Fuel Sorption into Polymers : Experimental and Machine Learning Studies

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Abstract

In the automotive industry, the introduction of alternative fuels in the market or even the consideration of new fluids such as lubricants requires continuous efforts in research and development to predict and evaluate impacts on materials (e.g., polymers) in contact with these fluids. We address here the compatibility between polymers and fluids by means of both experimental and modelling techniques. Three polymers were considered: a nitrile butadiene rubber (NBR), a fluorinated elastomer (FKM) and a fluorosilicon rubber (FVMQ), and a series of hydrocarbons mixtures were formulated to study the swelling of the polymers. The swelling of samples has been investigated in terms of weight and not volume variations as the measure of this former is assumed to be more accurate. Multi-gene genetic programming (MGGP) was applied to experimental data obtained in order to derive models to predict: (i) the maximum value of the mass gain (ΔM) and (ii) the sorption kinetics, *i.e.* the time evolution of ΔM. Predicted values are in excellent agreement with experimental data (with R^2 greater than 0.99), and models have demonstrated their predictive capabilities when applied to external fluids (not considered during the training procedure). Combining experiments and modelling, as proposed in this work, leads to accurate models which drastically reduce the time necessary to quantify polymeric materials compatibility with a fluid candidates as compared to experiments.

Keywords: Polymer, Fuels, Machine Learning, Sorption

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1. Introduction

In the context of global warming, conclusions of research dedicated to the reduction of greenhouse gases emissions advocate the use of alternative fuels [1]. In particular, advanced fuels and biofuels including conventional renewable fuels, respecting environmental criteria at a reasonable cost are of primary interest [2]. Biofuels are issued from organic raw materials and they can be seen as blends of renewable molecules such as normal- and iso-paraffins, naphtenic and aromatic compounds, normal- and iso-olefins, alcohols, and/or esters [3]. Normal- and iso-paraffins can be obtained by industrial processes such as Fisher-Tropsch (FT) [4] and hydrotreatment of vegetable oils (HVO) [5]. In the same way, naphtenic and aromatic compounds can be synthesized from the liquefaction or pyrolysis of biomass [6, 7]. Moreover, compositions constantly evolving and being different from one country to another, it has become essential to understand the impact of the introduction of these compounds on the physical properties of alternative fuels. The presence of these families of molecules with different chemistry requires extensive research and development activities. Indeed, it drives the conditions for storage, transportation, and combustion quality.

In combustion engine vehicles many pieces of the fuel-delivery systems are composed all or part of polymers. Polymeric materials in contact with fuels and/or biofuels may be subject to deformations such as swelling, caused by solvent ingress within their structure and leading to strong modifications and loss of their initial physical and chemical properties [8, 9]. To address this problem, one solution consists in using multilayer structures containing interleaved barrier polymers [10]. Up to date, only few works have been published in the litterature dealing with the compatibility between polymeric materials and fluids, and there is a lack of available experimental data [11]. The group of Izák *et al.* have investigated experimentally and theoretically gases and liquids sorption into polymers over the last decades [12, 13, 14] ; and more recently, Krajakova *et al.* focused on sorption of liquids into poly(ethylene) samples of different densities [15]. Regarding fuels, Haseeb *et al.* immersed some elastomeric materials such as nitrile butadiene rubber (NBR) and Viton® a fluorinated elastomer (FKM) in diesel and palm biodiesel to compare the degradation of physical properties like weight and volume changes, hardness and tensil strength [16, 17]. Kaas *et al.* studied the compatibility of elastomeric materials with gasoline blends containing ethanol and isobutanol, followed evolution of some polymer's properties, and

proposed a ranking of elastomer specimens according to their swelling [18]. Silva *et al.* ordered some rubbers as a function of their compatibility with biodiesels, and revealed that the mobility of chains of NBR in biodiesel increases without change in their chemical structures [19]. In the article by Trakarnpruk *et al.*, authors studied elastomer properties after immersion in biodiesel, focusing among others on NBR, copolymers, and terpolymer FKM. Authors concluded that among tested polymers fluoroelastomers undergo fewer physical degradation [20]. Weltschev *et al.* focused their research on the resistance of sealing materials such as FKM, NBR and fluorosilicon rubber (FVMQ), immersed during hours in biodiesel based fuels, as a function of the age and the temperature of fluids [21]. Authors noted that the percentage of degradation is proportional to the temperature and the age of the fuels. In regards to available experimental results, it appears that current methods used for the data acquisitions are time consuming, and the development of robust predictive models is of high relevance.

Plota and Masek recently reviewed kinetic based models used to predict the lifetime of polymeric materials and conclude to the necessity of developing new methods [22]. During last decades materials informatics has emerged as a new approach for the conception of new materials [23, 24, 25]. It consists in training learning algorithms on database content, in order to allow predictions for materials having structures similar to those contained within the database, or even to propose promizing candidates for specific applications. Polymer informatics necessitates relevant databases which integrate knowledge about properties related to thermodynamics, mechanics, optics, and transport [26, 27]. Litterature reviews report developments of quantitative structure property relationships (QSPR) for polymer properties [28, 29, 30]. In the case of transparent polymeric materials, QSPR methods have been used to model optical properties such as the refractive index, n [28, 30, 31, 32]. Holder *et al.* have shown that the use of dimeric repeating units for descriptor calculation leads to the most accurate models [33]. Duchowicz *et al.* used a Simplified Molecular Input Line Entry System (SMILES) – not dependent of 3D-molecular geometries – based model to predict n for 234 structurally diverse polymers [34]. Jabeen *et al.* developed a four-descriptor QSPR model with accurate predictions for a highly diverse set of 133 organic polymers [35]. Numerous works reported attempts to predict polymer properties such as glass transition temperature, T_g using QSPR [29, 36, 37, 38, 39]. The knowledge of T_g defines domains of rigid structure or rubber-like properties for polymeric materials, and thus is of utmost importance for many appli-

cations. Mercader *et al.* have demonstrated that T_g can be well predicted with QSPR and advocated the use of trimeric moities for descriptor calculation [37]. QSPR were also developed to predict mechanical properties for polymeric materials [40], and Cravero *et al.* proposed QSPR models to estimate tensile strength of polymers [41]. Another possible application of QSPR modelling is to predict sorption of chemicals into polymer matrices. Zhu *et al.* proposed a QSPR based model for the prediction of diffusion coefficients of hydrophobic organic contaminants in low density polyethylene [42]. Li *et al.* proposed models for predicting polymer/brine partition coefficients for chemicals, with polymers such as polyethylene, polypropylene and polystyrene [43]. Our group has previously proposed QSPR models to predict sorption values for neat compounds and up to quinary mixtures of hydrocarbons, alcohols, and ethers, and demonstrated their applicability to predict sorption values for some alternative fuels into a poly(ethylene) [44].

In the present work, we report the acquisition of new experimental sorption values at room temperature for neat compounds and alternative jet fuels based fluids into three polymers. Additionaly, we present QSPR based models developed using machine learning methods, and its application to model new experimental data. The paper is organized as follows: we present experimental data methods and the strategy followed to build new QSPR based models, new experimental data and the predictive performance of models are then exposed and discussed, and the last section gives our conclusions.

2. Materials and methods

2.1. Experimental procedure

2.1.1. Materials and Samples

Three polymers commonly considered for the design of fuel-delivery systems were selected for this study: NBR, FKM, and FVMQ. Polymers raw materials — plane square sheets with 0.3m size and 2.10^{-3}m thickness — were supplied either by Zodiac Aerotechnics or by Stacem. Rectangular parallelepiped shapes with 60x10x2 mm^3 were extracted from the polymer sheets using a cutting shape, and samples were subsequently used for the sorption tests. Some characteristics (grades for aerospace applications) for these materials are presented in Table 1. We also performed measurements, the Dynamic Mechanical Analysis (DMA) was used to determine the glass transition temperature for the three polymers. A sinusoidal stress was applied to each sample while the strain was measured, allowing one to determine

Table 1: Characteristics for polymeric materials considered in this study.

Polymer	Type	Standards	Hardness (IRHD[a])	T_g (°C)	Plasticizer (% wt.)
NBR	20B8	NF L 17-120	78	-36	11.0
FVMQ	61D8	NF L 17-261	80	-55	1.2
FKM	60C8	NF L 17-164	80	-1	0.5

[a]IRHD: International Rubber Hardness Degree. The dial of the durometer is graduated according to the Shore D scale, from 0 (soft) to 100 (hard) IRHD, with uncertainties associated to measurements of +5/-4 IRHD.

the complex modulus and the loss factor. So-obtained T_g values, reported in Table 1, correspond to the peak value of tan δ, the damping, a measure of the energy dissipation of a material. Additionally, the Thermal Gravimetric Analysis (TGA) was used, it consists in following the mass variations of a sample with the time as the temperature changes. This measurement provides information about chemical phenomena including thermal decomposition but also physical phenomena, such as the desorption of additives. This technique has allowed the determination of the plasticizer amount initially present in each studied polymer. It led to plasticizer amounts of 0.5 % wt. for FKM, 1.2 % wt. for FVMQ, and 11 % wt. for NBR, indicating that the amount in NBR is not negligible and may lead to measurement artifacts.

Fluids under consideration in this study are pure liquids and aviation fuels. Naphthenic and aromatic hydrocarbons (decaline (labeled D), xylene (labeled X), tetraline (labeled T), iso-propylbenzene (or cumene, labeled C), n-propylbenzene (labeled P), and methylnaphtalene (labeled M)), with high purity grades were purchased from Merck, and no additional purification was performed. One Jet A-1 (labeled J) being one of the fuels most commonly used in commercial aviation was selected for sorption measurements. Additionally, we considered alternative jet fuels approved for certification such as: Synthetic Paraffinic Kerosene (SPK) and Hydroprocessed Esters and Fatty Acids (HEFA). For instance, SPK can be FT fuels – composed of normal and isoparaffins, or Alcohol to Jet Synthetic Paraffinic Kerosene (ATJ-SPK) created from isobutanol which is derived from feedstocks. HEFA – similar to HVO – includes hydrocarbon-based jet fuels (100% paraffinic) produced from animal or vegetable oils by hydroprocessing [45]. The current certification for the use of HEFA in mixture with jet fuel allows a maximum of 50%

vol. We considered three HEFA with different cold flow properties such as crystallization temperatures: -50 ℃, -30 ℃, and -20 ℃ labeled H(50), H(30), and H(20), respectively. We considered three additional fuels (labeled A1, B1, and C1) to assess their compatibility with the polymers through sorption measurements, and later used to assess the predictive capability of models. A1 is a Jet A-1 fuel, noting that its composition sligthly differs from that of J. B1 is an ATJ-SPK mainly composed of i-paraffins. C1 is a jet fuel surrogate with high aromatics content (*ca.* 20 vol%). Note that Hall *et al.* recently considered these conventional and synthetic fuels [46], and representations for these fluids are proposed hereafter.

In order to deeply explore effects of the fluid composition on polymer mass variations when the polymer is immersed in a fluid, we defined different mixtures varying compositions for instance, in terms of naphthenes and aromatics content, paraffins chain length... Mixtures containing J and 25, 50, and 75 % vol. of H(50) were formulated. Nine mixtures containing H(50) and amounts 1, 5, and 10 % vol. of X, T, and D were also elaborated. Three blends of 90 % vol. of H(30) and 10 % vol. of C, P, and M were designed. J was mixed with X in 75, and 25 % vol. proportions, and a tenary mixtures containing J, X, and H(30) in equal volumetric proportions was formulated.

2.1.2. Sorption measurements

The term sorption is commonly used to describe the dissolution of a penetrant into a polymer matrix. Measurements of liquid sorption into polymers were performed using a gravimetric method, as detailed in our previous works [44]. Experiments consists in recording the mass variation (weight gain or loss) of a polymer sample with time when immersed into a large excess of the studied liquid. Noting that from sorption values, at equilibrium or saturation, it is possible to derive the solubility coefficient, and measurements must be accurately performed as the absorbed quantities are often very small. Rectangular parallelepiped polymer samples were first weighted ($m_{t=0}$) using an analytical balance METTLER TOLEDO (capacity up to 30 g, with a precision of 0.026 g), and then immersed in a large excess of studied liquid in a closed 100 ml glass vessel. Glass vessels were placed at ambient temperature (20 $\pm$ 1 ℃) in an air-conditioned laboratory, for all the duration of the sorption experiments. Polymer samples were regularly removed from glass vessels, wiped carefully, and weighted (m_t) in order to follow mass variations of each polymer materials in considered liquids. The mass variation (ΔM) is expressed in percent as the ratio between the amount of sorbed fluid and

the initial polymer weight, as follows:

$$\Delta \mathrm{M} = 100 \times \frac{m_t - m_{t=0}}{m_{t=0}}, \tag{1}$$

It has been checked that the repeatibility of the sorption values is excellent, with less than 2% of variation coefficients. Measurements are performed until the curve ΔM as a function of time reaches its equilibrium value, exhibiting a plateau. According to the considered polymer-fluid couple up to 40 days were needed to reach the plateau value. We emphasize that the sample swelling has been investigated in terms of weight variations and not volume swellings as this former is assumed to be more accurate. We previously noted the presence of plasticizers in NBR which can cause a weight loss of the samples during sorption tests, and can produce misleading results. Therefore, all NBR samples were pretreated to remove plasticizers, as follows: they have been washed with toluene during 3 weeks (at 50 ℃ to speed up the diffusion mechanism) and then dried.

2.2. Modelling Method

These last years, we have devoted large efforts in the development of QSPR based models for the prediction of various property values [47]. These approaches aim at identifying non-obvious correlations between property values of the matter and some features rendering information about the matter. Reviews have been published dealing with developments and applications of QSPR based models, and best practices in developing such models [29, 48].

2.2.1. Data Sets

The accuracy of predictive QSPR is related to the quality of data, and thus a keystone of such works is the database used to develop models. The used database contains reference sorption values, ΔM measured following the experimental procedure described above. The database contains 521 sorption values measured at room temperature, for neat compounds and mixtures. Table 2 presents an extract of our database, *i.e.* the maximum amounts of each fluid sorbed into NBR, FVMQ, and FKM. Indeed, the database contains the complete isotherms − evolution with time of the amount of sorbed fluid through NBR −, with in between 20 and 25 data points for each isotherm.

During last decades of QSPR model developments, the use of external validation has been shown as necessary to ensure its ability to extrapolate to new fluids, *i.e.* not considered within the database used to train the

Table 2: Maximum amounts of sorbed fluid (ΔM, in %) into NBR, FVMQ, and FKM. Fluids are labeled as follows: X, T, D, C, P, and M stand for xylene, tetraline, decaline, iso-propylbenzene, n-propylbenzene, and methylnaphtalene, respectively ; fluids mixtures are labeled as follows, for instance, H(50)90-T10 contains 90 % vol. of H(50) in mixture with 10 % vol. of tetraline.

Label	Fluid	ΔM (%)		
		NBR	FVMQ	FKM
F01	X	120.0	9.6	6.0
F02	T	97.4	4.8	0.5
F03	D	18.7	3.6	0.0
F04	J	16.8	4.3	0.2
F05	H(20)	3.5	1.5	0.1
F06	H(50)	4.1	1.8	0.0
F07	J75-H(50)25	12.3	3.6	0.1
F08	J50-H(50)50	9.1	3.1	0.1
F09	J25-H(50)75	6.8	2.5	0.1
F10	H(50)99-X01	4.5	1.9	0.1
F11	H(50)95-X05	6.2	2.5	0.1
F12	H(50)90-X10	8.4	3.0	0.2
F13	H(50)99-T01	4.5	1.9	0.0
F14	H(50)95-T05	6.7	2.3	0.1
F15	H(50)90-T10	9.4	2.6	0.1
F16	H(50)99-D01	4.1	1.9	0.0
F17	H(50)95-D05	4.6	2.0	0.0
F18	H(50)90-D10	5.1	2.1	0.0
F19	H(30)90-C10	7.6	2.6	0.1
F20	H(30)90-P10	7.9	2.6	0.1
F21	H(30)90-M10	14.8	3.0	0.2
F22	J75-X25	30.5	6.2	0.8
F23	J25-X75	81.6	8.8	3.7
F24	J33-X33-H(30)33	27.2	5.9	0.8

model [49]. Its popular version is the n-fold cross-validation (n-CV) in which the data set is randomly divided in approximately equal n portions. An aggregate of *(n-1)* portions forms the Training set – used to train models, and the remaining portion constitutes the Test set – used to evaluate model's performance. We emphasize that no data point belonging to external sets is used to derived models. This procedure is repeated n times choosing at each new fold another portion of data as a Test set. The subject of external validation for QSPR analysis of mixtures has been addressed by Muratov *et al.* [50], and the authors-defined "mixture out" strategy was applied in this study.

2.2.2. Fluids characterisation and representation

A fuel contains thousands of diverse chemicals and its exact composition is never known. The characterization of such complex fluids and identification of representative compounds or surrogates are of utmost importance when developing predictive models for application in the industry [51, 52]. The use of modern analytical instruments such as chromatography, helps in obtaining information about the composition and structure of fluids components. The two-dimensional gas chromatography (labeled GC-2D or GCxGC) has been proved as an interesting analysis technique for detailed characterisation of petroleum products [53]. Fuel candidates considered in this study were analyzed by means of GCxGC, and their compositions expressed as distributions of mass fractions as a function of the number of carbon atoms for hydrocarbon families such as n-paraffins, i-paraffins, naphthenes, aromatics... A molecular structure is attributed for each hydrocarbon family/number of carbon atom bin, and each fuel is thus represented by a maximum of 120 molecular structures. Figure 1 presents compositions of fluids A1, B1, C1, J, H(20), H(30), and H(50), simplified to four chemical families: n-paraffins, i-paraffins, naphthenes, and aromatics. It shows that ATJ-SPK (B1) and HEFA fuels are clearly mainly paraffinics, with B1 purely n-paraffinics. A1 and J have similar compositions with for J, slightly (*ca.* 3 %) lower and higher i-paraffins and aromatics contents, repsectively. The surrogate C1 is poor in paraffins and rich in naphthenes as compared to other fluids.

2.2.3. Molecular and mixture descriptors

From conclusions drawn in previous studies [2, 44], we chose to solely consider functional group count descriptors (FGCD). Such a simple representation of compounds has been shown to provide relevant descriptors us-

Table 3: Ranges of number of carbon atoms to represent jet fuel candidates.

Formulae	Family	Number of C atoms
C_nH_{2n+2}	n-paraffins	5 to 20
C_nH_{2n+2}	i-paraffins	5 to 30
C_nH_{2n}	mono-naphthenes	6 to 18
C_nH_{2n-2}	di-naphthenes	9 to 29
C_nH_{2n-4}	tri-naphthenes	13 to 16
C_nH_{2n-6}	mono-aromatics	7 to 17
C_nH_{2n-8}	naphthenes mono-aromatics	9 to 16
C_nH_{2n-10}	naphthenes mono-aromatics	10 to 15
C_nH_{2n-12}	di-aromatics	10 to 16
C_nH_{2n-14}	naphthenes di-aromatics	12 to 16
C_nH_{2n-16}	naphthenes di-aromatics	13 to 15

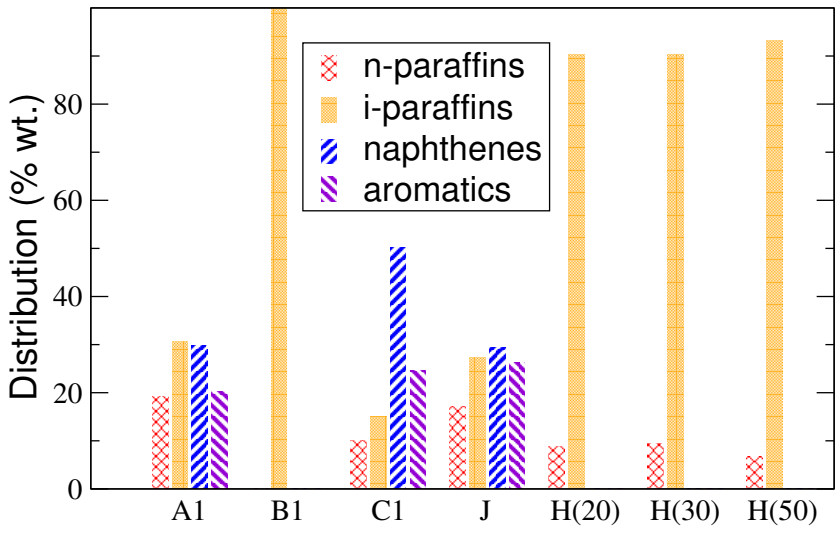

Figure 1: Simplified chemical compositions described in terms of n-paraffins, i-paraffins, naphthenes, and aromatics, for fluids A1, B1, C1, J, H(20), H(30), and H(50).

Table 4: List of the Functional Group Count Descriptors (FGCD) used to describe fluids in the database and associated SMARTS codes or definitions.

Label	SMARTS/Definition	Label	SMARTS/Definition
X1	[H]	X18	[C][CR]([!C])([!C])[C]
X2	[C,c]	X19	[C][CR]([!C])([C])[C]
X3	[CX4H3]	X20	[C]=[C]([C])[!C]
X4	[CX4H2]	X21	[CX3H1]=[CX3H1]
X5	[CX4H1]	X22	[c][CX4H3]
X6	[CX4H0]	X23	[c][CX4H2]
X7	[CX3H1]	X24	[c][CX4H1]
X8	[CX4H2R]	X25	[R]
X9	[CX4H1R]	X26	aromatic_rings
X10	[cX3H1](:*):*	X27	non-aromatic_rings
X11	[cX3H0](:*)(:*)*	X28	aliphatic_rings
X12	[cX3H0](:*)(:*):*	X29	number_of_rings
X13	[cX3H0]-[cX3]	X30	MM
X14	[cX3H0](:*)(:*)(-[CX4H2R])	X31	[C;R]
X15	[CX4H2]-[CX4H1]-[CX4H2]	X32	[c;R]
X16	[C][C]([!CX1])([!CX1])[!CX1]	X33	C1CCCCC1
X17	[!C][C]([C])([C])[C]		

able in QSPR procedure [3, 44]. This family of molecular descriptors gathers some counts of groups identified as relevant under chemical aspects. Table 4 gives the list of FGCD under consideration in this study and labelled from X1 to X33. For instance, the FGCD labelled X25 denotes the number of carbon atoms involved in a ring. As Villanueva *et al.* did [44], we have also computed the molar mass (MM) of neat compounds, this information being used as an additional descriptor (labelled X30). Simplified molecular input line entry specification (SMILES) notations were assigned to each neat compound considered in this sutdy. FGCD were counted using the RDKit's SMILES arbitrary target specification (SMARTS) matching functionalities [54, 55], and SMARTS codes corresponding to FGCD are given in Table 4.

The calculation of descriptors for mixtures has been addressed similarly as in previous works [44, 56]. We assumed mixture descriptors X_{mix} as linear combinations of pure component descriptors weighted with the associated molar fractions x_i. This approach has already been shown effective in pre-

dicting sorption values for some alternative fuels in a poly(ethylene) [44]. For instance, in the case of descriptor X1, the corresponding descriptor for a mixture $X1_{mix}$, is defined as follows:

$$X1_{mix} = \sum_{i=1}^{N} x_i \times X1_i, \tag{2}$$

where i runs over the N constituants in the mixture.

2.2.4. Chemical space representation

We preprocessed the data by applying a principal component analysis (PCA) on fluid descriptor values. Figure 2 represents the projections of F01 to F24 in the space formed by the three main principal components resulting from the PCA, providing one approximated representation of the chemical space for our database. Some of fluid candidates are at edges of the domain, isolated from all other samples, this is typically the case for fluids F01, F03, F04, and F05. These latter datapoints appear as outliers for the following reasons: (i) F01, xylene, is a pure compound with the highest property value ; (ii) F03, decaline, is a pure compound and has the highest value on PC2 axis ; (iii) F04, Jet-A1, has the highest value on PC3 axis ; (iv) F05, HEFA-20, has the lowest property value. The presence of outliers in external sets during the CV procedure may induce applicability domain violations. Fluids F01, F03, F04, and F05 were fixed, meaning they are placed in a fold always used to form Training sets. We used a *5*-CV procedure applied on the remaining 20 fluids candidates — four fluids per fold. The Training and Test sets thus represent 83% and 17% of the database, respectively. In Figure 2, each symbol is filled according to the fold the fluid belongs to.

2.2.5. Machine learning algorithm

In the frame of past studies [47], we have observed that QSPR models derived from Support Vector Machine (SVM) algorithms frequently outperform others evaluated learning algorithms such as neural networks, partial least squares, genetic algorithm... Table 2 shows that the number of data points — fluids candidates — is quite limited and the application of SVM does not seem appropriate in this case. We focused on developing multilinear equations which moreover have the advantage to be explicit models and easily implemented in a spreadsheet. Such multilinear models can be, for instance, generated by means of Evolutionary Algorithms (EA) techniques inspired

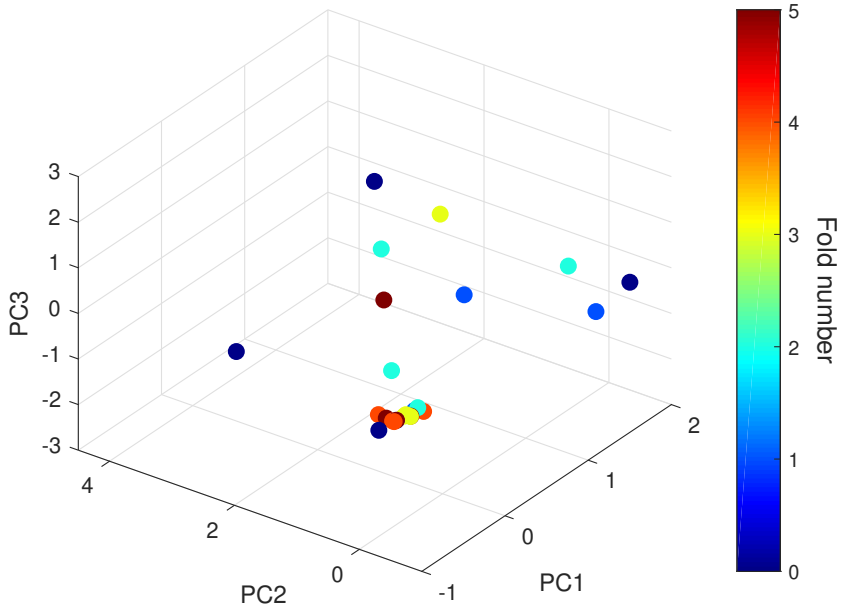

Figure 2: Projections of jet fuel based fluids on the space formed by PC1, PC2 and PC2, the three first principal components resulting from the PCA. Symbols are filled according to a gradient of colors, as legended in the colorbar each of the six folds is represented by one color.

from the Darwinian evolution theory of biological species. The application of EA to regression problems consists in an iterative evolution of a population of equations initially randomly set. Equations can be summarized under the general following form:

$$Property = \lambda_0 + \sum_{i=1}^{N} \lambda_i G_i, \tag{3}$$

where λ_0 is the inercept, λ_i denotes a weight associated to the gene i (G_i), and N is the total number of genes in the model. Each gene consists in a combination of descriptors (see Table 4) and mathematical functions (see Table 5), and can be though as a tree with nodes and branches (Figure 3). Such construction allows to catch non-linearity in property variations. Multi-Gene Genetic Programming (MGGP) was applied to generate models, using the genetic programming toolbox for the identification of physical systems (GPTIPS) coded in the MATLAB environment [57, 58, 59]. The evolution of the initial population – initial equations – is ensured by survival of fitter individuals, and reproduction of individuals consists in applying crossover as well as mutation operations to produce child equations. Genetic operators act upon sub-tree elements, thus making the structure of trees evolve during the iterative procedure. The procedure ends when one of the pre-defined criteria such as maximum number of generations, best fitness values... is reached. Some of GPTIPS parameters such as the maximum numbers of genes and nodes per tree, must be lowered to prevent any overfitting problems. Similarly, the maximum numbers of generations and runs have to be optimized to ensure convergence of calculations for reasonable computational ressources [60, 61]. Parameters of performed GPTIPS calculations were optimized according to the procedure defined by Creton *et al.* [60]. Table 5 reports details about values and/or ranges of investigated GPTIPS settings in this work.

Models are evaluated according to their capability in predicting fluids properties. Predicted values are compared to reference experimental data, and performances of models are evaluated by means of metrics such as MAE (Mean Absolute Error, equation (4)), RMSE (Root Mean Squared Error, equation (5)) or R^2 (Coefficient of determination, equation (6)), defined as follows:

$$\mathrm{MAE} = \frac{1}{N} \sum_{i=1}^{N} |\widehat{y}_i - y_i|, \tag{4}$$

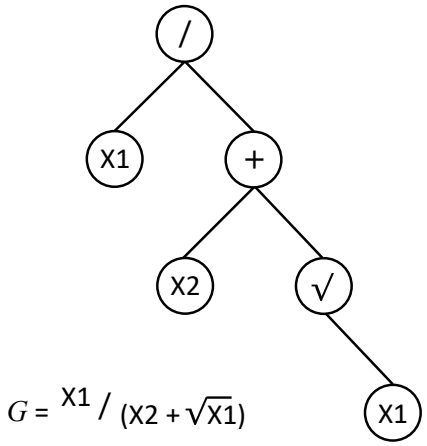

Figure 3: Example of a gene G, and its tree-like architecture as considered in MGGP.

Table 5: Investigated parameter settings for the MGGP based method.

Parameter	Corresponding values
Function set	$+$, -, $\times$, $\div$, $\sqrt{}$, exp, ln
Population size	250
Number of runs	1, 5, 10, 15, 20,25, 30, 40
Tournament size	25
Maximum tree depth	4
Number of generations	100, 500, 1000, 2000
Maximum number of genes	1 to 5
Maximum number of nodes per tree	1 to 8
Mutation events	0.1
Crossover events	0.85
Reproduction events	0.05

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\widehat{y}_i - y_i)^2}, \tag{5}$$

$$\mathrm{R}^2 = \frac{\sum_{i=1}^{N}(\widehat{y}_i - \overline{y})^2}{\sum_{i=1}^{N}(y_i - \overline{y})^2}, \tag{6}$$

where in equations (4) to (6), $\widehat{y}_i$ stands for the predicted value, y_i represents the experimental value, $\overline{y}$ denotes the mean property value calculated on experimental data set candidates, and N is the number of data.

3. Results and discussion

3.1. Experimental results

We performed sorption experiments to evaluate polymers (*i.e.*, NBR, FVMQ, and FKM) compatibility with a series of hydrocarbons mixtures and more specially, to mixtures containing different amounts and types of aromatics. Details about tested fluids mixtures are given in the Table 2. The weight variation of the polymer is very dependent on the considered system, the chemical compositions of both the polymer and the fluid. The measured maximum uptakes of hydrocarbons in each polymer (or maximum ΔM) are presented in Table 2. From tested polymer/fluid couples, ΔM values range from *ca.* 0% (FKM immersed in HEFA) to 120% (NBR immersed in xylene). Clearly, none of tested hydrocarbons is significantly absorbed into FKM, and from measured values, FKM can be assumed as a barrier polymer in case of hydrocarboned fluids. ΔM values obtained for the FVMQ polymer are negligible as compared to those of NBR. Within the fluids matrix (Table 2), we considered mixtures having from about 0% vol. aromatics (*e.g.*, HEFA) to 100% vol. aromatics (*e.g.*, xylene). In Figure 4, we plot the ΔM plateau value for NBR as a function of mono-aromatics content in the fluid tested. Considering all these systems, deplasticized NBR presents a higher level of sorption and is very sensitive to the aromatics content of the fluids. Figure 4 shows that mixtures rich in paraffins such as HEFA fuels (left part of the diagram) lead to low ΔM values as compared to mono-aromatics rich mixtures (right part of the diagram). From these elements a quadratic (of the % vol. of mono-aromatics) trend could describe the observed behavior. Noting that fluids containing polyaromatic compounds, *e.g.* the fluid F21 containing 10% vol. methylnaphtalene, deviate from this trend with upper ΔM values.

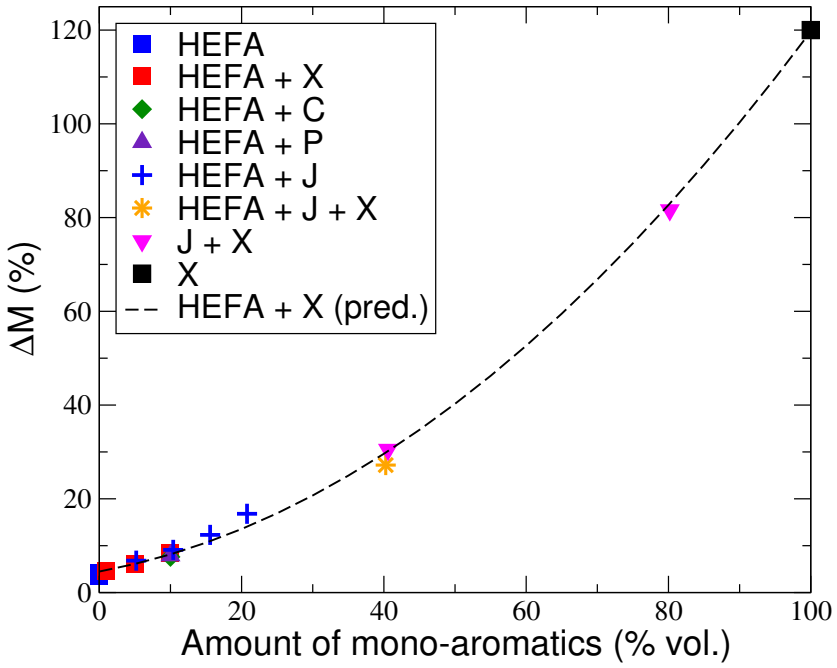

Figure 4: Evolution of the ΔM plateau value for NBR, with the mono-aromatics volumetric percent of the fluid. Fluids are labeled as in Table 2: X, C, P, and J stand for xylene, iso-propylbenzene, n-propylbenzene, and Jet-A1, respectively. The dashed line stands for values predicted using equation 7.

Table 6: Maximum amounts of sorbed (ΔM) A1, B1, and C1 into NBR, FVMQ, and FKM.

Fluid	ΔM (%)		
	NBR	FVMQ	FKM
A1	14.2	4.7	0.3
B1	2.7	4.4	0.1
C1	30	3.9	0.4

Fluids A1, B1 and C1 – conventional and synthetic jet fuels – were considered to experimentally assess their compatibility with the three polymers of interest, and Table 6 presents measured ΔM values. In agreement with conclusions drawn previously, amounts of fluids adsorbed into FKM or FVMQ are roughly much lower than that measured for NBR. On the basis of compositions proposed in Figure 1 for A1, B1, and C1, ΔM plateau values appear to follow the previously observed relationships with paraffins and aromatics contents.

3.2. Machine learning models

Obtained experimental values were used to feed machine learning techniques in order to derive predictive models. Based on the conclusions drawn in the previous section, small quantities of hydrocarbons were adsorbed into FKM and FVMQ and therefore, we only focus on modelling of the sorption of hydrocarbons into NBR. We hereafter report the development of two types of predictive models: models which predict the maximum mass gain (maximum ΔM) and models which predict the sorption kinetics *i.e.* the time evolution of ΔM, in NBR.

3.2.1. Modelling plateau values

As a first attempt, we considered a subpart of our database extracting for each fluid the sorption plateau value – the maximum mass percentage gain –, and data are presented in Table 2. Parameters of the MGGP such as numbers of runs, generations, genes, and nodes that will further be used to develop models were optimized using a 5-CV and according to the procedure proposed by Creton *et al.* [60]. This procedure can be summarized as follows: The numbers of genes and nodes are first set to their respective maximum allowed value to consider models having the highest complexity. Numbers of

Table 7: Performance characteristics (statistical indices) of MGGP based models applied to plateau values. Fold-i stands for performances calculated on the fold i when it is external to the learning procedure.

Indices	Fold-01	Fold-02	Fold-03	Fold-04	Fold-05
MAE	9.21	1.90	0.63	1.60	0.42
RMSE	17.23	2.87	0.75	2.80	0.54
R^2	0.786	0.992	0.995	0.614	0.929

generations and runs are optimized within the response surface with boundaries as defined in Table 5. Then, numbers of generations and runs are set to optimized values, and numbers of genes and nodes are optimized within the response surface defined according to boundaries indicated in Table 5. The optimization procedure applied to our regression problem led to numbers of runs, generations, genes, and nodes of 20, 500, 4, and 3, respectively.

Five MGGP based models were developed using the GPTIPS code and following a *5*-fold cross-validation procedure. All models exhibit excellent performances over the Training sets. Performances of models evaluated on external fluids are presented in Table 7. Values returned by indices for Fold-01 and Fold-04 indicate overfitting trends for these two models that can originate from fold constitution. For instance, Fold-01 contains the fluid F02 having the second highest property value in the database, and the model fails in predicting this value. Among the three remaining models, best performances on external sets are obtained for Fold-05, Fold-03, and then Fold-02. However, the chemical diversity is not similar for these three folds. The model that best generalizes the database has been developed using Fold-02 as Test set. Details about this latter model such as the four weighted genes and the intercept value are presented in Equation (7).

$$\begin{aligned} \lambda_0 &= \text{Intercept} = -30.12 \\ \lambda_1 G_1 &= -36.70 * \exp\left(-\exp\left(\text{-X4}\right)\right) \\ \lambda_2 G_2 &= 70.87 * \exp\left(\text{X26}\right) \\ \lambda_3 G_3 &= -12.38 * \sqrt[4]{\text{X21}} \\ \lambda_4 G_4 &= 7.26 * \exp\left(\text{X33 - X10}\right) \end{aligned} \tag{7}$$

where Xi stands for descriptors as defined in the Table 4. In Equation (7),

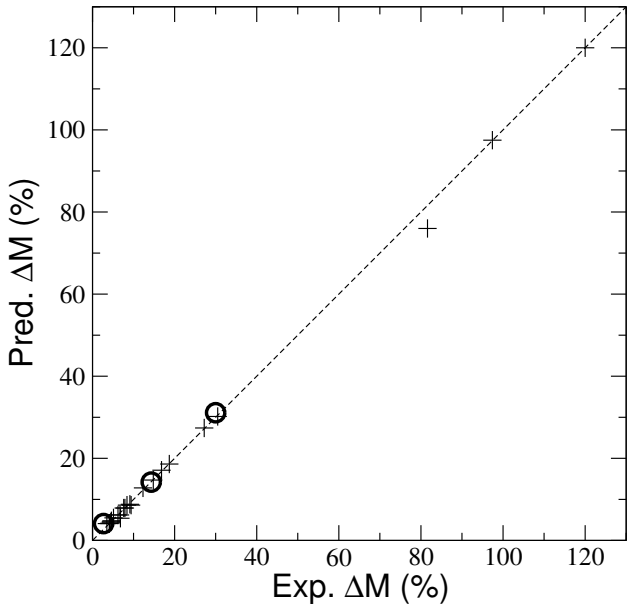

Figure 5: Scatterplots of experimental sorption values *vs.* predicted sorption values using Equation (7). Symbols + stand for fluids in Table 2, and ◯ represent fuels A1, B1, and C1.

each gene non-linearly contributes to the predicted sorption value, and Equation (7) highlights some interesting contributions of chemical function to the amount of fluid sorbed into NBR. For instance, Equation (7) indicates that increasing the number of -CH_2- groups (X4) in fluid decreases the sorption value. On the contrary, increasing the number of aromatic rings (X26) in fluid increases its amount sorbed into NBR. These elements are in line with the analysis of Figure 4. G_4 is a combination between numbers of saturated 6-rings (X33) and hydrogenated aromatic carbon atom bonded to two atoms by aromatic bonds (X10). Figure 5 presents scatterplots of experimental sorption values *vs.* predicted sorption values using equation (7). All data points are roughly located on the bisector (dashed line) indicating that predicted plateau values are in excellent agreement with reference experimental data. Moreover, values predicted for fuels A1, B1, and C1 (14.2, 4.1, and 31.1, respectively) are in excellent agreement with corresponding experimental values as reported in Table 6.

Table 8: Optimized parameter settings used to train MGGP based models on our database.

Parameter	Optimized values
Number of runs	20
Number of generations	1000
Maximum number of genes	4
Maximum number of nodes	6

3.2.2. Modelling the sorption kinetic

We then considered the whole content of our database with for each fluid, the time evolution of the maximum mass percentage gain. Parameters of the MGGP as implemented in the GPTIPS code were optimized according to the procedure proposed by Creton *et al.* [60]. Additionally, we applied a 5-CV procedure together with folds' chemistry — the same fluids in each fold — associated to the above described development of models to predict plateau values. Table 8 presents obtained optimized parameter values subsequently used in GPTIPS to develop QSPR models. The number of nodes is twice higher as compared to parameters values optimized to derive Equation (7), and most probably due to this increase in complexity, the number of generations is here 1000.

Five MGGP based models were developed removing for each, one of the five folds defined for the 5-CV procedure. Performances of models evaluated on the Training and Test (external fluids) sets are presented in Table 9. All models exhibit excellent performances over the Training sets with RMSE lower than 2.6 (in ΔM unit) and R^2 greater than 0.99. Indices calculated for Test sets of models indicate various trends regarding their prective capabilities. However, as discussed previously, the chemical diversity is not similar within the five folds, and external validation performed for these five scenarios are difficult to compare with each other. Values taken by indices over the database are presented in Table 9. Considering these latter values, the model developed using Fold-01 as Test set leads to a greater RMSE value as compared to others. Although none of models outperforms others, the model that best generalizes the database was obtained using Fold-05 as Test set. Details about this latter model such as the four weighted genes and the intercept value are presented in Equation (8).

Table 9: Performance characteristics (statistical indices) of MGGP based models applied to sorption curves. Fold-i stands for performances calculated on the fold i when it is external to the learning procedure.

Metrics	Fold-01	Fold-02	Fold-03	Fold-04	Fold-05
Training:					
MAE	1.02	1.29	1.52	1.49	1.38
RMSE	1.82	2.45	2.56	2.52	2.53
R^2	0.995	0.992	0.993	0.993	0.993
Test:					
MAE	2.96	1.42	1.27	1.54	0.69
RMSE	5.54	2.63	1.64	2.24	0.96
R^2	0.975	0.992	0.978	0.776	0.859
Database:					
MAE	1.34	1.31	1.48	1.50	1.26
RMSE	2.80	2.48	2.42	2.48	2.34
R^2	0.990	0.992	0.992	0.992	0.993

$$
\begin{aligned}
\lambda_0 &= \text{Intercept} = -38.40 \\
\lambda_1 G_1 &= 12.23 * \exp\left(\exp\left(\text{X26}\right)\right) \\
\lambda_2 G_2 &= 0.86 * \left(\text{X9}^4 + \text{X22}^3\right) \\
\lambda_3 G_3 &= 4.51 * \sqrt{\exp\left(\text{X10}\right) * \ln\left(\text{t}\right)} \\
\lambda_4 G_4 &= -2.35 * \exp\left(\text{X10}\right)
\end{aligned}
\tag{8}
$$

where t is the time (expressed in hours) and Xi stands for descriptors as defined in Table 4. In Equation (8), G_1 reveals that increasing the number of aromatic rings (X26) in fluid increases its amount sorbed into NBR. G_2 can be considered as a sum of contributions of branchings on saturated (X9) and aromatic (X22) rings. The descriptor X10 — number of hydrogenated aromatic carbon atom bonded to two atoms by aromatic bonds — is involved both in genes G_3 and G_4 where in this former, X10 acts as a weight for the time evolution. Figure 6 presents scatterplots of experimental sorption values *vs.* predicted sorption values using Equation (8). All data points are not too scattered on both sides of the bisector indicating that predicted values are in good agreement with reference experimental data. However, Figure 6 shows

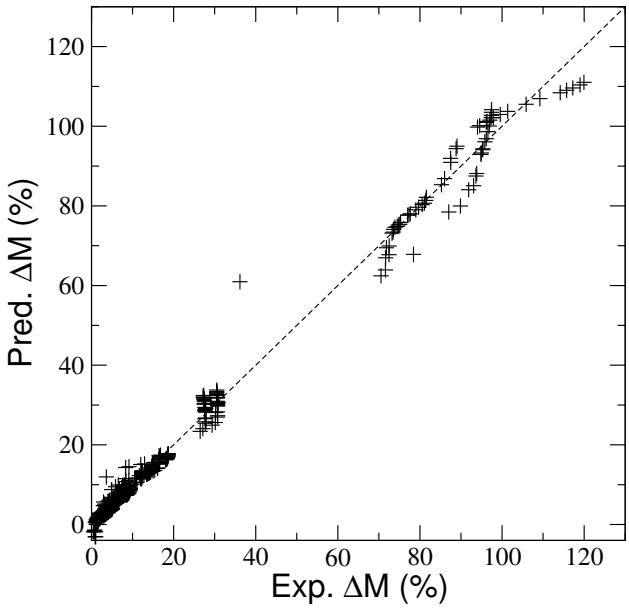

Figure 6: Scatterplots of experimental sorption values *vs.* predicted sorption values using Equation (8).

that one point is poorly predicted, the sorption value measured after 5 hours immersion in tetraline is 36.1 (%) while the model returns 61 (%). Noting that for tetraline, only this data point is poorly predicted.

We performed consensus modelling to investigate whether combining models' predictions can lead to more accurate predicted values. It reveals that combining predictions of models obtained using Fold-04 and Fold-05 as Test sets improve performances as compared to individual models. We used this combinaison to predict the time evolutions of sorption values for real fuels A1, B1, and C1. Figure 7 presents comparisons between predicted values and experimental data measured in this study. The models successfully reproduce the sorption kinetics for the fluids A1 and C1, with however significant deviations from experimental values for the first hours. The models well predict B1 as a low ingress fluid in NBR but a shift of few percents is observed with reference experimental values.

4. Conclusion

We proposed here an investigation of fuels' sorption into polymers by means of experimental and machine learning techniques. Three polymers

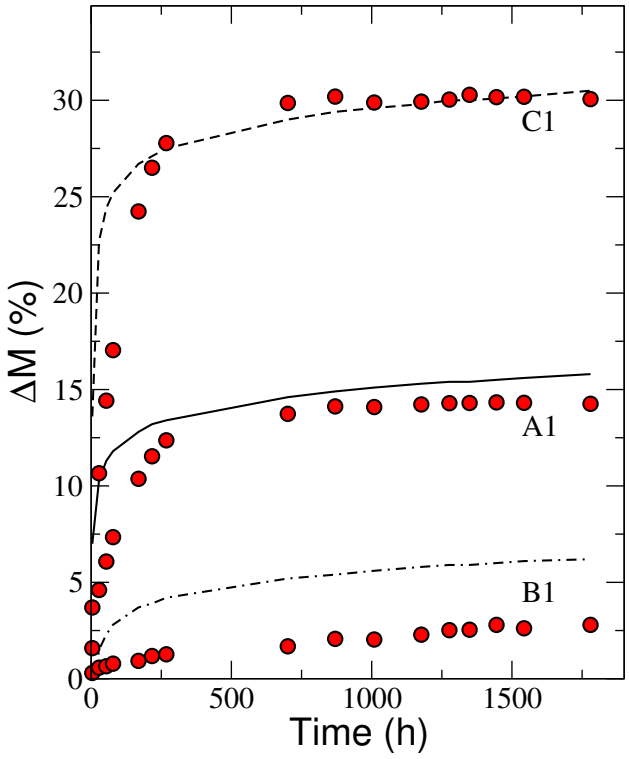

Figure 7: Time evolutions of sorption values for fuels A1, B1, and C1 predicted using the consensus model. Red circles stand for experimental values obtained in this work.

commonly considered for the design of fuel-delivery systems were selected for this study: NBR, FKM, and FVMQ. Polymers samples were immersed into liquids, and fluids under consideration were pure liquids and aviation fuels — conventional and synthetic jet fuels. Sorption measurements were performed for polymer/fluid couples, and experimental values were analysed with chemoinformatics tools, and a machine learning method (*i.e.* MGGP) and molecular descriptors (*i.e.* FGCD) were used to derive predictive models.

Performed sorption experiments to evaluate NBR, FVMQ, and FKM compatibility with a series of hydrocarbons mixtures, have shown that FKM can be assumed as a barrier polymer in case of such fluids, and that ΔM values obtained for the FVMQ are small as compared to those for NBR. If n- and iso-paraffins are fewly ingress into the NBR matrix, we demonstrated that the swelling of NBR is strongly related to the amount of aromatics in the studied liquids.

Machine learning techniques were used to derive two types of predictive models. The first type of models aimed in predicting plateau ΔM values, the maximum mass percentage gains. Models successfully reproduced experimental data, and indicate that increasing the number of -CH_2- groups and aromatic rings in the fluid leads to decreasing and increasing the amount of liquid sorbed into NBR, respectively. Application of the models to external multi-component mixtures (not considered during the training procedure) have demonstrated their predictive capabilities. The second type of models aimed in predicting the sorption kinetics, *i.e.* the time evolution of ΔM. Models reasonably reproduced experimental data, and in these models too, increasing the number of aromatic rings in fluid contributes in increasing predicted values of ΔM, in NBR. Application of these models to external fluids have demonstrated their capabilities in predicting both the kinetics and the maximum ΔM values.

The determination of gases and liquids sorption into polymers is fundamental in many applications: fuels, lubricants, packaging, gas and liquids transport and storage, among others. Our work shows that when using a good quality database and relevant descriptions of fluids, machine learning approaches are capable to catch soprtion phenomenon, and the so-obtained predictive models are powerful tools to accurately estimate the sorption of chemicals into a polymer. Moreover, such a modelling approach contributes to drastically reduce the time necessary to quantify polymeric materials compatibility with a fluid candidate only knowing some of its structural characteristics. This work is to be extended to other families of polymers and

fluids, as well as to explore new conditions of temperature and pressure. The use of such models is interesting for assessing the impact of advanced fuels formulations, for evaluating the impact of certain chemical families, or even for determining the maximum amounts of biomass-based fluids into fuels. In addition, these models could be used to replace the current qualitative information — green, orange, and red symbols — in polymer compatibility charts provided by resellers on their websites. The inversion of models based on machine learning represents another interesting prospect for the design of new polymers with desired properties [62, 63, 64].

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References

[1] H. K. Jeswani, A. Chilvers, A. Azapagic, Environmental sustainability of biofuels: a review, Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences 476 (2020) 20200351.

[2] D. A. Saldana, B. Creton, P. Mougin, N. Jeuland, B. Rousseau, L. Starck, Rational formulation of alternative fuels using QSPR methods: Application to jet fuels, Oil Gas Sci. Technol. - Rev. IFP Energies nouvelles 68 (2013) 651–662.

[3] D. A. Saldana, L. Starck, P. Mougin, B. Rousseau, L. Pidol, N. Jeuland, B. Creton, Flash point and cetane number predictions for fuel compounds using quantitative structure property relationship (QSPR) methods, Energy & Fuels 25 (2011) 3900–3908.

[4] H. Schulz, Short history and present trends of fischer-tropsch synthesis, Applied Catalysis A: General 186 (1999) 3–12.

[5] K. Murata, Y. Liu, M. Inaba, I. Takahara, Production of synthetic diesel by hydrotreatment of jatropha oils using Pt-Re/H-ZSM-5 catalyst, Energy & Fuels 24 (2010) 2404–2409.

[6] W. Weiss, H. Dulot, A. Quignard, N. Charon, M. Courtiade, Direct coal to liquids (DCL): High quality jet fuels, in: 27th Annual International Pittsburgh Coal Conference, 2010.

[7] T. R. Carlson, G. A. Tompsett, W. C. Conner, G. W. Huber, Aromatic production from catalytic fast pyrolysis of biomass-derived feedstocks, Topics in Catalysis 52 (2009) 241–252.

[8] S. Akhlaghi, U. W. Gedde, M. S. Hedenqvist, M. T. Conde Braña, M. Bellander, Deterioration of automotive rubbers in liquid biofuels: A review, Renewable and Sustainable Energy Reviews 43 (2015) 1238–1248.

[9] X.-F. Wei, L. De Vico, P. Larroche, K. J. Kallio, S. Bruder, M. Bellander, U. W. Gedde, M. S. Hedenqvist, Ageing properties and polymer/fuel interactions of polyamide 12 exposed to (bio)diesel at high temperature, npj Materials Degradation 3 (2019) 1.

[10] P. M. Subramanian, Polymer Blends, American Chemical Society, Washington, DC, 1990, pp. 252–265. doi:10.1021/bk-1990-0423.ch013.

[11] S. M. Alves, V. S. E. Mello, F. K. Dutra-Pereira, Biodiesel compatibility with elastomers and steel, in: E. Jacob-Lopes, L. Queiroz Zepka (Eds.), Frontiers in bioenergy and biofuels, InTech, Rijeka, 2017. doi:10.5772/65551.

[12] P. Izák, L. Bartovská, K. Friess, M. Šípek, P. Uchytil, Comparison of various models for transport of binary mixtures through dense polymer membrane, Polymer 44 (2003) 2679–2687.

[13] A. Randová, L. Bartovská, K. Friess, Š. Hovorka, P. Izák, Fundamental study of sorption of pure liquids and liquid mixtures into polymeric membrane, European Polymer Journal 61 (2014) 64–71.

[14] A. Randová, L. Bartovská, P. Izák, K. Friess, A new prediction method for organic liquids sorption into polymers, Journal of Membrane Science 475 (2015) 545–551.

[15] L. Krajakova, M. Laskova, J. Chmelar, K. Jindrova, J. Kosek, Sorption of liquid diluents in polyethylene: Comprehensive experimental data for slurry polymerization, Industrial & Engineering Chemistry Research 58 (2019) 7037–7043.

[16] A. Haseeb, M. A. Fazal, M. I. Jahirul, H. H. Masjuki, Compatibility of automotive materials in biodiesel: A review, Fuel 90 (2011) 922–931.

[17] A. Haseeb, T. S. Jun, M. A. Fazal, H. H. Masjuki, Degradation of physical properties of different elastomers upon exposure to palm biodiesel, Energy 36 (2011) 1814–1819.

[18] M. D. Kass, T. Theiss, S. Pawel, J. Baustian, L. Wolf, W. Koch, C. Janke, Compatibility assessment of elastomer materials to test fuels representing gasoline blends containing ethanol and isobutanol, SAE Int. J. Fuels Lubr. 7 (2014) 445–456.

[19] L. M. Silva, E. G. Filho, A. J. Simpson, M. R. Monteiro, T. Venâncio, Comprehensive multiphase NMR spectroscopy: A new analytical method to study the effect of biodiesel blends on the structure of commercial rubbers, Fuel 166 (2016) 436–445.

[20] W. Trakarnpruk, S. Porntangjitlikit, Palm oil biodiesel synthesized with potassium loaded calcined hydrotalcite and effect of biodiesel blend on elastomer properties, Renewable Energy 33 (2008) 1558–1563.

[21] M. Weltschev, F. Heming, M. Haufe, M. Heyer, The influence of the age of biodiesel and heating oil with 10 % biodiesel on the resistance of sealing materials at different temperatures, Materialwissenschaft und Werkstofftechnik 48 (2017) 837–845.

[22] A. Plota, A. Masek, Lifetime prediction methods for degradable polymeric materials? a short review, Materials 13 (2020) 4507.

[23] N. Nosengo, Can artificial intelligence create the next wonder material?, Nature 533 (2016) 22–25.

[24] Y. Liu, Z. Hu, Z. Suo, L. Hu, L. Feng, X. Gong, Y. Liu, J. Zhang, High-throughput experiments facilitate materials innovation: A review, Science China Technological Sciences 62 (2019) 521–545.

[25] Y. Liu, O. C. Esan, Z. Pan, L. An, Machine learning for advanced energy materials, Energy and AI 3 (2021) 100049.

[26] D. J. Audus, J. J. de Pablo, Polymer informatics: Opportunities and challenges, ACS Macro Letters (2017) 1078–1082.

[27] L. Chen, G. Pilania, R. Batra, T. D. Huan, C. Kim, C. Kuenneth, R. Ramprasad, Polymer informatics: Current status and critical next steps, Materials Science and Engineering: R: Reports 144 (2021) 100595.

[28] A. R. Katritzky, S. Sild, M. Karelson, Correlation and prediction of the refractive indices of polymers by QSPR, Journal of Chemical Information and Computer Sciences 38 (1998) 1171–1176.

[29] A. R. Katritzky, M. Kuanar, S. Slavov, C. D. Hall, M. Karelson, I. Kahn, D. A. Dobchev, Quantitative correlation of physical and chemical properties with chemical structure: utility for prediction, Chemical reviews 110 (2010) 5714–5789.

[30] T. Le, V. C. Epa, F. R. Burden, D. A. Winkler, Quantitative structure-property relationship modeling of diverse materials properties, Chemical reviews 112 (2012) 2889–2919.

[31] M. E. Erickson, M. Ngongang, B. Rasulev, A refractive index study of a diverse set of polymeric materials by QSPR with quantum-chemical and additive descriptors, Molecules 25 (2020).

[32] S. A. Schustik, F. Cravero, I. Ponzoni, M. F. Daz, Polymer informatics: Expert-in-the-loop in QSPR modeling of refractive index, Computational Materials Science 194 (2021) 110460.

[33] A. J. Holder, L. Ye, J. D. Eick, C. C. Chappelow, A quantum-mechanical QSAR model to predict the refractive index of polymer matrices, QSAR & Combinatorial Science 25 (2006) 905–911.

[34] P. R. Duchowicz, S. E. Fioressi, D. E. Bacelo, L. M. Saavedra, A. P. Toropova, A. A. Toropov, QSPR studies on refractive indices of structurally heterogeneous polymers, Chemometrics and Intelligent Laboratory Systems 140 (2015) 86–91.

[35] F. Jabeen, M. Chen, B. Rasulev, M. Ossowski, P. Boudjouk, Refractive indices of diverse data set of polymers: A computational QSPR based study, Computational Materials Science 137 (2017) 215–224.

[36] A. G. Mercader, P. R. Duchowicz, Encoding alternatives for the prediction of polyacrylates glass transition temperature by quantitative structure–property relationships, Materials Chemistry and Physics 172 (2016) 158–164.

[37] A. G. Mercader, D. E. Bacelo, P. R. Duchowicz, Different encoding alternatives for the prediction of halogenated polymers glass transition temperature by quantitative structure–property relationships, International Journal of Polymer Analysis and Characterization (2017) 1–10.

[38] A. Karuth, A. Alesadi, W. Xia, B. Rasulev, Predicting glass transition of amorphous polymers by application of cheminformatics and molecular dynamics simulations, Polymer 218 (2021) 123495.

[39] A. Toropov, A. Toropova, V. Kudyshkin, N. Bozorov, S. Rashidova, Applying the monte carlo technique to build up models of glass transition temperatures of diverse polymers, Structural Chemistry 31 (2020) 1739–1743.

[40] F. Cravero, M. J. Martnez, I. Ponzoni, M. F. Daz, Computational modelling of mechanical properties for new polymeric materials with high molecular weight, Chemometrics and Intelligent Laboratory Systems 193 (2019) 103851.

[41] F. Cravero, M. J. Martnez, G. Vazquez, M. F. Daz, I. Ponzoni, Feature learning applied to the estimation of tensile strength at break in polymeric material design, Journal of Integrative Bioinformatics 13 (2016) 15–29.

[42] T. Zhu, Y. Jiang, C. Haomiao, R. P. Singh, B. Yan, Development of pp-LFER and QSPR models for predicting the diffusion coefficients of hydrophobic organic compounds in ldpe, Ecotoxicology and Environmental Safety 190 (2020) 110179.

[43] M. Li, H. Yu, Y. Wang, J. Li, G. Ma, X. Wei, QSPR models for predicting the adsorption capacity for microplastics of polyethylene, polypropylene and polystyrene, Scientific Reports 10 (2020) 14597.

[44] N. Villanueva, B. Flaconnèche, B. Creton, Prediction of alternative gasoline sorption in a semicrystalline poly(ethylene), ACS combinatorial science 17 (2015) 631–640.

[45] L. Starck, L. Pidol, N. Jeuland, T. Chapus, P. Bogers, J. Bauldreay, Production of hydroprocessed esters and fatty acids (HEFA) - optimisation of process yield, Oil Gas Sci. Technol. - Rev. IFP Energies nouvelles 71 (2016) 10.

[46] C. Hall, B. Rauch, U. Bauder, P. Le Clercq, M. Aigner, Predictive capability assessment of probabilistic machine learning models for density prediction of conventional and synthetic jet fuels, Energy & Fuels 35 (2021) 2520–2530.

[47] B. Creton, Chemoinformatics at IFP energies nouvelles: Applications in the fields of energy, transport, and environment, Molecular Informatics 36 (2017) 1700028.

[48] C. Nieto-Draghi, G. Fayet, B. Creton, X. Rozanska, P. Rotureau, J.-C. de Hemptinne, P. Ungerer, B. Rousseau, C. Adamo, A general guidebook for the theoretical prediction of physicochemical properties of chemicals for regulatory purposes, Chemical Reviews 115 (2015) 13093–13164.

[49] P. Gramatica, Principles of QSAR models validation: Internal and external, QSAR and Combinatorial Science 26 (2007) 694–701.

[50] E. N. Muratov, E. V. Varlamova, A. G. Artemenko, P. G. Polishchuk, V. E. Kuz'Min, Existing and developing approaches for QSAR analysis of mixtures, Molecular Informatics 31 (2012) 202–221.

[51] T.-B. Nguyen, J.-C. de Hemptinne, B. Creton, G. M. Kontogeorgis, Characterization scheme for property prediction of fluid fractions originating from biomass, Energy & Fuels 29 (2015) 7230–7241.

[52] D. Steinmetz, K. R. Arriola Gonzlez, R. Lugo, J. Verstraete, V. Lachet, A. Mouret, B. Creton, C. Nieto-Draghi, Experimental and mesoscopic modeling study of water/crude oil interfacial tension, Energy & Fuels (2021).

[53] C. Vendeuvre, R. Ruiz-Guerrero, F. Bertoncini, L. Duval, D. Thiébaut, Comprehensive two-dimensional gas chromatography for detailed characterisation of petroleum products, Oil Gas Sci. Technol. - Rev. IFP Energies nouvelles 62 (2007) 43–55.

[54] SMARTS - a language for describing molecular patterns; daylight chemical information systems inc.: Laguna niguel, ca, Accessed in 2020. URL: http://www.daylight.com/dayhtml/doc/theory/theory.smarts.html.

[55] RDKit: Open-Source Cheminformatics Software, Accessed in 2020. URL: http://www.rdkit.org/.

[56] C. Muller, A. G. Maldonado, A. Varnek, B. Creton, Prediction of optimal salinities for surfactant formulations using a quantitative structure-property relationships approach, Energy Fuels 29 (2015) 4281–4288.

[57] D. Searson, D. Leahy, M. Willis, GPTIPS: an open source genetic programming toolbox for multigene symbolic regression, Proceedings of the International MultiConference of Engineers and Computer Scientists 2010 (IMECS 2010), Hong Kong, 17-19 March (2010) 77–80.

[58] A. Gandomi, A. Alavi, C. Ryan, Handbook of Genetic Programming Applications, Springer International Publishing, New York, 2015.

[59] D. Searson, Handbook of Genetic Programming Applications, in: [58], 2015.

[60] B. Creton, I. Lévêque, F. Oukhemanou, Equivalent alkane carbon number of crude oils: A predictive model based on machine learning, Oil Gas Sci. Technol. - Rev. IFP Energies nouvelles 74 (2019) 30.

[61] O. Agwu, J. U. Akpabio, A. Dosunmu, Modeling the downhole density of drilling muds using multigene genetic programming, Upstream Oil and Gas Technology (2021) 100030.

[62] P. Gantzer, B. Creton, C. Nieto-Draghi, Inverse-QSPR for de novo design: A review, Molecular Informatics 39 (2020) 1900087.

[63] P. Gantzer, B. Creton, C. Nieto-Draghi, Comparisons of molecular structure generation methods based on fragment assemblies and genetic graphs, Journal of Chemical Information and Modeling 61 (2021) 4245–4258.

[64] K. Sattari, Y. Xie, J. Lin, Data-driven algorithms for inverse design of polymers, Soft Matter 17 (2021) 7607–7622.