter
175 compounds; in the blend diesel fuel samples these components
176 would be normally registered early in the distillation curve. An
177 example of this effect is the concentration found of diethyl
178 carbonate at 10, 20 and 30% (v/v) in the work of Bruno et al.¹⁸
179 Another example of measuring an additive through a distillation
180 curve comes from the measurement of molar concentration of
181 tetraethyl lead in commercial aviation gasoline approaching the
182 trace concentration level.²⁹

183 Figure 2 presents a full cross-validation (leave-one-out) of
184 the whole set of 120 samples, differentiating groups of samples
185 used in calibration, validation and prediction sets. Each sample
186 was predicted using four latent variable of a model calculated
187 with the 119 remaining samples. In this plot of predicted vs
188 reference values, is outlined as the KS algorithm separated the
189 samples, and the linear behavior of the 120 samples.

190 The PLS modeling correlates the distillation curve data with
191 the EHN content, giving the ability to predict additive
192 concentrations in unknown fuel samples assaying only with
193 the data obtained from the distillation curve test.

194 Table 1 presents the analytical figures of merit of the two
195 strategies to validate the chemometric models, using a full
196 cross-validation (CV) leave-one-out of 90 samples (calibration
197 and validation sets founded with KS algorithm) and a test set
198 validation (using calibration set of 60 samples and 30 samples
199 of the validation set chosen by KS, too). Both ways of
200 validation had comparable results, which can be shown with the
201 relative error of prediction (%), which for CV is 13.18% and for
202 the test set is 14.81%. However, as the number of samples used
203 in the calibration step was higher for CV, the results were little
204 better. This result may indicate that a larger set of samples for
205 the calibration process could improve even better the
206 prediction results. For all three calculated models, four latent
207 variables were chosen. Also, Table 1 presents the prediction
208 results for the external set of 30 samples which had not been
209 used in the mathematical calculation of the chemometric
210 models. This means that, once the statistical relationship

Table 1. Analytical Performance of PLS Models To Predict Different Sets of Samples

	all samples	validation set		prediction set	
	CV	CV	test set	CV	test set
samples	120	90	30	30	30
slope	0.9478	0.9489	0.8207	0.9654	0.9045
offset	0.0090	0.0089	0.0256	0.0059	0.0212
correlation	0.9730	0.9736	0.9720	0.9701	0.9717
R ²	0.9476	0.9490	0.9216	0.9404	0.9374
RMSE ^a	0.0186	0.0189	0.0200	0.0178	0.0200
SE ^b	0.0187	0.0190	0.0193	0.0183	0.0195
bias	0.00046	-0.00005	0.00599	0.00026	0.00572

^aRMSE, root mean squared error [% EHN (v/v)]. ^bSE, standard error [% EHN (v/v)].

between distillation curve data and EHN content was obtained,
the chemometric technique can be used from the results of the
distillation curves, in order to calculate the concentration of the
analyte.

The limit of quantification (LOQ) was defined as the lowest
amount of an analyte in a sample that can be determined
quantitatively with convenient precision and accuracy. It was
calculated as $LOQ = 10S$, where S is the standard deviation of
20 prediction values for samples with 0% (v/v). The LOQ
found for our methods is 0.0298% (v/v). The lower limit of
detection (LOD) is the lowest quantity of a substance that can
be distinguished from the absence of that substance. It was
calculated as $LOD = 3.28S$. The LOD found for our methods is
0.0101% (v/v). The resultant LOD and LOQ are comparable
with those found in the bibliography.^{23–25}

The elliptical joint confidence region (EJCR) of the
regression³⁰ of predicted versus nominal concentrations in
the prediction set was studied for the two calibration models.
The corresponding plots are shown in Figure 3. All confidence
regions contain the ideal point of unit slope and zero intercept
(indicating accuracy) at 95% confidence level, and the elliptical
sizes obtained were comparable, suggesting that both chemo-
metric methodologies shown similar predictive abilities.

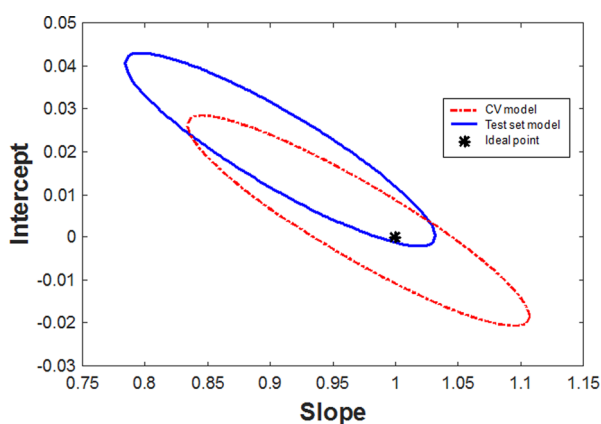


Figure 3. Elliptical joint regions (at 95% confidence level) for the slope and intercept of the regression of test set model (solid line) and CV model (dashed line) results. Black asterisk marks the theoretical (intercept = 0, slope = 1) point.

4. CONCLUSIONS

234 With the use of distillation curve data and multivariate
235 calibration, the content of 2-ethylhexyl nitrate, which is an
236 important additive to improve the cetane number, was
237 predicted efficiently. The distillation curves were obtained
238 following ASTM D86 specifications.

239 The proposed method reduces the time and costs of analysis
240 since distillation assays are within the scope of laboratory
241 analysis. The advantage of this quantification methodology is
242 the use of data that is obligatorily acquired in daily routine
243 analysis in every refinery. This new method avoids the need to
244 perform another experimental analysis.

245 The ability to relate the changing composition with
246 distillation curves is critical since many quality parameters
247 could be estimated exploiting the data recorded in the ASTM
248 D86 assay.

249 As the developed method is cheap and does not use any
250 organic compound, it can be proposed as an alternative to the
251 established standard method of EHN determination.

252 The refineries and petrochemical industries (where EHN has
253 to be determined) could benefit from taking advantage of the
254 present method. Commonly, adding biodiesel to diesel
255 produces a decrease of the cetane number; thus, the improver
256 is added. The new determining method could be helpful in
257 adapting out-of-date laboratories to test biodiesel/diesel blends.

258 ■ AUTHOR INFORMATION

259 Corresponding Author

260 *Tel.: +54 291 4595100. Fax: +54 291 4595160. E-mail:
261 matiasi@conicet.gov.ar.

262 Notes

263 The authors declare no competing financial interest.

264 ■ ACKNOWLEDGMENTS

265 The authors acknowledge the support of CONICET (research
266 funds).

267 ■ REFERENCES

268 (1) Li, R.; Wang, Z.; Ni, P.; Zhao, Y.; Li, M.; Li, L. Effects of cetane
269 number improvers on the performance of diesel engine fuelled with
270 methanol/biodiesel blend. *Fuel* **2014**, *128*, 180–187.
271 (2) Burger, J. L.; Lovestead, T. M.; Gough, R. V.; Bruno, T. J.
272 Characterization of the Effects of Cetane Number Improvers on Diesel

Fuel Volatility by Use of the Advanced Distillation Curve Method. *273*
Energy Fuels **2014**, *28*, 2437–2445. *274*

(3) Suppes, G. J.; Rui, Y.; Rome, C.; Chen, Z. Cetane-Improver
275 analysis and impact of activation Energy on the Relative Performance
276 of 2-Ethylhexyl Nitrate and Tetraethylene Glycol Dinitrate. *Ind. Eng.*
Chem. Res. **1997**, *36*, 4397–4404. *278*

(4) Clothier, P.; Aguda, B.; Moise, A.; Pritchard, H. How do
279 dieselfuel improvers work? *Chem. Soc. Rev.* **1993**, *22*, 101–108. *280*

(5) Albahri, T. A. Developing correlations for the properties of
281 petroleum fuels and their fractions. *Fluid Phase Equilib.* **2012**, *315*,
113–125. *283*

(6) *Standard Test for Distillation of Petroleum Products at Atmospheric*
Pressure; ASTM D86; American Society for Testing and Materials:
285 Washington, DC, 2010. *286*

(7) de Oliveira, F. S.; Teixeira, L. S. G.; Araújo, M. C. U.; Korn, M.
287 Screening analysis to detect adulterations in Brazilian gasoline samples
288 using distillation curves. *Fuel* **2004**, *83*, 917–923. *289*

(8) Bruno, T. J. Improvements in the measurement of distillation
290 curves. Part 1: A composition-explicit approach. *Ind. Eng. Chem. Res.*
2006, *45*, 4371–4380. *292*

(9) Smith, B. L.; Bruno, T. J. Advanced distillation curve
293 measurement with a model predictive temperature controller. *Int. J.*
Thermophys. **2006**, *27*, 1419–1434. *295*

(10) Aleme, H. G.; Costa, L. M.; Barbeira, P. J. S. Determination of
296 gasoline origin by distillation curves and multivariate analysis. *Fuel*
2008, *87*, 3664–3668. *298*

(11) Burger, J.; Lovestead, T. M.; Windom, B. C.; Bruno, T. J.
299 Characterization of renewable fuels and additives with the advanced
300 distillation curve method. *Abstracts of Papers*, 242nd National Meeting
of the American Chemical Society, Denver, CO, Aug 28–Sept 1, 2011;
302 American Chemical Society: Washington, DC, 2011; p 145. *303*

(12) Maheshwari, A. S.; Chellani, J. G. Correlations for pour point
304 and cloud point of middle and heavy distillates using density and
305 distillation temperatures. *Fuel* **2012**, *98*, 55–60. *306*

(13) Aleme, H. G.; Costa, L. M.; Barbeira, P. J. S. Determination of
307 ethanol and specific gravity in gasoline by distillation curves and
308 multivariate analysis. *Talanta* **2009**, *78*, 1422–1428. *309*

(14) Aleme, H. G.; Assunção, R. A.; Carvalho, M. M. O.; Berbeira, P.
310 J. S. Determination of specific gravity and kinematic viscosity of diesel
311 using distillation curves and multivariate calibration. *Fuel Process.*
Technol. **2012**, *102*, 90–95. *313*

(15) Mendes, G.; Aleme, H. G.; Berbeira, P. J. S. Determination of
314 octane numbers in gasoline by distillation curves and partial least
315 squares regression. *Fuel* **2012**, *97*, 131–136. *316*

(16) Aleme, H. G.; Barbeira, P. J. S. Determination of flash point and
317 cetane index in diesel using distillation curves and multivariate
318 calibration. *Fuel* **2012**, *102*, 129–134. *319*

(17) Aleme, H. G.; Barbeira, P. J. S. Determination of biodiesel
320 content in diesel using distillation curves and multivariate calibration.
Energy Fuels **2012**, *26*, 5769–5774. *322*

(18) Bruno, T. J.; Ott, L. S.; Lovestead, T. M.; Huber, M. L. The
323 composition-explicit distillation curve technique: Relating chemical
324 analysis and physical properties of complex fluids. *J. Chromatogr. A*
2010, *1217*, 2703–2715. *326*

(19) American Chemistry Council Petroleum Additives Panel. *High*
Production Volume: Challenge Program for Nitric Acid, 2-Ethylhexylester;
2006. *329*

(20) Ickes, A. M.; Bohac, S. V.; Assanis, D. N. Effect of 2-Ethylhexyl
330 Nitrate Cetane Improver on NOx Emissions from Premixed Low-
331 Temperature Diesel Combustion. *Energy Fuels* **2009**, *23*, 4943–4948. *332*

(21) Nadai, D.; Simões, J. B.; Gatts, C. E. N.; Miranda, P. C. M. L.
333 Inference of the biodiesel cetane number by multivariate techniques.
Fuel **2013**, *105*, 325–330. *335*

(22) Day, D. A.; Liu, S.; Russell, L. M.; Ziemann, P. J. Organonitrate
336 group concentrations in submicron particles with high nitrate and
337 organic fractions in coastal southern California. *Atmos. Environ.* **2010**,
44, 1970–1979. *339*

- 340 (23) Dvořák, B.; Bajerová, P.; Eisner, A.; Nykodýmová, O.; Ventura,
341 K. Determination of 2-ethylhexyl nitrate in diesel fuel. *J. Sep Sci.* **2011**,
342 *34*, 1664–1668.
- 343 (24) Wang, C. X.; Firor, R. *Analysis of Trace 2-Ethylhexyl Nitrate in*
344 *Diesel Using Chemiluminescence Detector*; Agilent Technologies,
345 Application Brief; 2010.
- 346 (25) Bajerová, P.; Bajer, T.; Adam, M.; Eisner, A.; Ventura, K. Fast
347 determination of 2-ethylhexyl nitrate in diesel oils by infrared
348 spectrometry. *Fuel* **2014**, *117*, 911–916.
- 349 (26) PAC [Internet], Advance Analytical Instrumentation for Lab
350 and Process Application. <http://www.pacp.com/>.
- 351 (27) Soares, S. F. C.; Gomes, A. A.; Galvão Filho, A. R.; Araujo, M.
352 C. U.; Galvão, R. K. H. The successive projections Algorithm. *TrAC,*
353 *Trends Anal. Chem.* **2013**, *42*, 84–98.
- 354 (28) Wold, S.; Sjöström, M.; Eriksson, L. PLS-regression: a basic tool
355 of chemometrics. *Chemom. Intell. Lab. Syst.* **2001**, *58*, 109–130.
- 356 (29) Lovestead, T. M.; Bruno, T. J. Application of the Advanced
357 Distillation Curve Method to the Aviation Fuel Avgas 100LL. *Energy*
358 *Fuels* **2009**, *23*, 2176–2183.
- 359 (30) Riu, J.; Rius, F. X. Method comparison using regression with
360 uncertainties in both axes. *TrAC, Trends Anal. Chem.* **1997**, *16*, 211–
361 216.