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CO₂ Capture, Transport and Storage

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Editors:
Nils A. Røkke and Hanna Knuutila

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HIGH CONCENTRATED MEA SOLVENT SYSTEMS FOR CO₂ ABSORPTION – AN FT-NIR AND RAMAN SPECTROSCOPIC INVESTIGATION

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Abstract

This study investigates the use of Fourier Transform Near-Infrared (FT-NIR) spectroscopy and Raman spectroscopy to monitor the CO₂ absorption process when over 65 wt % concentrated monoethanolamine (MEA) solutions are used. Using high concentrated amines instead of the conventional 30 wt %, is a strategy to decrease the cost of CO₂ capture plants by minimizing the energy consumption spent for amine regeneration and reducing the size of the process equipment. In addition, higher solvent concentration has a positive impact on mass transfer. CO₂ loading and solvent strength are two main parameters that are used to characterize the well-known CO₂ capture process by MEA. Several analytical methods are in practice to determine these two parameters but most of them are time-consuming and not favourable when quick results are demanded. Process analyzers such as Raman spectroscopy or NIR (Near Infrared) spectroscopy can be used for real-time monitoring of chemical or physical attributes in a system and have advantages over traditional analytical methods. Authors have previously published spectroscopic methods combined with chemometrics to determine CO₂ loading in 30 wt % MEA solutions by Raman spectroscopy in laboratory scale and pilot plant experiments. The aim of this paper is to extend these spectroscopic investigations when both the amine concentration and loading are spanned in a range. CO₂ loading range was selected between 0-0.6 mol CO₂ / mol MEA and solvent concentration was varied between 66-99.5 wt %. Two analyzers were selected; Raman and Fourier transform near infrared (FT-NIR) spectrometers. It is relatively easy to generate data in a short time by these instruments, however identification of components of a chemical mixture and calibration methods become challenging as the FT-NIR and Raman spectral data are not straightforward. Many spectral responses appear similarly and therefore the choice of chemometrics methods is more reliable than the traditional univariate methods. In this study, chemometrics has been applied for data preprocessing, data exploration and finally for multivariate calibration of four models to predict CO₂ loading and MEA concentration from FT-NIR and Raman spectroscopy.

Keywords: *high concentrated MEA, CO₂ loading, MEA weight percentage, spectroscopy, chemometrics*

1. Introduction

Body Carbon capture, utilization and storage (CCUS) is an obligatory action in the global climate change mitigation plans. Electricity/thermal power generation and transport account for two thirds of total CO₂ emissions and 32.8 billion tons of global CO₂ emissions in the atmosphere are the results of fuel combustion [1]. Post-combustion CO₂ capture using amines is the most widespread method in CCUS. Monoethanolamine (MEA) has prioritized the other amines to remove CO₂ from flue gas at atmospheric pressure and is considered to be a “first generation solvent”.

30 wt% MEA has been the benchmark for most of the experimental, theoretical and modelling work. 15-20 wt% was the recommended amine concentration and since 1960s 30 wt % has been the standard [2, 3]. The limitations to avoid using higher amine concentration are the thermal degradation, corrosion and fouling problems [4, 5]. Raksajati, Ho [6] show that the development of aqueous chemical absorption technology for CO₂ capture should also focus on new solvents with high solvent concentration to make a significant impact on the capture cost. They claim if the solvent concentration increases

from 30 to 50 wt %, the capture cost decreases by about 16% from US\$88 to US\$72 per metric ton of CO₂ avoided. When the solvent concentration is increased, the solvent flow rate decreases and the mass transfer increases which makes to have a reduced absorption unit size [6]. In this aspect, moving from the traditional ‘30 wt % MEA based capture process’ to ‘high concentrated MEA process’ has a significant interest. However, the corrosion, degradation and fouling effects which are more in high concentrated MEA process should also be carefully addressed [7, 8]. EFG plants by Fluor Inc. and CO₂ capture plants by Union Engineering in Denmark have upgraded amine technology for commercial applications using over 30 wt % MEA.

Process information described by CO₂ loading (mol CO₂/mol amine) and the amine concentration (wt%) are used in R&D experiments and capture plant operations to characterize absorption and regeneration. Loading is defined as the ratio between number of moles of CO₂ and the number of moles of the solvent and the solvent concentration, is expressed as the solvent mass fraction. Samples extracted from rich stream, lean stream and water wash in amine based CO₂ capture plants, are continuously analyzed offline for CO₂ loading and amine

concentration. The frequency of sample extraction is limited by several factors such as the time spent for lab analysis, sample preservation facilities during lab-to-plant transport, risk factors during sample extraction and availability of laboratory resources such as chemical and skilled manpower. In addition, operational delays are unavoidable when decisions are dependent on laboratory results. In this aspect, process analytical technology (PAT) plays a vital role which speeds up the analysis time and opens the opportunity to give live feedback while minimizing sampling errors, risk and health issues [9].

1.1 PAT tools

PAT tools in industrial applications has more than 70 years history, and today many sophisticated analyzers are across chemical and petrochemical industries [9]. Some types of spectroscopic methods have been tested for liquid and gas analysis in CO₂ capture plants particularly during last 10 years and have shown a positive impression. A list of published work where spectroscopic methods were used for liquid analysis in amine based CO₂ capture process is given by Jinadasa [10]. IR (Infrared), UV/Vis (Ultra-Violet Visible) and NIR (Near Infrared) and Raman spectrometers have been used for qualitative and quantitative analysis of chemical components. NIR spectral data was combined with other measurement data to determine MEA wt% and CO₂ % [11, 12]. CO₂ absorption by an amine mixture at high pressure was monitored by a predictive statistical model where NIR data was one of measurements [13]. Raman spectroscopy has also become a popular method in liquid phase analysis in laboratory experiments and pilot plant trials as reported in several literature [14-19]. These authors have used the high spectral features of Raman data to determine species concentration.

Spectroscopy reveal in-depth chemical information of a system because molecular vibrations produce unique spectra. Weak Raman scattering for water, compact chemical information in fingerprint area for organic solvents and non-invasive remote monitoring facility are some of the features which have made Raman spectroscopy appropriate to analyse MEA-CO₂-H₂O system. Various organic compounds exhibit selective absorption for infrared radiation. Water molecules provide a very strong signal on the NIR spectra as they are highly polarized and used as an indication on water content in a sample. FT-NIR spectroscopy is considered as the best performing among other NIR analysers based on speed of analysis, higher signal (S/N) to noise ratio and precision and accuracy of wavelength. It uses the Fourier transform algorithm on the interferogram to convert a spectrum and provides easy transfer of calibration models between instruments [20].

Figure 1 shows a schematics representation of using an immersion probe for in-situ analysis of gas loading and solvent concentration. The immersion probe is connected to a process analyzer such as Raman spectrometer where it acquires data from a process stream. The spectral data is converted into chemical data using a calibration model. This model can be prepared using a univariate analysis or a multivariate analysis (Næs & Martens, 1984), and the figure mentions a PLS model which is one type of a multivariate analysis method (described in section 2.4.3).

For highly correlated data, multivariate analysis become the preferred choice over univariate. Our previous studies demonstrated the use of Raman spectroscopy for a complete in-situ speciation of CO₂ capture by 30 % MEA [19, 21]. In this study, a similar approach was used for developing multivariate regression models for CO₂ absorption by higher concentrated MEA.

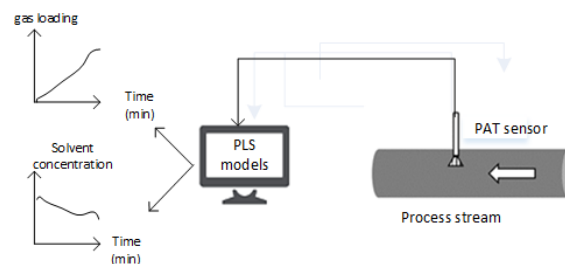


Figure 1: An immersion probe used as a process monitoring tool in gas absorption process; (PLS = partial least squares regression)

2. Experimental section

2.1 Chemicals and samples

MEA purchased from Merck (>99%) and CO₂ from AGA were used as received without further purification. Degassed milli-Q water (18.2 MΩ.cm) was used for all the sample preparation. 105 samples were prepared for both calibration and validation at room temperature (25 °C) and pressure maintaining the same experimental conditions.

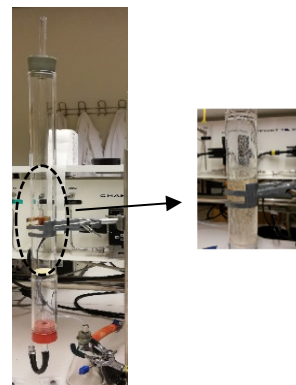


Figure 2: CO₂ loading apparatus

Amine stock solutions were prepared by mixing (>99%) MEA and degassed Milli-Q water in different ratios. To ensure the homogeneity of the mixture, these stock solutions were stirred for 20 minutes at 300 rpm after mixing. The prepared stock solutions were then loaded with CO₂ by bubbling a CO₂ gas stream (0,15 l/min) using a fritted glass column (Figure 2). CO₂ feeding was carried out for a sufficient period of time, to ensure saturation of stock solutions with gaseous CO₂ at experimental conditions. After that, the CO₂ loaded solutions were stirred for 20 minutes at 300 rpm in a closed vessel and kept for 24 hours to give adequate time for equilibrium. To obtain a sample set having variation in both amine and CO₂ concentration, each sample was prepared by mixing a liquid portion from CO₂ unloaded MEA stock solution with a portion from CO₂ loaded MEA stock solution. Analytical balance Mettler Toledo

(± 0.0001 g) was used to prepare samples gravimetrically. Figure 3 and Figure 4 show the actual MEA strength and CO₂ loading values of 105 samples as obtained from titration measurements for each sample.

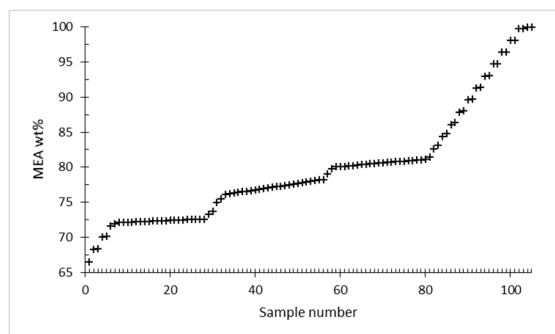


Figure 3. MEA concentration of calibration and validation samples

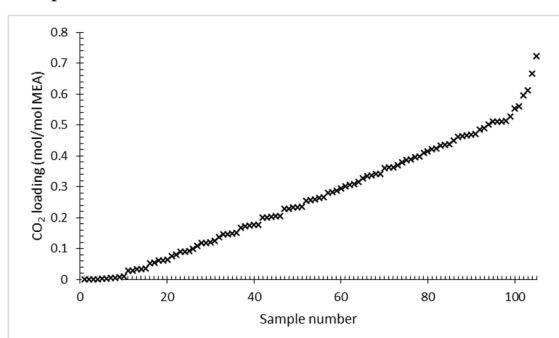


Figure 4. CO₂ loading of calibration and validation samples

2.2 Raman spectroscopy

The Raman measurements were taken with a 785 nm RXN2 Kaiser Raman System (Figure 5). Since the Raman measurements are light sensitive, the sample to be measured was placed inside a black plastic sample holder to avoid fluorescent disturbances and was covered with an aluminium foil to further get rid of any disturbances from the background light. The immersion probe was washed with deionized water followed by acetone before each measurement to remove impurities on the probe tip and avoid contamination of measurements by each other. Presence of air bubbles on the probe tip gives incorrect spectra. Therefore, the Raman probe tip was examined for any air bubbles after immersing in the liquid. S/N ratio was optimized by varying the acquisition time and the number of scans. 4 scans having 30 second exposure time per scan was selected as the optimum S/N ratio. Raman measurements were taken from several spatial locations inside the each sample bottle and compared to ensure that the solutions were chemically and physically homogeneous throughout the sample.

2.3 FT-NIR spectroscopy

Figure 6 shows the FT-NIR instrument (Q-Interline; MB 3000, 760nm laser wavelength) used for this study. The optimized instrument setting used per each measurement was 128 scans and a resolution of 16. Wavelength between 0–15000 cm⁻¹ was considered for all the measurements. It was not possible to maintain stable

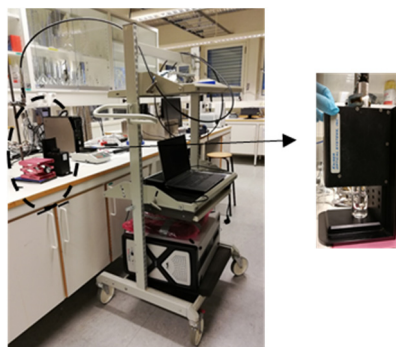


Figure 5: Raman instrument and sample compartment

temperatures below 40°C inside the FT-NIR sample holder accessory due to instrument configuration. Therefore, all the measurements were taken at 40°C in 5mm diameter sample vials. Since the solutions were highly viscous it was difficult to fill the solution into the small diameter vials without forming air bubbles. By tapping few times and holding upwards the sample vials, most of the trapped air bubbles could be released.

2.4 Spectral data

2.4.1. Data pretreatment

A process analyzer such as Raman or NIR spectroscopy generate several responses, but very often the irrelevant response to solve the analytical problem is larger. These responses hinder the relevant information and usually dominate the entire spectra such as by giving baseline offsets and multiplicative effects. The environmental light, stray light, fluctuation of laser intensity, fluorescence from the sample and instrument inherited noise are some of components that come with the raw spectroscopic data. These data (“noise part”) should be stripped from raw data to keep the most relevant chemical responses (“structure part”). In chemometrics, data pretreatment (preprocessing) algorithms are applied on raw data prior to the detailed data analysis for this purpose. The selection of the type of pretreatment methods is dependent on several parameters such as the type of chemical/physical system that we analyze and the instrument. In addition, the selected pretreatment methods highly affect the subsequent data analysis. The preprocessing methods can be classified into five categories such as offsetting, variable-wise scaling, sample-wise scaling, filtering and compression [22].

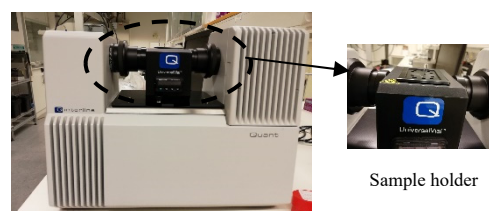


Figure 6: FT-NIR instrument and the sample compartment

There are some common pretreatment algorithms which fits well with many NIR data such as scatter correction

methods and spectral derivatives [23]. The impact of preprocessing methods of Raman data for chemometric modelling has been reviewed by [24, 25].

2.4.2. Exploratory analysis – PCA

Principal component analysis (PCA) is a popular data compression method in chemometrics where a several number of original measured variables are compressed into fewer number of uncorrelated variables called principal components (PCs). The PC1 which includes the highest variance describes the maximum variation of the data set. PCA decomposes data into scores (which describe the relationship between observations) and loadings (which show the relationship of the variables) using a mathematical algorithm [26].

2.4.3. Developing calibration models - PLS

Partial least squares regression (PLS) is a multivariate calibration method which can be used to directly correlate a chemical or physical property of a sample with a spectra collected [27]. In this method, the co-variance existing between the observation data (x data) and the reference values (y data) is explored. Then a linear regression model is built by estimating the regression coefficients \mathbf{b} in such a way as to maximize the covariance between \mathbf{y} and $\mathbf{x}_{\text{preprocessed}}$, as shown in equation (1).

$$\mathbf{y} = \mathbf{x}_{\text{preprocessed}} \mathbf{b} + \mathbf{f} \quad \text{Equation 1}$$

\mathbf{f} is the vector of residuals [27]. Instead of using raw x data, preprocessed x data are used in equation 1 to get rid of noisy data. In our case, x data is the spectroscopic measurements (FT-NIR or Raman spectra). \mathbf{y} is a vector of CO₂ loading or MEA concentration of calibration samples. x variables represent values in x data matrix which are Raman shifts for Raman data and wavenumbers for FT-NIR data.

The chemical information distributed inside large number of x variables are compressed into a small number of variables called latent variables or PLS components when the covariance between x and y data are maximized. These fewer number of latent variables can interpret the entire chemical system which would otherwise become impractical with thousands of variables. The most common performance indicators of PLS models are root mean square error of cross validation (RMSECV), root mean square error of prediction (RMSEP), coefficient of determination (r^2) and *bias*.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad \text{Equation 2}$$

The root mean square error (RMSE) is defined as in equation 2 (when all samples are included in the model), where n is the number of samples (observations), \hat{y}_i is the values of the predicted property value (CO₂ loading or MEA wt in our case) and y_i is the measured property value. RMSECV is defined similar to the equation 2 where y_i are samples not included in the model formulation. RMSEP is also calculated similar to equation 2 where all y are new data. y_i and \hat{y}_i are measured property values and predicted property values respectively from previously calibrated model (using

calibration data). RMSEP is an indicator how well the model predicts for future samples and therefore all the models in this study were validated with a validation data set to obtain RMSEPs for each model. r^2 gives the measure of how well the regression predictions approximate the real data points. *Bias* shows the tendency of overestimate or underestimate of parameter.

Figure 7 shows, four PLS calibration models in this study where two models were developed from each spectrometer for each chemical property. Preprocessing of x and y data and PLS regression were carried out in PLS toolbox 8.6 in Matlab 2017.

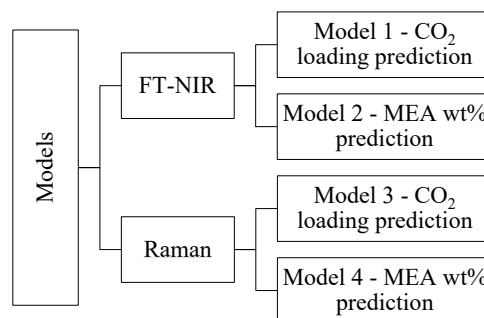


Figure 7: Description of four calibration models

3. Results and Discussion

3.1 Data exploration

3.1.1. FT-NIR data

Identifying the “*structure part*” and “*noise part*” becomes primarily important to extract the useful chemical information from spectral data. The *structure part* from a signal acquired by Raman spectroscopy or FT-NIR for this study represents correlation with CO₂ loading and amine concentration. Knowledge on NIR overtones and Raman vibrational modes related to the MEA-CO₂-H₂O chemical system is helpful to identify this *structure part*.

The raw FT-NIR data in this study are 105 multivariate signals of different CO₂ loaded amine samples in the range of 5500 – 10000 cm⁻¹. They are shown in Figure 8 which are also grouped according to their CO₂ loading value. It is possible to see variations between each sample with naked eye through this figure but they are not systematic sufficiently to correlate with CO₂ loading values due to overlap of overtones. The MEA-CO₂-H₂O system has bonds between C, H, N and O atoms which generate different vibrations when excited by laser power. The C-H stretching vibration makes first and second overtone in the NIR region 5500-6250 cm⁻¹ [28]. Deformation vibration of the O-H group occurs at 7140 cm⁻¹ and primary amines have two bands for N-H first overtone region in 6500-7000 cm⁻¹ [28]. These vibrational modes are not clearly visible in Figure 8 however, they are apparent in the baseline corrected FT-NIR data as shown in Figure 10 (a) and (b).

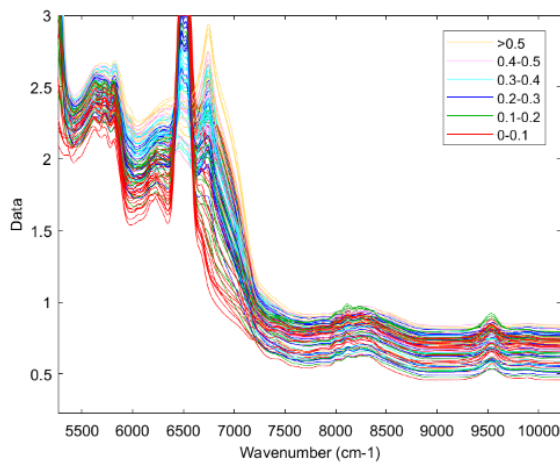


Figure 8: FT-NIR wavenumber vs absorbance data for different CO₂ loaded amine samples

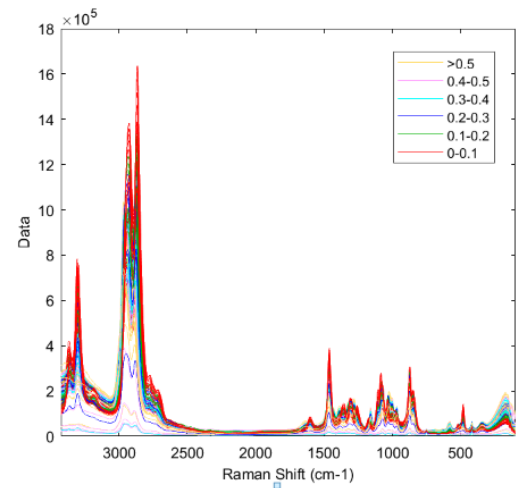
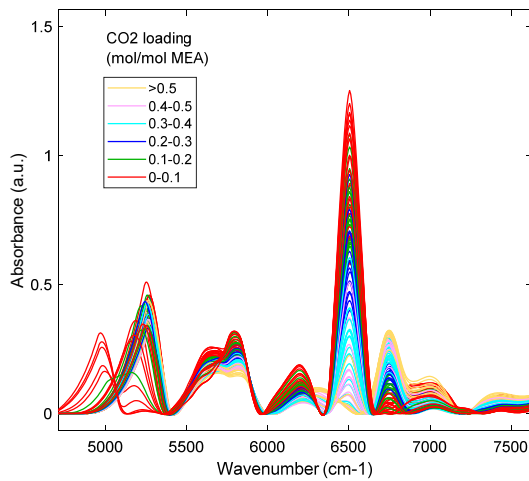
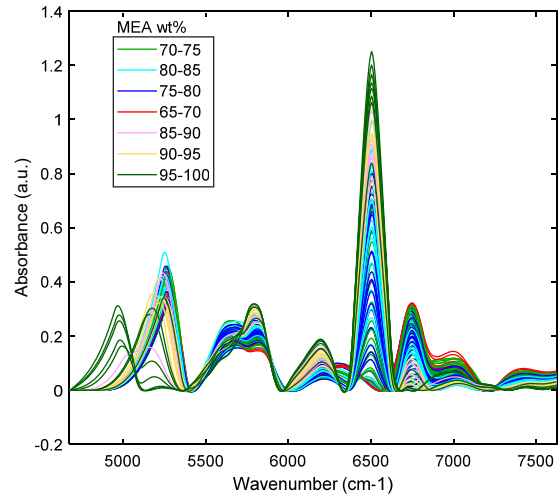


Figure 9: Raman shift vs Raman intensity (a.u.) for different CO₂ loaded amine samples

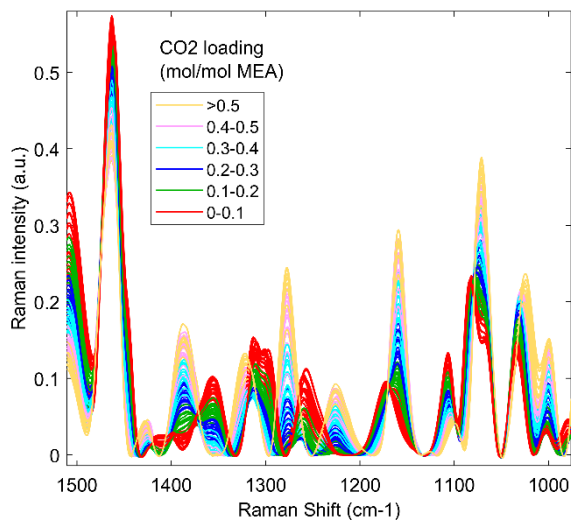


(a) Variation according to CO₂ loading

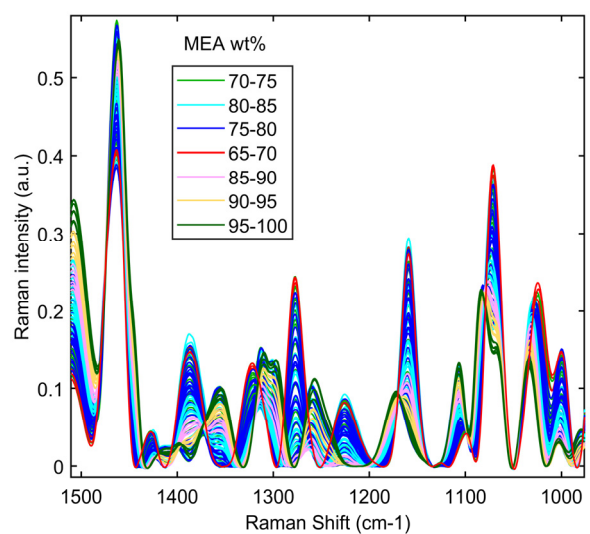


(b) Variation according to MEA wt%

Figure 10: FT-NIR data in the wavenumber range 4500-7500 cm⁻¹ after baseline correction



(a) Variation according to CO₂ loading



(b) Variation according to MEA wt%

Figure 11: Raman data in the fingerprint region after baseline correction

3.1.2. Raman data

The raw data obtained from Raman spectrometer between wavenumber 100-3426 cm⁻¹ for different CO₂ loaded amine samples are shown in Figure 9. Spectral variations can be hardly correlated to distinguish between chemical compositions of samples. After removing the baseline variations of Raman data, the spectra become more informative as shown in Figure 11. Raman active vibrational modes for CO₂ loaded amine data are denser in the fingerprint region from 1000 -1500 cm⁻¹ Raman wavenumbers. They belong to bands rising due to carbon species in the system which are carbonate, bicarbonate and carbamate as well as protonated amines and free amines. The bands observed in this study are comparable with our previous studies [19, 21].

3.2 Qualitative data analysis – PCA

The *structure parts* of FT-NIR and Raman data which have correlations with CO₂ loading and MEA concentration identified in section 3.1, were used for the PCA.

3.2.1. PCA for FT-NIR

Figure 12 shows the results of the PCA, which shows the score plot for PC1 vs PC2 for FT-NIR data. The preprocessing methods applied for input data were, Savitzky-Golay method, detrend, standard normal variate, and mean centering [23]. The best PCA results were achieved for 6000-7190 cm⁻¹ wavenumbers. PCA analysis proves high correlation of spectroscopic data when both solvent strength and gas loading vary. According to Figure 12, PC1 describes 73% and PC2 describes 24% of the data variation for FT-NIR. The number of samples which belong to the amine concentration 70-75 wt%, 75-80 wt% and 80-85 wt% are considerably higher in the data set (refer Figure 3). Samples which belong to these categories are aligned tangentially in the score plot. Arrow A in Figure 12 (a) marks the direction of increasing CO₂ loading of the samples while Arrow B marks the increasing MEA concentration in Figure 12 (b).

3.2.2. PCA for Raman

Score plot of PC1 vs PC2 for Raman data is shown in Figure 13. The input data was preprocessed using standard normal variate, Whittaker filter [29] and mean centered. The wavenumbers in the range 790-1525 cm⁻¹ and 2734-3077 cm⁻¹ resulted more meaningful overview for PCA. Among these two Raman shifts regions, the first one includes most of the vibrational modes related to carbon species and the second region include mainly the vibrational modes related to protonated amines and free amines. PC1 describes 85% and PC2 describes 11% of the data variation. On the other hand, as the CO₂ loading is expressed as mole CO₂ absorbed per mole MEA, even when there are different amounts of CO₂ moles absorbed, different MEA concentration can yield same CO₂ loading. PC1 vs PC2 plot in Figure 13 (a) shows sample distribution according to the CO₂ loading. Line 1, Line 2 and Line 3 represent CO₂ loaded samples for 70-75 MEA wt %, 75-80 MEA wt % and 80-85 MEA wt % in these figures. These lines are distinct at lower CO₂ loading concentrations, but overlap at higher CO₂ loading

concentrations. This is due to the complex correlation of spectroscopic data when both solvent and gas concentration vary.

3.3 PLS for FT-NIR and Raman

Quantitative determination of CO₂ loading and MEA concentration are shown in this section. Derivatives of raw data were used to preprocess FT-NIR data because they have the capability to remove both additive and multiplicative effects in NIR data [23]. Similarly, Whittaker filter was used to correct baseline in Raman data [29]. The overview of the four calibration models is shown in Table 1. Model 1 and 2 correspond to FT-NIR spectroscopy to determine CO₂ loading and MEA concentration respectively. The NIR region from 5570-7291 cm⁻¹ were included for the PLS model and this region includes the first overtones of C-H, O-H and N-H [28]. Some samples were removed as outliers from the data set and the reasons were abnormal spectra due to instrument noise, unstable temperature in the sample holder compartment and human errors during the reference analysis.

Model 3 and 4 correspond to Raman spectroscopy to determine CO₂ loading and MEA concentration respectively. The Raman wavenumber region from 940-1490 cm⁻¹ was included as it represented chemical characteristics for all the carbon and amine species in the system [16, 19, 30, 31]. This wavenumber region also gave the minimum RMSEP value for each model. Few samples were removed as outliers which negatively affected to the stability of the model. The reasons for removing them were mainly the instrument related noise.

Table 1: Summary of the model results

Model no:	Model name (instrument_ measured property)	No. of cal*	No of val*	Wavenumber range (cm ⁻¹)	RMSEP
1	FT-NIR_CO ₂	43	33	5570 -7291	0.01695 mol/mol MEA
2	FT-NIR MEA	43	31	5570 -7291	0.72893 wt%
3	Raman_CO ₂	44	43	940 - 1490	0.01338 mol/mol MEA
4	Raman_ME A	44	49	940 - 1490	0.90178 wt%

* (after removing outliers); cal = calibration samples; val = validation samples

The results of PLS calibration models which are significant for quantitative determination are shown from Figure 14 to Figure 17.

Each figure shows the measured property (i.e. CO₂ loading and MEA wt% from titration which were considered as actual property of the sample) and the predicted property (based on the developed PLS model in this study) for calibration and validation set. The number of calibration and validation samples after removing outliers are also shown in Table 1. Presence of outliers makes the model unstable (poor predictability) and therefore such samples were removed after a careful investigation. The RMSEP value, *r*² and bias values can be used to understand the fit of correlation between an actual property and modelled property.

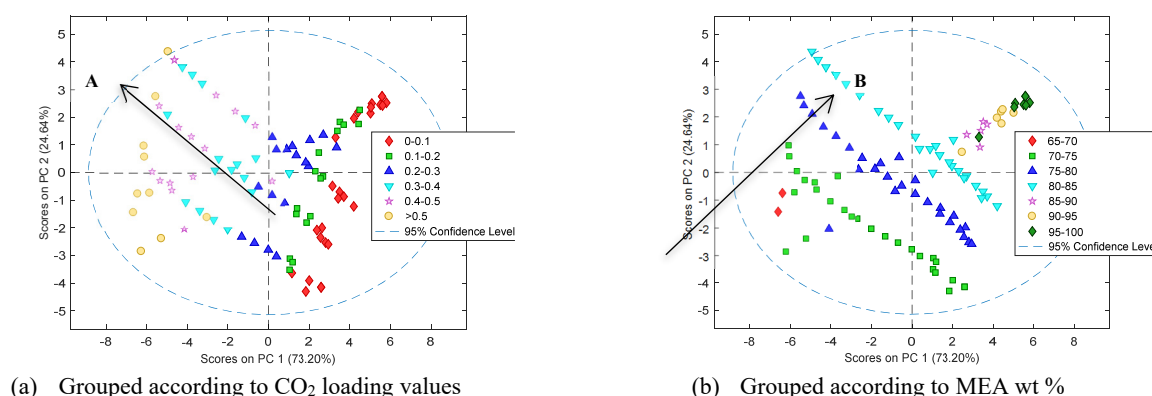


Figure 12: PCA analysis for preprocessed FT-NIR data - sample distribution in PC1/PC2 space

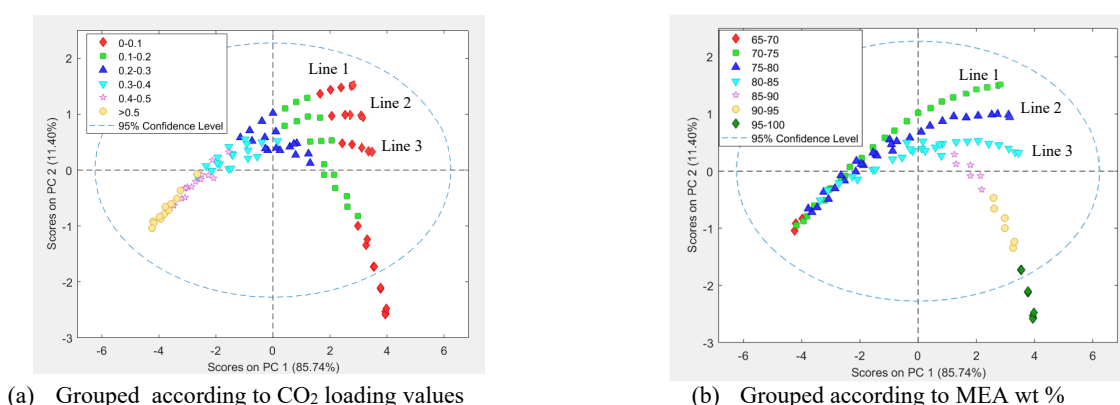


Figure 13: PCA analysis for preprocessed Raman data - sample distribution in PC1/PC2 space

Estimated uncertainty of the model predictions have been shown as error bars. The line “fit” corresponds to the regression line and 1:1 is the target line when measured and predicted values overlap. For all the models, *fit* and 1:1 lines were almost same and r^2 value was more than 0.98. The red points mark the validation samples which are a completely new data set (data not used for model calibration) and therefore they represent future data. The good agreement of these validation samples with the 1:1 line is an indicator of the model predictability with future samples.

The wavelength of the spectrometer included in the calibration model and the RMSEP value are shown in Table 1. For model 1 the RMSEP is 0.0169 mol/mol MEA which implies for a future sample tested by the FT-NIR spectrometer, the CO₂ loading will be the actual value $\pm 2 \cdot 0.01695$. When the same sample is measured by Raman spectrometer this value will be predicted by Model 3 as actual value $\pm 2 \cdot 0.01338$. The MEA wt% of a future sample will be predicted with an RMSEP of 0.7 and 0.9 by FT-NIR and Raman instruments respectively. The wavenumber region for FT-NIR PLS models were 5570 -7291 cm⁻¹ where the first overtone of N-H, C-H and O-H absorption bands occur. The Raman wavenumber region for model 3 and 4 was selected from 940-1490 cm⁻¹ because it contains most of the vibrational modes related to characterize amine and absorbed CO₂ concentration.

4. Conclusion

This study aimed for developing a quick and reliable analysis method to determine two most important chemical properties frequently measured in an amine based CO₂ capture process which are the gas loading and solvent strength. The standard procedure of analysis these parameters are offline laboratory methods such as titration. Raman spectroscopy and FT-NIR spectroscopy were used for this study to investigate their feasibility to report quantitative determination of CO₂ loading (mol/mol) and MEA wt%.

Both spectroscopic methods show similar competencies for these analyses in the CO₂ loading range from 0 – 0.6 mol CO₂/mol MEA and MEA strength from 66-99.5 wt %. The paper shows the methodology of transforming a difficult-to-explain spectra into meaningful chemical information by a chemometric approach. Qualitative analysis of data was performed by PCA for the pretreated spectral data. Results show that there is possibility to distinguish samples in different CO₂ loading and MEA concentration using score plots. Eventhough PCA did not provide a perfect discretization of the data it proved having opportunity to explore data. PLS algorithm was used to develop prediction models for CO₂ loading and solvent strength. There was a reasonable fit between calibration and validation data in the PLS regression. RMSEP values for 4 PLS models were in an acceptable

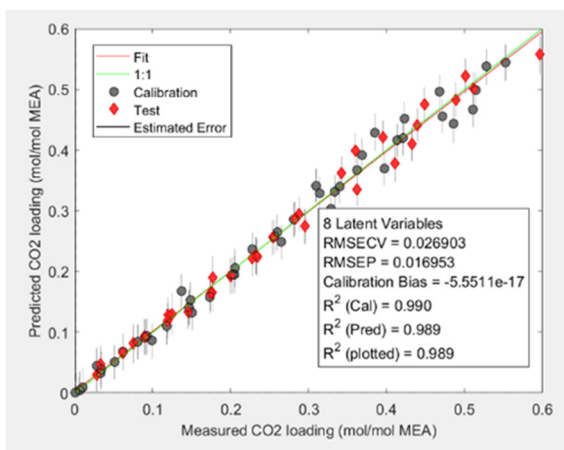


Figure 14: CO₂ loading prediction by FT-NIR (Model 1)

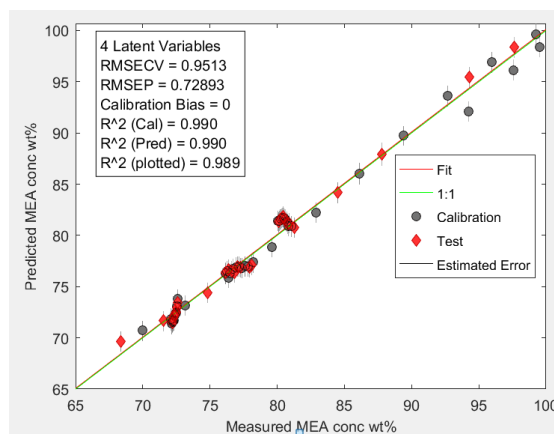


Figure 15: MEA wt prediction by FT-NIR (Model 2)

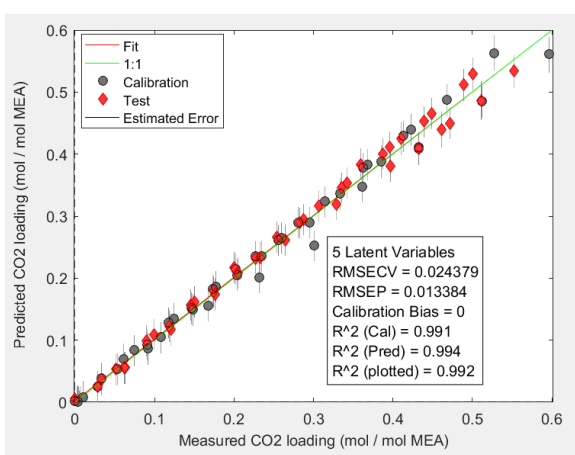


Figure 16: CO₂ loading prediction by Raman (Model 3)

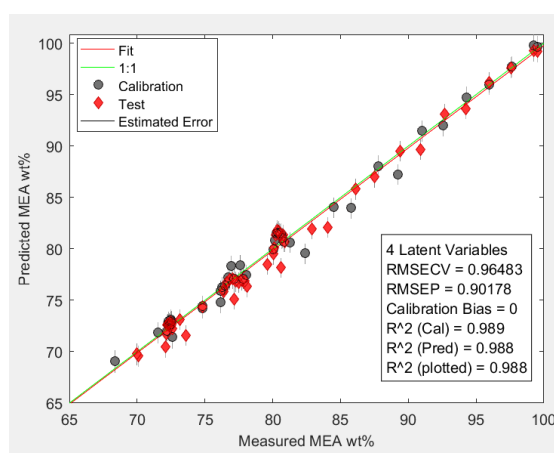


Figure 17: MEA wt prediction by Raman (Model 4)

region. The models are competent enough to be used as real-time monitoring tools when high concentrated amine is used. In addition, these models are also useful in optimization of CO₂ capture process such as to find the absorption capacity with time, optimum lean and rich loadings, minimum liquid & steam flow rates and optimum CO₂ feed gas flow rate.

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