

# In Silico Design of New Ionic Liquids Based on Quantitative Structure–Property Relationship Models of Ionic Liquid Viscosity

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This work is devoted to establishing a quantitative structure–property relationship (QSPR) between the chemical structure of ionic liquids (ILs) and their viscosity followed by computer-aided design of new ILs possessing desirable viscosity. The modeling was performed using back-propagation artificial neural networks on a set of 99 ILs at 25 °C, covering a large viscosity range from 3 to 800 cP. The ISIDA fragment descriptors were used to encode molecular structures of ILs. These models were first validated on 23 new ILs from Solvionic company and then used to predict the viscosity of three new ILs which then have been synthesized and tested. The models display high predictive performance in external 5-fold cross validation: determination coefficients  $R^2 > 0.73$  and absolute mean root mean square error  $< 70$  cP. For three ILs synthesized and tested in this work, predicted viscosities are in good qualitative agreement with the experimentally measured ones.

## Introduction

Because of their “green properties”, ionic liquids (ILs) are gaining interest as potential media in replacement of the traditional (volatile) organic solvents currently in use in many fields of industry and research.<sup>1,2</sup> However, ILs present some drawbacks for industrial applications. Thus, practically all known ILs are relatively viscous, only few of them display a viscosity ( $\eta$ ) below 20 cP at  $T = 25$  °C, while the most popular ILs (imidazolium and tetraalkylammonium families) have viscosities in the range of 40–80 cP, which is pretty high compared to  $\eta = 0.40$  cP for  $\text{CH}_2\text{Cl}_2$  or 0.29 cP for hexane.<sup>3</sup> Nonetheless, it has been emphasized<sup>1,2</sup> that all IL physicochemical properties, such as viscosity, density, conductivity, or melting point, are tunable, therefore adjustable, through a judicious choice of their cationic and anionic components. As a matter of fact, a subtle variation of ILs' chemical structure, e.g., lengthening of an alkyl chain onto the imidazolium cationic skeleton, may lead to dramatic changes of various ILs' properties.<sup>4–7</sup> In this respect, ILs could formally be considered as “design solvents”. However, this tunability is hardly applicable in practice. Indeed, since we do not master the relation between structure and properties of ILs yet, tuning of ILs' properties is merely achieved through a trial/error procedure. Considering the almost infinite number of potential ILs to be tested, the task of conceiving the “best” IL for a given application is more a desirable dream than a user-friendly reality.

The goal of this work is to build predictive quantitative structure–property relationship (QSPR) models linking structure and viscosity of ILs. Most of early QSPR studies<sup>8–18</sup> have been performed for IL melting points for data sets in which the anion was always taken the same. This allowed one to vary the structure of only cationic part of ILs. Carrera et al.<sup>19</sup> performed

modeling of melting points on the data set of guanidinium ILs containing 4 different anions. Descriptors were generated only for the cationic part and for each anion an individual model has been prepared using counter-propagation neural networks.

In this work, we describe an original procedure to generate descriptor vector for the species containing different cation and anion. This approach has been used to build and validate the models for viscosity on the initial set of 99 ILs. The external validation has been performed on 23 new ILs recently produced by Solvionic company. Finally, the developed models have been used for in silico design of new three ILs, which viscosities have been predicted before their synthesis and experimental tests. To our knowledge, no QSPR models for ILs viscosity, the property of dramatic importance to industrial applications, have been published so far.

## Materials and Methods

**Experimental Procedure. Synthesis.** All reagents used were analytical grade. Starting materials were purchased from commercial sources and used as received. <sup>1</sup>H and <sup>13</sup>C NMR spectra were recorded in  $\text{CDCl}_3$  unless otherwise specified on a spectrometer operating at 300 and 282 MHz, respectively. Mass spectra were measured on a JEOL MS-DX 300 mass spectrometer.

**Tetraheptylammonium Bistrifluoromethylsulfonamide.**



To a solution of 5.9 mmol (2.9 g) of tetraheptylamine bromide in 10 mL of deionized water and 5 mL of acetone, 6.5 mmol (1.86 g) of bis(trifluoromethane)sulfonimide lithium (1.85 g) in 5.0 mL of acetone was added at 25 °C. The reaction mixture was stirred for 12 h. Evaporation of the solvent under vacuum gave the crude compound. The product was extracted with dichloromethane (30 mL) and washed several times with aliquots of water (20 mL) until bromide residues no longer were

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TABLE 1: Cations and Anions Constituting 99 ILs from the Initial Data Set

cations	no. ILs	reference	Anions	no. ILs	reference
imidazolium	47	4, 5, 39, 40	Tf <sub>2</sub> N <sup>−</sup> (CF <sub>3</sub> SO <sub>2</sub> ) <sub>2</sub> N <sup>−</sup>	28	5, 41–45
tetraalkylammonium	46	41–47	PF <sub>6</sub> <sup>−</sup>	5	5
pyridinium	2	41,48	BF <sub>4</sub> <sup>−</sup>	5	4,39, 41, 44, 48
pyrolidinium	4	46,47	fluorinated boron-containing alkyl chains	39	4,39, 44
			cyanamide	4	46
			trifluoroacetyl-trifluoromethane-sulfonylazide	7	47
			carbanion	9	49
			hexafluorostibaneide	1	40
			heptafluorotengsteneide	1	40

detected by the AgNO<sub>3</sub> test. Evaporation of the solvent yielded the compound as a transparent and slightly viscous liquid. Liquid yield was 95%.

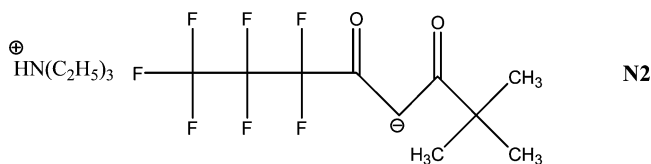
Active charcoal (10 wt %) was added to the IL, and the liquid was stirred for 24 h. After adding 20 mL of dichloromethane to reduce the viscosity of the IL, the mixture was filtrated over a filter paper. The solvent was removed under reduced pressure. The IL was thereafter pumped at room temperature for 18 h and, additionally, at 50 °C for 10 h at 50 °C.

<sup>1</sup>H NMR (400 MHz, CDCl<sub>3</sub>): δ 0.90 (t, 12H), 1.32 (m, 32H), 1.60 (m, 8H), 3.14 (m, 8H).

<sup>13</sup>C NMR (100 MHz, CDCl<sub>3</sub>): δ 13.92, 21.78, 22.39, 26.03, 28.58, 31.40, 58.65, 113.53, 117.80, 122.06, 126.32.

Electrospray MS (+ve): *m/z* 410.47 (100%, C<sub>28</sub>H<sub>60</sub>N<sup>+</sup>), MS (−ve) *m/z* 279.91 (100%, C<sub>2</sub>F<sub>6</sub>NO<sub>4</sub>S<sub>2</sub><sup>−</sup>).

**Triethylammonium 2,2-Dimethyl-6,6,7,7,8,8,8-heptafluoro-3,5-octanedionate.**



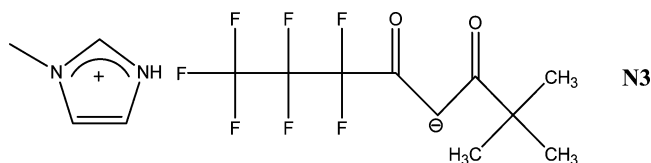
To a solution of 20 mmol (2.05 g) of triethylamine in 10 mL of anhydrous acetonitrile, 20 mmol (5.95 g) of 6,6,7,7,8,8,8-Heptafluoro-2,2-dimethyl-3,5-octanedione in 5.0 mL of acetonitrile was added at 25 °C. The reaction mixture was stirred for 24 h. Evaporation of the solvent under vacuum gave the crude compound (yield 95%). The IL was thereafter pumped at room temperature for 18 h and, additionally, at 50 °C for 10 h at 50 °C.

<sup>1</sup>H NMR (400 MHz, CDCl<sub>3</sub>): δ 1.10 (s, 9H), 1.13 (t, 9H), 2.90 (q, 6H), 5.79 (s, 1H).

<sup>13</sup>C NMR (100 MHz, CDCl<sub>3</sub>): δ 8.81, 27.62, 41.05, 45.32, 90.39, 119.65, 171.94, 202.76.

Electrospray MS (+ve): *m/z* 102.12 (100%, C<sub>6</sub>H<sub>16</sub>N<sup>+</sup>), MS (−ve) *m/z* 295.05 (100%, C<sub>10</sub>H<sub>10</sub>O<sub>2</sub>F<sub>7</sub><sup>−</sup>).

**1-Methylimidazolium 2,2-Dimethyl-6,6,7,7,8,8,8-heptafluoro-3,5-octanedionate.**



To a solution of 20 mmol (1.72 g) of 1-methylimidazole in 10 mL of anhydrous acetonitrile, 20 mmol (5.95 g) of 6,6,7,7,8,8,8-heptafluoro-2,2-dimethyl-3,5-octanedione in 5.0

mL of acetonitrile was added at 25 °C. The reaction mixture was stirred for 24 h. Evaporation of the solvent under vacuum gave the crude compound (yield 95%). The IL was thereafter pumped at room temperature for 18 h and, additionally, at 50 °C for 10 h at 50 °C.

<sup>1</sup>H NMR (400 MHz, CDCl<sub>3</sub>): δ 1.21 (s, 9H), 3.69 (s, 3H), 6.05 (s, 1H), 6.85 (s, 1H), 7.04 (s, 1H), 7.53 (s, 1H).

<sup>13</sup>C NMR (100 MHz, CDCl<sub>3</sub>): δ 26.93, 33.24, 39.85, 93.61, 119.69, 129.34, 137.77, 177.22, 203.87.

Electrospray MS (+ve): *m/z* 84.06 (100%, C<sub>4</sub>H<sub>7</sub>N<sub>2</sub><sup>+</sup>), MS (−ve) *m/z* 295.05 (100%, C<sub>10</sub>H<sub>10</sub>O<sub>2</sub>F<sub>7</sub><sup>−</sup>).

**Viscosity Measurements.** Chemicals were packed under an argon atmosphere after a careful degassing procedure at the Solvionic plant and were used as received. Flasks were open just prior to the viscosity measurement. All samples, either from Solvionic or synthesized in our group, were measured on a ARES viscosimeter (Rheometric Scientific), with a cone/plate geometry (Ø 40 mm, ϕ = 0.0436 rad, gap 5/100), requiring some 1.5 mL of IL. Temperature was controlled at 25 ± 0.1 °C.

**Computational Procedure. Data Sets.** For the QSPR analysis, we critically selected from the literature the data set of 99 ILs whose viscosities were measured at 25 °C, and the experimental protocol of viscosity measurements was clearly described. All common names of the ILs cations and anions were converted into standard IUPAC names. Lewis structures of each species were obtained from the IUPAC names using the OpenEye Lexichem “nam2 mol” software<sup>20</sup> and saved as SD file.

It should be noted that ILs’ viscosities are very sensitive to temperature,<sup>21</sup> and there exists no well-established relation  $\eta = f(T)$ . Therefore, only viscosity data measured at  $T = 25$  °C were retained for the modeling. The selected data set contains four families of cations and 9 different anions (Table 1). The ILs involving the Tf<sub>2</sub>N<sup>−</sup> anion and fluorinated anions, empirically known to lower viscosity, represent about 80% of the data. The data distribution in Figure 1 shows that only 20% of studied ILs are very viscous (>200 cP).

Unlike UNIFAC-VISCO<sup>22</sup> and some other methods, we report here the models for the IL’s viscosity itself rather than for its logarithm. In fact, the models for the logarithm of the viscosity were also obtained but they do not display any improvement of the predictive performance.

**Descriptors.** The ISIDA descriptors were used to build the QSPR models. They represent the counts (occurrences) of some fragments in a molecular graph.<sup>23</sup> Three types of fragments are considered: *sequences* (type 1), *augmented atoms* (type 2) and *extended augmented atoms* (type 3). A sequence is the shortest path connecting two given atoms. For each type of sequence, the lower (l) and upper (u) limits for the number of constituent atoms must be defined. The program generates all “intermediate” sequences involving  $n$  atoms ( $1 \leq n \leq u$ ) recording both atoms

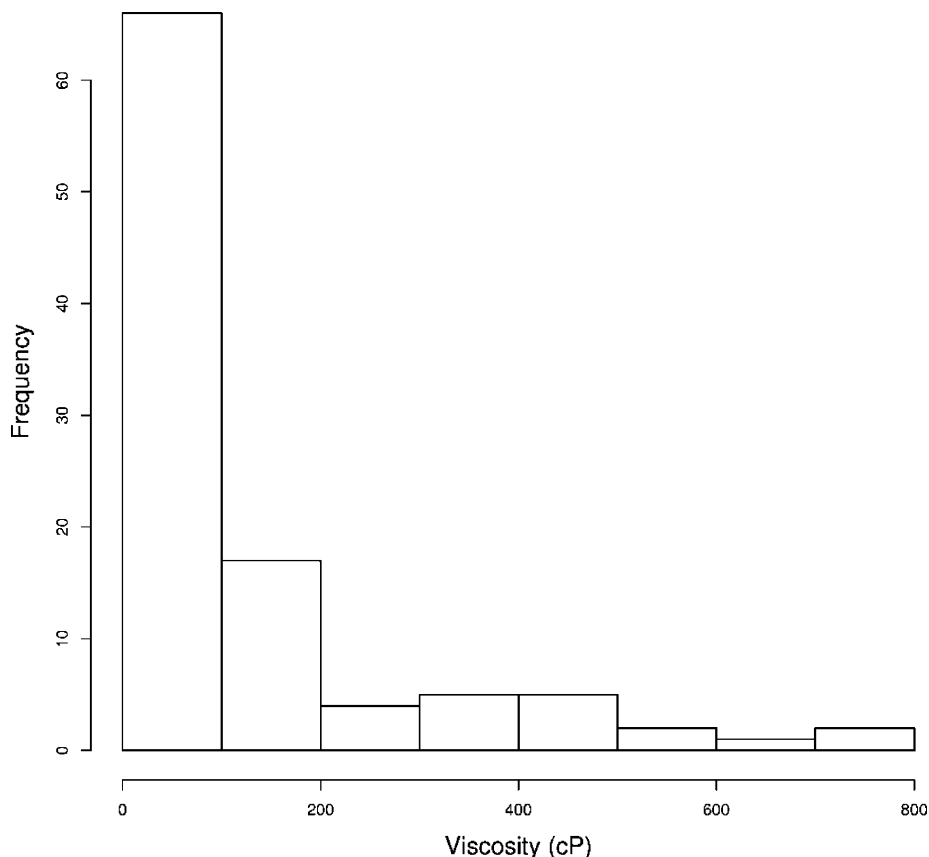


Figure 1. Viscosity data distribution for the initial set of 99 ILs.

and bonds. Augmented atom represents a selected atom with its closest environment. Extended augmented atom is a combination of types 1 and 2: an atom representing an origin of several sequences containing from l to u atoms. Three subtypes, AB, A, and B, are defined for each class. They represent sequences of atoms and bonds (AB), of atoms only (A), or of bonds only (B).<sup>24</sup>

Since studied ILs represent the 1:1 mixture of cation and anion, the descriptor vector of an IL has been generated by concatenation of the descriptor vectors of the constituted species, as it is shown in Figure 2. In total, 24 initial pools of descriptors corresponding to different fragmentation types have been generated for the training set.

**Machine Learning Methods.** The back-propagation artificial neural networks (NN) implemented in the Weka 5.8 program<sup>25</sup> have been used. This is a well-reputed machine-learning method able to produce predictive models even on noisy and insufficiently prepared data. The network was trained using the early stopping procedure<sup>26</sup> in which the model built on the training set was systematically applied to the tuning set containing 20% of the training data. The training procedure was stopped as soon as the predictive performance deterioration was observed. For each initial pool of descriptors, the number of neurons in the hidden layer ( $N_{\text{HN}}$ ) was systematically varied from 2 to the half of the number of descriptors. The optimal size of the hidden layer corresponds to models displaying the highest predictive performance in cross-validation calculations. Typically, this number ranges from 2 to 11.

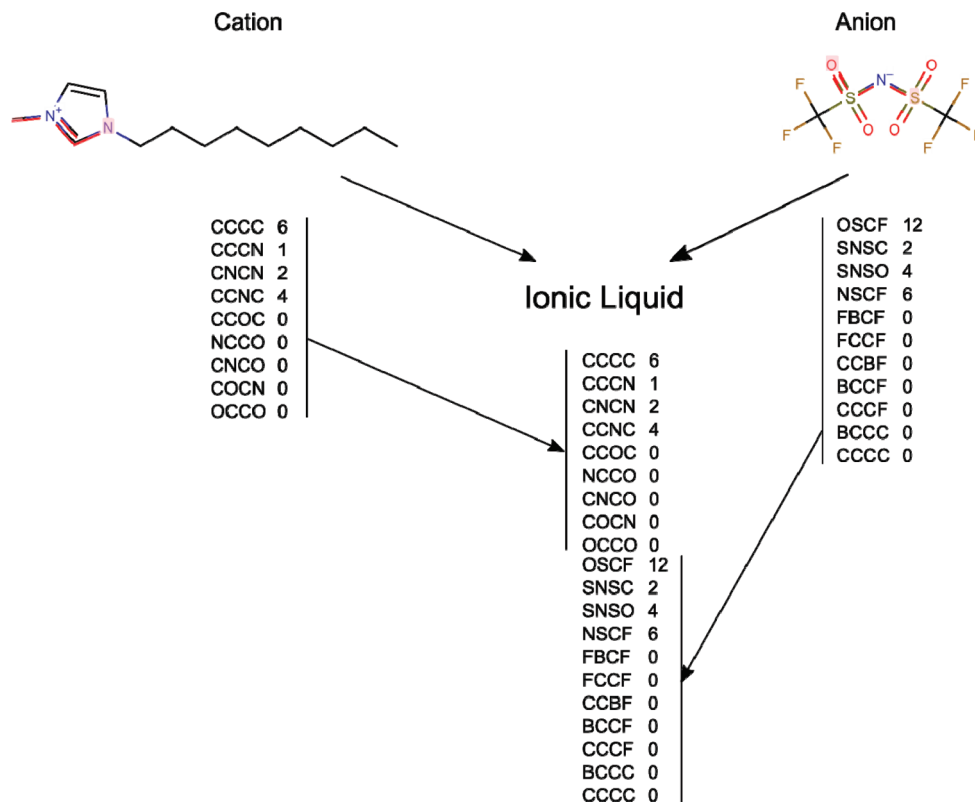
The partial least-squares regression (PLS) implemented in the Weka5.8<sup>40</sup> program has been used for the purpose of comparison. No significant changes of the predictive performance of the PLS vs NN models have been observed. Therefore, here we report only results obtained with the NN method.

**Validation of Individual Models.** To assess predictive performance of QSPR models, they must be validated on unknown data. Here, the 5-fold cross-validation (5-CV) procedure has been used. The initial data set was split into 5 nonoverlapping subsets; each subset was used as a test set, whereas an ensemble of other four subsets was used to train a model. Thus, each compound of the data set was predicted using 80% of the data. This procedure has been repeated 3 times in order to estimate the fluctuations of statistical parameters of the models.

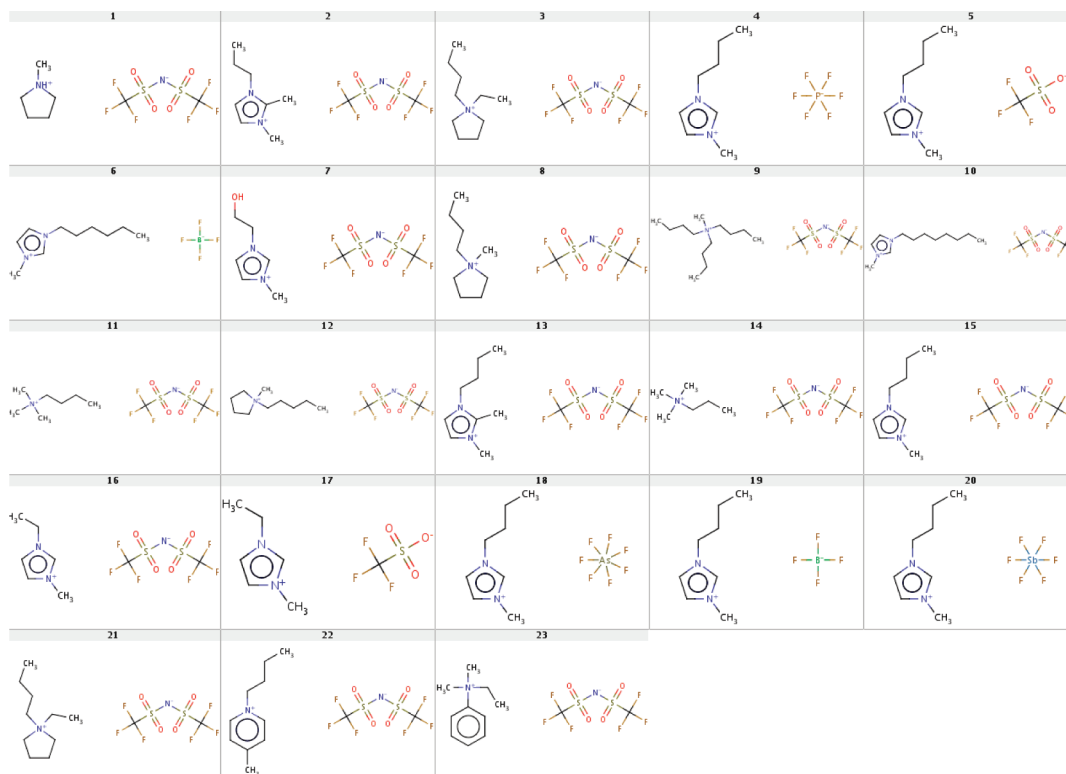
Two statistical parameters are used to evaluate the performance of the predictions: the determination coefficient<sup>27</sup> ( $R^2$ ) and the root-mean-square error<sup>27</sup> (RMSE) for the linear correlation predicted vs experimental viscosity values.

**Consensus Predictions.** The 5-CV calculations were performed on the training set systematically varying fragmentation type and  $N_{\text{HN}}$ . This resulted in 360 models. Then, 12 models with  $R^2 \geq 0.5$  have been selected and the corresponding parameters (fragmentation type and  $N_{\text{HN}}$ ) were further used to generate an ensemble of the final models on the entire initial data set. All these models were then systematically applied to the compounds from the Solvionic catalogue<sup>28</sup> as well as to three new compounds synthesized in this work. For each test compound, the predictions were calculated as an arithmetic mean of the values calculated with the selected individual NN models.

**Applicability Domain.** The Applicability Domain (AD) is a meta-model which decides if a QSAR model could be applied to a given test object. Indirectly, AD measures a similarity between the test object and the training set. If they are considered dissimilar, the QSPR model may lead to wrong value and, therefore, should not be involve in property assessments. Here, as AD, we used the Fragment Control approach<sup>29</sup>



**Figure 2.** Generation of the ISIDA fragment descriptors for an IL by concatenation of those separately generated for the cation and anion.



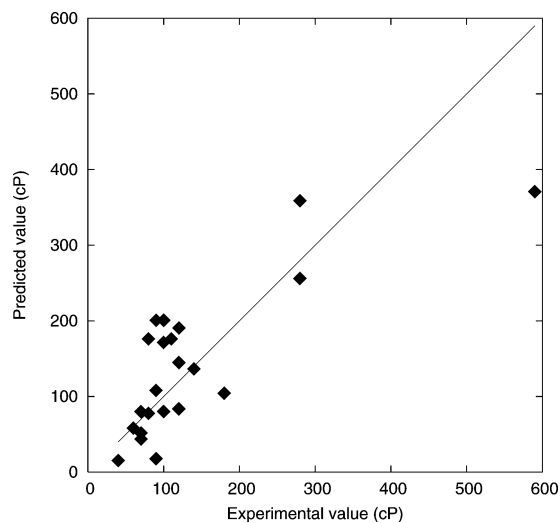
**Figure 3.** Structure of 23 new ILs from the Solvionic data set.

discarding the model if a test compound possess the fragments absent in the initial pool of descriptor generated for the training set. The number of discarded models (and, hence, the number of models used for the consensus predictions) varies from one compound to another.

## Results and Discussion

Predictive performance of the consensus NN models assessed in 5-fold external cross validation is reasonably high: determination coefficient  $R^2 = 0.73$  and RMSE = 67.5 cP. Prediction error represents about 10% of the viscosity range of the data





**Figure 4.** Prediction performance of the neural networks models on the Solvionic data set.

**TABLE 2: Predicted and Experimental Viscosity (cP) for the Three ILs Synthesized in This Work**

IL	predicted	experimental
N1	28	56
N2	53	49
N3	469	600

set. Despite this rather big RMSE value, the models are able to distinguish several viscosity ranges of weakly, medium and highly viscous ILs.

At the next step, the viscosity of 23 new ILs from Solvionic (Figure 3) was measured and compared with the theoretically predicted values. Prediction error is 73 cP, which is consistent with that observed during cross-validation. A major underestimated outlier is tributyl(methyl)azaniumTf<sub>2</sub>N (structure 9 in Figure 3) for which calculated values are about 200 cP lower than the experimentally measured one (Figure 4). This could be explained by low population of viscous ILs in the initial data set used for model building (Figure 1).

Finally, all cations and anions from the bibliographic data set were combined to generate over 1000 new ILs. The models were used to predict the viscosity of each of them, and a pool of either low viscous or high viscous ones was selected. Then, starting from these structures, and considering synthetic feasibility and availability of starting compounds, three completely new ILs have been suggested for the synthesis and experimental tests. Table 2 shows that predicted viscosity values are in qualitative agreement with the experimental data: compounds N1 and N2 are medium viscous, whereas N3 is highly viscous.

We believe that relatively modest quantitative precision of the models (RMSE ~70 cP) is related to the noise in the experimental data collected from different bibliography sources. As an example, one can mention viscosity values published for 1-butyl-3-methylimidazolium hexafluorophosphate at 298 K: 450,<sup>30</sup> 200,<sup>31</sup> 270,<sup>32</sup> 271,<sup>33</sup> 250,<sup>34</sup> 247,<sup>35</sup> 218,<sup>36</sup> 212,<sup>37</sup> 270<sup>38</sup> cP. Albeit all authors used similar procedures of drying and measurements, the standard deviation in this series is 74 cP, which is very similar to the errors of predictions obtained in this work. New high quality data are needed to improve predictive performance of our models.

## Conclusion

In this paper we report predictive models for viscosity of ILs used to in silico design of new ILs with desirable properties.

For the first time, QSAR modeling has been performed on the data set of ILs where both cation and anion varied. Relatively modest predictive performance of the models (about 70 cP) is attributed to inaccuracies in experimental data used for the model building.

To sum up, the models developed on the initial data set of 99 ILs were able to predict with the reasonable accuracy the viscosity for new ILs recently synthesized by Solvionic. Moreover, three new ILs, whose viscosities were assessed theoretically before the synthesis, have been designed and tested experimentally.

The key point of our modeling is the technique of descriptors generation suggested in this work. This approach can be used to model properties of 1:1 two-component mixtures. New method of descriptors generation for any mixtures is in progress in our group. In particularly, this approach could be applied to ILs containing monocharged cations and doubly (as SO<sub>4</sub><sup>2-</sup>) or triply charged (PO<sub>4</sub><sup>3-</sup>) anions.

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