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|  | <b>QMRF identifier (JRC Inventory): Q17-19-0020</b>     |
|   | <b>QMRF Title: OPERA-model for Henry's Law constant</b> |
|   | <b>Printing Date: Apr 16, 2018</b>                      |
|   |   |

## 1. QSAR identifier

### 1.1. QSAR identifier (title):

OPERA-model for Henry's Law constant

### 1.2. Other related models:

No related models

### 1.3. Software coding the model:

OPERA V1.5

OPERA (OPEn (quantitative) structure-activity Relationship Application) is a standalone free and open source command line application. It provides a suite of QSAR models to predict physicochemical properties and environmental fate of organic chemicals based on PaDEL descriptors. It is available for download in Matlab, C and C++ languages from github under MIT license.

Kamel Mansouri (mansourikamel@gmail.com)

<https://github.com/kmansouri/OPERA.git>

PaDEL descriptors V2.21

Open source software to calculate molecular descriptors and fingerprints.

Chun Wei Yap (phayapc@nus.edu.sg)

<http://padel.nus.edu.sg/software/padeldescriptor>

MATLAB V8.2

MATrix LABoratory is a multi-paradigm numerical computing environment and fourth-generation programming language

[http://www.mathworks.com/company/aboutus/contact\\_us/?s\\_tid=gn\\_cntus](http://www.mathworks.com/company/aboutus/contact_us/?s_tid=gn_cntus)

<http://www.mathworks.com/products/matlab/>

## 2. General information

### 2.1. Date of QMRF:

1 November 2016

### 2.2. QMRF author(s) and contact details:

[1]Kamel Mansouri, ORISE research fellow at National Center for Computational Toxicology (NCCT), U.S. Environmental Protection Agency, mansourikamel@gmail.com

[2]Antony Williams, National Center for Computational Toxicology (NCCT), U.S. Environmental Protection Agency, Williams.Antony@epa.gov

### 2.3. Date of QMRF update(s):

### 2.4. QMRF update(s):

### 2.5. Model developer(s) and contact details:

Kamel Mansouri, ORISE research fellow at National Center for Computational Toxicology (NCCT),  
U.S. Environmental Protection Agency, mansourikamel@gmail.com

## **2.6.Date of model development and/or publication:**

2016

## **2.7.Reference(s) to main scientific papers and/or software package:**

- [1]An automated curation procedure for addressing chemical errors and inconsistencies in public datasets used in QSAR modeling. 2016. Kamel Mansouri, Chris M. Grulke, Ann M. Richard, Richard S. Judson and Antony J. Williams. SAR & QSAR in Environ. Res; Vol. 27 , Iss. 11,2016. doi: 10.1080/1062936X.2016.1253611. <http://www.qsar2016.com/program>
- [2]OPERA: A free and open source QSAR tool for physicochemical properties and environmental fate predictions. Kamel Mansouri, Chris Grulke, Richard Judson, Antony Williams, Journal of Cheminformatics (2017)
- [3]PaDEL-descriptor: an open source software to calculate molecular descriptors and fingerprints. Chun Wei Yap. (2011). J. Comput. Chem., 32: 1466–1474. doi:10.1002/jcc.21707 <http://onlinelibrary.wiley.com/doi/10.1002/jcc.21707/abstract>
- [4]A KNIME workflow for chemical structures curation and standardization in QSAR modeling. Kamel Mansouri, Sherif Farag, Jayaram Kancherla, Regina Politi, Eugene Muratov, Denis Fourches, Nikolai Nikolov, Eva Bay Wedebay, Christopher Grulke, Ann Richard, Richard Judson, Alexander Tropsha. (in preparation)
- [5]The influence of data curation on QSAR Modeling – examining issues of quality versus quantity of data (SOT). Williams, A., K. Mansouri, A. Richard, AND C. Grulke. Presented at Society of Toxicology, New Orleans, LA, March 13 - 17, 2016. [https://cfpub.epa.gov/si/si\\_public\\_record\\_report.cfm?dirEntryId=311418](https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=311418)
- [6]An Online Prediction Platform to Support the Environmental Sciences (American Chemical Society). Richard, A., C. Grulke, K. Mansouri, R. Judson, AND A. Williams. Presented at ACS Spring Meeting, San Diego, CA, March 13 - 17, 2016. [https://cfpub.epa.gov/si/si\\_public\\_record\\_Report.cfm?dirEntryId=311655](https://cfpub.epa.gov/si/si_public_record_Report.cfm?dirEntryId=311655)
- [7]The importance of data curation on QSAR Modeling: PHYSPROP open data as a case study. Kamel Mansouri, Christopher Grulke Ann Richard Richard Judson Antony Williams. Presented at QSAR2016 14 June 2016, Miami, FL <http://www.qsar2016.com/program>
- [8]Mansouri K. (2017) OPERA: A QSAR tool for physicochemical properties and environmental fate predictions. doi: 10.6084/m9.figshare.4836428 [https://figshare.com/articles/OPERA\\_A\\_QSAR\\_tool\\_for\\_physicochemical\\_properties\\_and\\_environmental\\_fate\\_predictions/4836428](https://figshare.com/articles/OPERA_A_QSAR_tool_for_physicochemical_properties_and_environmental_fate_predictions/4836428)

## **2.8.Availability of information about the model:**

Non-proprietary suite of QSAR models freely available as a command line standalone application (OPERA: OPEn saR App) from github under MIT license: <https://github.com/kmansouri/OPERA.git>. Its predictions for the full DSSTox 720k chemicals are published on the EPA CompTox Chemistry Dashboard ( <https://comptox.epa.gov/dashboard>). Training and validation sets are available for visualization on the dashboard and as SDF files provided in supporting information Section 9.3 and from the

p a p e r [ r e f 1 - 2 , S e c t i o n 2 . 7 ] . ( [ftp://newftp.epa.gov/COMPTOX/Sustainable\\_Chemistry\\_Data/Chemistry\\_Dashboard/PHYSPROP\\_Analysis](ftp://newftp.epa.gov/COMPTOX/Sustainable_Chemistry_Data/Chemistry_Dashboard/PHYSPROP_Analysis))

## **2.9.Availability of another QMRF for exactly the same model:**

Not to date

### **3.Defining the endpoint - OECD Principle 1**

#### **3.1.Species:**

Not applicable

#### **3.2.Endpoint:**

1.Physical Chemical Properties 1.9.Air- water partition coefficient (Henry's law constant, H)

#### **3.3.Comment on endpoint:**

Henry's Law is defined that at a constant temperature, the amount of a given gas that dissolves in a given type and volume of liquid is directly proportional to the partial pressure of that gas in equilibrium with that liquid.

#### **3.4.Endpoint units:**

Log atm-m<sup>3</sup>/mole

#### **3.5.Dependent variable:**

LogHL

#### **3.6.Experimental protocol:**

The experimental data were downloaded from the EPI Suite data webpage (<http://esc.syrres.com/interkow/EpiSuiteData.htm>).

These data are from PHYSPROP (The Physical Properties Database) which is a collection of a wide variety of sources built by Syracuse Research Corporation (SRC). Experimental protocols of the different parts of data can be traced back to the original referenced literature from the database.

#### **3.7.Endpoint data quality and variability:**

The original data collected from the PHYSPROP database (1829 chemicals) have undergone a series of processes to curate the chemical structures and remove duplicates, obvious outliers and erroneous entries. This procedure also included a consistency check to ensure only good quality data is used for the development of the QSAR model (1758 chemicals).

Then, QSAR-ready structures were generated by standardizing all chemical structures and removing duplicates, inorganic and metallo-organic chemicals (1711 chemicals). The descriptions of KNIME workflows that were developed for the purpose of the cleaning and standardization of the data are available in the papers [ref 1 and ref 4 Section 2.7].

The curated outlier-free experimental data (591 chemicals) was divided into training and validation sets before the machine learning and modeling steps.

### **4.Defining the algorithm - OECD Principle 2**

#### **4.1.Type of model:**

QSAR/QSPR model derived derived from weighted nearest neighbors algorithm (kNN) based on PaDEL descriptors [ref2 Sect 1.3].

#### 4.2. Explicit algorithm:

Distance weighted k-nearest neighbors (kNN). k=5

This is a refinement of the classical k-NN classification algorithm where the contribution of each of the k neighbors is weighted according to their distance to the query point, giving greater weight to closer neighbors. The used distance is the Euclidean distance. kNN is an unambiguous algorithm that fulfills the transparency requirements of OECD principle 2 with an optimal compromise between model complexity and performance.

#### 4.3. Descriptors in the model:

[1]nHBDon, Unitless, Hbond donor count: Number of hydrogen bond donors (using CDK HBondDonorCountDescriptor algorithm).

[2]MLFER\_S, Unitless, Molecular linear free energy relation: Combined dipolarity/polarizability. Platts JA, Butina D, Abraham MH, Hersey A. Estimation of molecular free energy relation descriptors using a group contribution approach. J Chem Inf Comput Sci. 1999;39(5):835-45.

[3]GATS1e, Unitless, Geary autocorrelation - lag 1 / weighted by Sanderson electronegativities. Todeschini, R. and Consonni, V. (2009). Molecular descriptors for chemoinformatics, (Weinheim: Wiley VCH) pg 27-37

[4]ndssC, Unitless, Atom type electrotopological state: Count of atom-type E-State: =C<. Hall, L. H., and Kier, L. B. (1995). Electrotopological state indices for atom types: A novel combination of electronic, topological, and valence state information. J Chem Inf Comput Sci 35, 1039-1045; Liu, R., Sun, H., and So, S. S. (2001). Development of quantitative structure-property relationship models for early ADME evaluation in drug discovery. 2. Blood-brain barrier penetration. J Chem Inf Comput Sci 41, 1623-1632.; Gramatica, P., Corradi, M., and Consonni, V. (2000). Modelling and prediction of soil sorption coefficients of non-ionic organic pesticides by molecular descriptors. Chemosphere 41, 763-777.

[5]ATS3m, Unitless, Broto-Moreau autocorrelation - lag 3 / weighted by mass. Todeschini, R. and Consonni, V. (2009). Molecular descriptors for chemoinformatics, (Weinheim: Wiley VCH) pg 27-37

[6]nHBint6, Unitless, Atom type electrotopological state: Count of E-State descriptors of strength for potential Hydrogen Bonds of path length 6. Hall, L. H., and Kier, L. B. (1995). Electrotopological state indices for atom types: A novel combination of electronic, topological, and valence state information. J Chem Inf Comput Sci 35, 1039-1045; Liu, R., Sun, H., and So, S. S. (2001). Development of quantitative structure-property relationship models for early ADME evaluation in drug discovery. 2. Blood-brain barrier penetration. J Chem Inf Comput Sci 41, 1623-1632.; Gramatica, P., Corradi, M., and Consonni, V. (2000). Modelling and prediction of soil sorption coefficients of non-ionic organic pesticides by molecular descriptors. Chemosphere 41, 763-777.

[7]nHBAcc2, Unitless, Number of hydrogen bond acceptors (any oxygen; any nitrogen where the formal charge of the nitrogen is non-positive (i.e. formal charge  $\leq 0$ ) except a non-aromatic nitrogen that is adjacent to an oxygen and aromatic ring, or an aromatic nitrogen with a hydrogen atom in a ring, or an aromatic nitrogen with 3 neighbouring atoms in a ring, or a nitrogen with total bond order  $\geq 4$ ; any fluorine).

[8]AATSC0i, Unitless, Average centered Broto-Moreau autocorrelation - lag 0 / weighted by first ionization potential. Todeschini, R. and Consonni, V. (2009). Molecular descriptors for chemoinformatics, (Weinheim: Wiley VCH) pg 27-37

[9]SpAD\_Dzm, Unitless, Barysz matrix: Spectral absolute deviation from Barysz matrix / weighted by mass. Todeschini, R. and Consonni, V. (2009). Molecular descriptors for chemoinformatics, (Weinheim: Wiley VCH) pg 714-726

#### 4.4.Descriptor selection:

PaDEL software was used to calculate 1440 molecular descriptors. A first filter was applied in order to remove descriptors with missing values, constant and near constant (standard deviation of 0.25 as a threshold) and highly correlated descriptors (96% as a threshold). The remaining 765 descriptors were used in a feature selection procedure to select a minimum number of variables encoding the most relevant structural information to the modeled endpoint. This step consisted of coupling Genetic Algorithms (GA) with the weighted kNN algorithm and was applied in 5 fold cross validation on the training set (441 chemicals). This procedure was run for 200 consecutive independent runs maximizing  $Q^2$  in cross-validation and minimizing the number of descriptors. The number of k neighbors is optimized within the range of 3 to 7. The descriptors were then ranked based on their frequency of selection during the GA runs. The best model showed an optimal compromise between the simplicity (minimum number of descriptors) and performance ( $Q^2$  in cross-validation) to ensure transparency and facilitate the mechanistic interpretation as required by OECD principles 2 and 5. More details in paper [ref2 Section 2.7].

#### 4.5.Algorithm and descriptor generation:

PaDEL descriptors were calculated based on two-dimensional (2D) chemical structures generated by the Indigo cheminformatics suite of tools implemented in KNIME. 2D descriptors were selected over 3D to avoid complicated and usually irreproducible geometrical optimizations. The calculated descriptors fall into different groups such as constitutional indices, ring descriptors, topological indices, 2D matrix based descriptors, functional group counts and atom counts. Details and references provided in Section 4.3.

#### 4.6.Software name and version for descriptor generation:

PaDEL-Descriptors V2.21

An open source software to calculate molecular descriptors and fingerprints.

Chun Wei Yap (phayapc@nus.edu.sg)

<http://padel.nus.edu.sg/software/padeldescriptor>

#### 4.7.Chemicals/Descriptors ratio:

441 chemicals (trainingset)/9 descriptors= 49

### 5.Defining the applicability domain - OECD Principle 3

#### 5.1.Description of the applicability domain of the model:

The model is applicable to heterogeneous organic chemicals. In the implementation of the model several pieces of information are given to help the user in evaluating the reliability of a prediction. The chemical structure is first assessed to see if it is falling within the Applicability Domain of the model or not. Then the accuracy of the predicted value is reported based on the similarity of the query chemical to its neighboring chemicals in the training set of the model. This fulfills the requirements of the 3rd OECD principle by defining

the limitations in terms of the types of chemical structures, physicochemical properties and mechanisms of action for which the model can generate reliable predictions.

### **5.2.Method used to assess the applicability domain:**

The applicability domain of the model is assessed in two independent levels using two different distance-based methods. First, a global applicability domain is determined by means of the leverage approach that checks whether the query structure falls within the multidimensional chemical space of the whole training set.

The leverage of a query chemical is proportional to its Mahalanobis distance measure from the centroid of the training set. The leverages of a given dataset are obtained from the diagonal values of the hat matrix. This approach is associated with a threshold leverage that corresponds to  $3 \cdot p/n$  where  $p$  is the number of model variables while  $n$  is the number of training compounds. A query chemical with leverage higher than the threshold is considered outside the AD and can be associated with unreliable prediction.

The leverage approach has specific limitations, in particular with respects to gaps within the descriptor space of the model or at the boundaries of the training set. To obviate such limitations, a second tier of applicability domain assesment was added. This comprised a local approach which only investigated the vicinity of the query chemical. This local approach provides a continuous index ranging from 0 to 1 which is different from the first approach which only provides Boolean answers (yes/no). This local AD-index is relative to the similarity of the query chemical to its 5 nearest neighbors in the  $p$  dimensional space of the model. The higher this index, the more the prediction is likely to be reliable.

### **5.3.Software name and version for applicability domain assessment:**

Implemented in OPERA V1.5

An implementation of a local similarity index and the leverage approach based on the work of Sahigara, F.; Mansouri, K.; Ballabio, D.; Mauri, A.; Consonni, V.; Todeschini, R. Comparison of Different Approaches to Define the Applicability Domain of QSAR Models. *Molecules* 2012, 17, 4791-4810.

Kamel Mansouri (mansourikamel@gmail.com);  
<https://github.com/kmansouri/OPERA.git>

### **5.4.Limits of applicability:**

These two AD methods described in Section 5.2 are complementary and can be interpreted in the following way:

- If a chemical is considered outside the global AD with a low local AD-index, the prediction can be unreliable
- If a chemical is considered outside the global AD but the local AD-index is average or relatively high, this means the query chemical is on the boundaries of the training set but has quite similar neighbors. The prediction can be trusted.
- If a chemical is considered inside the global AD but the local

AD-index is average or relatively low, this means the query chemical fell in a "gap" of the chemical space of the model but still within the boundaries of the training set and surrounded with training chemicals.

The prediction should be considered with caution.

- If a chemical is considered inside the global AD with a high local AD-index, the prediction should be considered reliable.

Even though the applicability domain is necessary to set the limits of the interpolation space of the model, it doesn't necessarily inform about the quality of the prediction especially in the empty spaces and around the edges of the descriptor space. In order to overcome this limitation and help the user decide about the reliability of a prediction, we added a confidence level index ranging from 0 to 1 relative to the accuracy of prediction of the 5 nearest neighbors to the query chemical. The higher this index, the more the prediction is likely to be reliable.

## **6.Internal validation - OECD Principle 4**

### **6.1.Availability of the training set:**

Yes

### **6.2.Available information for the training set:**

Internal ID; CAS checksum; name validity; preferred name; IUPAC name; Original SMILES; QSAR-ready canonical smiles; InChI; Salt information; DSSTox GSID; Experimental reference; Consistency flag

CAS RN: Yes

Chemical Name: Yes

Smiles: Yes

Formula: No

INChI: Yes

MOL file: Yes

### **6.3.Data for each descriptor variable for the training set:**

All

### **6.4.Data for the dependent variable for the training set:**

All

### **6.5.Other information about the training set:**

The training set consists of 441 chemicals. The structures are randomly selected to represent 75% of the available data keeping a similar normal distribution of HL values in both training and test sets using the Venetian blinds method. The values are ranging from ~-13 to ~1.5. A plot of the distribution of HL values is provided in the supporting information Section 9.3.

### **6.6.Pre-processing of data before modelling:**

No preprocessing of the values.

### **6.7.Statistics for goodness-of-fit:**

Performance in training:

$R^2=0.84$

RMSE=1.91

**6.8. Robustness - Statistics obtained by leave-one-out cross-validation:**

**6.9. Robustness - Statistics obtained by leave-many-out cross-validation:**

Performance in 5-fold cross-validation:

$$Q^2=0.84$$

$$RMSE=1.96$$

A plot of the experimental versus predicted values

for the training set is provided in supporting information Section 9.3.

**6.10. Robustness - Statistics obtained by Y-scrambling:**

**6.11. Robustness - Statistics obtained by bootstrap:**

**6.12. Robustness - Statistics obtained by other methods:**

## **7. External validation - OECD Principle 4**

**7.1. Availability of the external validation set:**

Yes

**7.2. Available information for the external validation set:**

Internal ID; CAS checksum; name validity; preferred name; IUPAC name; Original SMILES; QSAR-ready canonical smiles; InChI; Salt information; DSSTox GSID; Experimental reference; Consistency flag

CAS RN: Yes

Chemical Name: Yes

Smiles: Yes

Formula: No

INChI: Yes

MOL file: Yes

**7.3. Data for each descriptor variable for the external validation set:**

All

**7.4. Data for the dependent variable for the external validation set:**

All

**7.5. Other information about the external validation set:**

The validation set consists of 150 chemicals.

The values are ranging from ~-10 to ~0.5.

**7.6. Experimental design of test set:**

The structures are randomly selected to represent 25% of the available data keeping a similar normal distribution of HL values in both training and test sets using the Venetian blinds method. A plot of the distribution of HL values is provided in the supporting information [Section 9.3](#).

**7.7. Predictivity - Statistics obtained by external validation:**

Performance in test:

$$R^2=0.85$$

$$RMSE=1.82$$

**7.8. Predictivity - Assessment of the external validation set:**



The validation set consisting of 150 chemicals which is equivalent to a third (1/3) of the training set is sufficient for the evaluation of the predictivity of the model and a good representation of the chemical space as shown in the multi-dimensional scaling plot provided in supporting information Section 9.3. A plot of the experimental versus predicted values for the validation set is provided in supporting information Section 9.3.

#### **7.9. Comments on the external validation of the model:**

The choice of proportions between the training set and the validation set as well as the splitting method helped in accurately evaluating the model and covering most of the training set chemical space. This goal was accomplished without the need to do a structural sampling that usually shows over-optimistic evaluation of the predictivity or a complete random selection that risks biasing the evaluation towards a certain region of the chemical space.

### **8. Providing a mechanistic interpretation - OECD Principle 5**

#### **8.1. Mechanistic basis of the model:**

The model descriptors were selected statistically but they can also be mechanistically interpreted.

Henry's Law definition: the mass of gas dissolved by a given volume of solvent is proportional to the pressure of the gas with which it is in equilibrium. So Henry's law constant is a measure of the relative affinity of a compound for the vapor phase and water.  $H$  depends mainly on interactions in the aqueous phase because in the gas phase, behavior is close to ideal. Interactions with water molecules is a constitutive property of the molecule and can involve hydrogen bonding and dipole-dipole, dipole-induced dipole, ion-dipole, and ion-induced dipole interactions, which are all exoergic. The molecular descriptors selected in our model include hydrogen donor and acceptor counts (nHBDon, nHBint6 and nHBacc2) as well as descriptors encoding information about the electronic profile of the molecule (AATSC0i, MLFER\_S, GATS1e and ndssC).

Dunnivant and Elzerman [ref 1,2 Section 9.2]

indicated that molecular size and shape are major factors controlling the magnitude of  $H$ . Molecular size plays a significant role here, since the larger the solute molecule, the larger the cavity that has to be created in water (by the breaking of hydrogen bonds) to accommodate it. Dearden and Schuurmann stated that increasing molecular size when considering both (quantum chemically calculated) electrostatics and surface area as a composite descriptor for cavitation and dispersion energies, increases Henry's law constant [ref 3 Section 9.2]. In our model, molecular size is encoded in 2 descriptors

(ATS3m and ApAD\_Dzm).

### **8.2.A priori or a posteriori mechanistic interpretation:**

A posteriori mechanistic interpretation.

### **8.3.Other information about the mechanistic interpretation:**

For more details and full reference, see  
references in Section 4.3 and Section 9.2.

## **9.Miscellaneous information**

### **9.1.Comments:**

This QSAR model for HL prediction is part of the NCCT\_Models Suite that is a free and open-source standalone application for the prediction of physicochemical properties and environmental fate of chemicals. This application is available in the Supporting information Section 9.3 of this report and in the paper ref 2 Section 2.7. The detailed results of this suite of models applied on more than 700k DSSTox chemicals are available on the iCSS chemistry dashboard (<https://comptox.epa.gov/dashboard>).

This current version of the model is mainly based on curated and standardized data collected from the Physprop database. All NCCT\_Models are designed to fulfil the requirement of the 5 OECD principles to ensure transparency and reproducibility of the results. In order to predict new chemicals, the models only require 2D chemical structures that are used to calculate molecular descriptors by PaDEL 2.21 software. Then a simple weighted kNN algorithm is used to make the prediction based on the observed values of the k closest molecules. All models showed high robustness and statistics stability between training, 5-fold cross-validation and the external validation set.

Considering the full applicability domain of the 591 chemicals with available data and the same models parameters described earlier, the calibration statistics would be an  $R^2$  of 0.85 and an RMSE of 1.83.

### **9.2.Bibliography:**

- [1]Dunnivant FM, Elzerman AW (1988). Aqueous solubility and Henry's law constant data for PCB congeners for evaluation of quantitative structure-property relationships (QSPRs). Chemosphere 17, 525–541.
- [2]Dunnivant FM, Elzerman AW, Jurs PC, Hasan MN (1992). Quantitative structure-property relationships for aqueous solubilities and Henry's law constants of polychlorinated biphenyls. Environ Sci Technol 26, 1567–1573.
- [3]Dearden JC, Schüürmann G (2003) Quantitative structure-property relationships for predicting henry's law constant from molecular structure 22 (8) 1755–1770

### **9.3.Supporting information:**

## **10.Summary (JRC QSAR Model Database)**

**10.1.QMRF number:**

Q17-19-0020

**10.2.Publication date:**

2017-09-21

**10.3.Keywords:**

Henry's Law constant;PaDEL;OPERA;

**10.4.Comments:**

To be entered by JRC