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How the "Liquid Drop" Approach Could Be Efficiently Applied for Quantitative Structure−Property Relationship Modeling of Nanofluids

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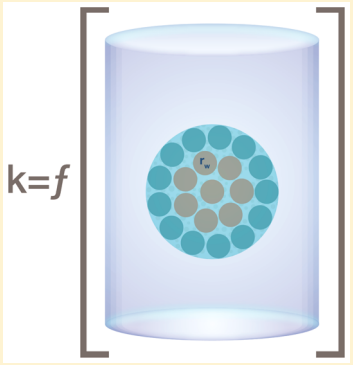
Supporting Information

ABSTRACT: The main goal of this paper is the evaluation of the applicability of the geometrical "liquid drop" model (LDM) to describe physicochemical properties of nanofluids in quantitative structure−property relationship (QSPR) modeling. LDM-based descriptors are size-dependent, which allows them to be applied for a series of nanoparticles with the same chemical composition but different sizes. Thermal conductivity of nanofluids as the target property was investigated. Random forest regression as a nonparametric approach was utilized to determine important structural features of nanofluids responsible for enhancing their thermal conductivity.



INTRODUCTION

Increasingly, the interest of scientists is focused on synthesizing novel nanoparticles and studying their properties.[1] Nanomaterials demonstrate unusual properties distinguishing them from bulk chemicals.[2] For instance, a small volume fraction of nanoparticles dispersed homogeneously into a base fluid (so-called "nanofluids") has a significant impact on the effective thermal conductivity of the fluid.[3]

The thermal conductivity of nanofluids plays a vital role in the development of energy efficient heat transfer equipment. However, the exact mechanism of the heat transfer in nanofluids is not yet well understood. There are four hypothetical mechanisms or features that have been proposed as most probably responsible for this phenomenon: (1) Brownian motion of the nanoparticle, (2) nanolayer formation, (3) clustering and aggregation, or (4) the nature of heat transport in the nanoparticles.[3−10] Many theoretical models are based on some approximations, for example, (1) the most probable shape of nanoparticles is spherical, (2) recognition or nonrecognition of dilution and suspending processes, and (3) absence of interaction between nanoparticles.[3−10] There are three excellent reviews presenting currently available thermal conductivity models for nanofluids.[11−13]

One of the most promising techniques to build mathematical models explaining variability in different properties of chemical compounds is qualitative or quantitative structure−property relationships (SPR or QSPR).[14] In the case of nanosized compounds, the technique is often referred to as "nano-SPR" or "nano-QSPR". Finally, when the model describes biological activity, it is usually abbreviated as "nano-SAR" or "nano-QSAR". A number of nano-QSAR models has been developed for inorganic nanoparticles.[15−23] However, physicochemical properties of inorganic nanoparticles have been modeled only by a few authors, for example, by Toropov and co-workers, who have employed SMILES-based optimal descriptors.[24,25] Our group has also previously developed a nano-QSPR model using a series of physicochemical descriptors (Figure 1).[26]

This study is aimed at generalizing the accumulated experience in this field and, on this basis, performing a detailed analysis of the thermal conductivity of nanofluids by means of nano-QSPR. On the basis of our previous successful experience with simplified representation of possible interactions at the nanolevel by means of the "liquid drop" model (LDM),[21] we are expanding the application of this approach to physical−chemical properties of nanofluids.

MATERIALS AND METHODS

Experimental Data. The original experimental data on the thermal conductivity were taken from the literature.[11−13,27] As was discussed in previous contributions,[28] physical properties of nanofluids depend not only on the size but also on the shape of the nanoparticles. In the current investigation, however, only particles reported to be spherical were included. As such, applicability domain of the model is restricted to spherical and

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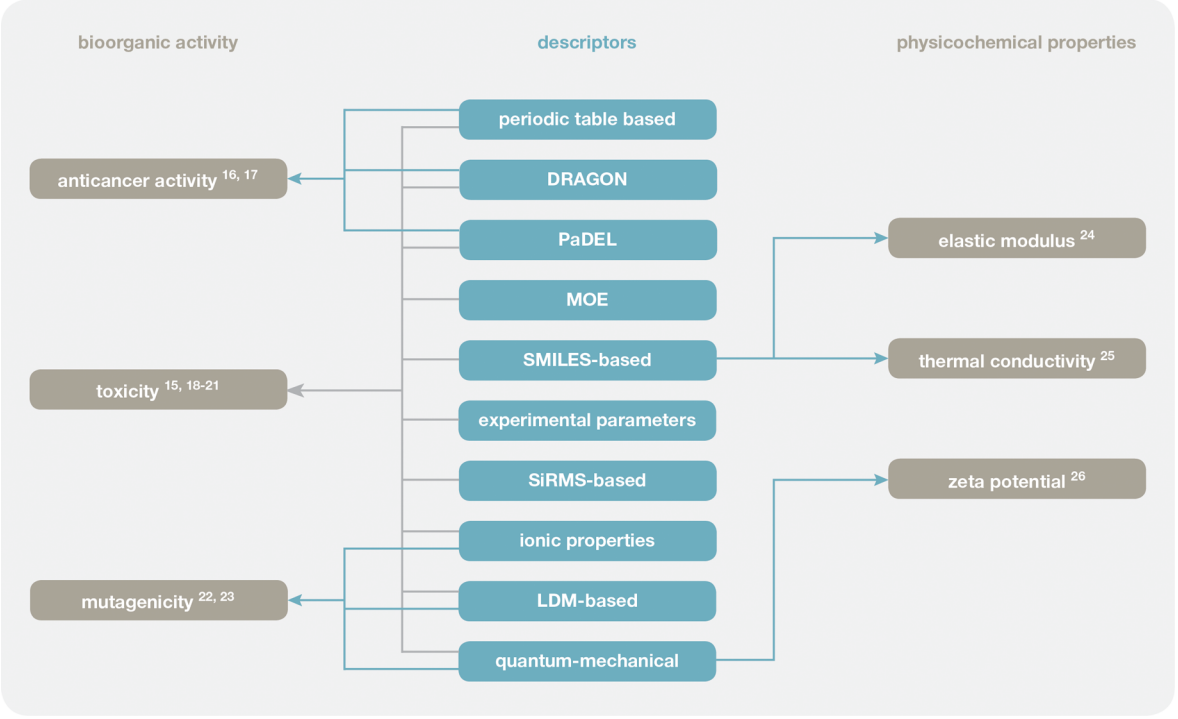

Figure 1. Descriptors previously used in nano-QSAR and nano-QSPR modeling.

near-spherical nanoparticles. Moreover, only nanofluids that involve water as a base fluid and volume fraction of nanoparticles between 0.01 and 0.55 were selected.[29−34] Thermal conductivity measurements were conducted at temperatures between 21 and 25 °C. The modeled property (endpoint), k, was defined as the ratio between the thermal conductivity of the nanofluid (k_{eff}) and the thermal conductivity of water not containing nanoparticles (eq 1):

$$k = \frac{k_{eff}}{k_w} \quad (1)$$

where k = thermal conductivity enhancement, k_{eff} = thermal conductivity of the nanofluid, and k_w = thermal conductivity of base fluid (water).

For assessing the quality of the literature data, we have applied criteria recently developed by Lubinski at al.[35] The reports we have investigated used comparable procedures in different laboratories and studies. The collected data set was assigned to 2C: reliable with restrictions and of limited use for nano-QSPR. This category includes published data with a characterization of nanoparticles but without all necessary details being provided. This category is used for a small amount of data, when data may be provided from sources that may or may not be determined according to international standards. Data are only suitable for local QSPR modeling.

The extracted data set consisted of 23 enpdoint values (Table 1) to be modeled. In addition, we collected experimental data on the average nanoparticle size (S_A) and the volume fraction of nanoparticles (φ_i) for each studied nanofluid. The values of S_A and φ_i were used as structural descriptors (independent variables in the QSPR model) together with the "liquid drop" model (LDM) descriptors presented in the next section.

"Liquid Drop" Model Descriptors. As previously mentioned, the "liquid drop" model (LDM) encodes possible interactions between nanoparticles using a simplified representation of the particles at nanolevel.[21,36] In LDM (Figure 2), the basic elements (here, nanoparticles) are densely packed and the density (ρ) of the "liquid drop" is equal to the mass density (ρ). In this model, the minimum radius of interactions between elementary particles in the cluster is described by Wigner−Seitz radius (eq 2):

Table 1. Experimental Data on Average Nanoparticle Size (S_A), Volume Fraction of Nanoparticles (φ_i), and Thermal Conductivity Enhancement (k) of the Studied Nanofluids

no.	nanofluid	S_A [nm]	φ_i [%]	k	ref
1	Cu−water	40	0.05	1.180	29
2	Cu−water	150	0.05	1.085	30
3	Cu−water	40	0.10	1.240	29
4	Cu−water	75	0.10	1.238	30
5	Cu−water	40	0.20	1.480	29
6	Cu−water	150	0.20	1.097	30
7	Cu−water	40	0.30	1.750	29
8	Fe−water	10	0.20	1.130	31
9	Fe−water	10	0.30	1.155	31
10	Fe−water	10	0.40	1.170	31
11	Fe−water	10	0.55	1.180	31
12	Al_2O_3−water	30	0.01	1.002	32
13	Al_2O_3−water	30	0.025	1.0024	32
14	Al_2O_3−water	30	0.10	1.004	32
15	Al_2O_3−water	30	0.20	1.010	32
16	Al_2O_3−water	30	0.30	1.014	32
17	Fe_2O_3−water	10	0.10	1.170	33
18	TiO_2−water	50	0.10	1.040	34
19	TiO_2−water	50	0.50	1.090	34
20	TiO_2−water	25	0.10	1.100	31
21	TiO_2−water	25	0.30	1.110	31
22	ZrO_2−water	20	0.10	1.110	34
23	ZrO_2−water	20	0.50	1.140	34

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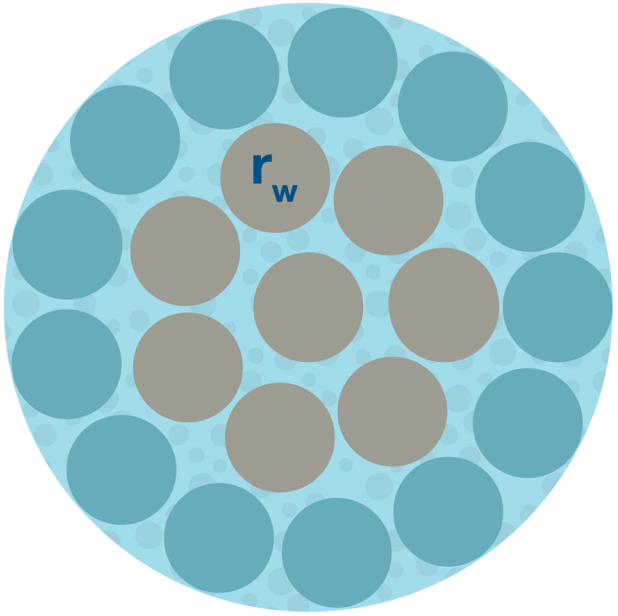

Figure 2. General schema of the "liquid drop" model.

$$r_w = \left(\frac{3M}{4\pi\rho}\right)^{1/3} \quad (2)$$

where M = molecular weight and ρ = mass density.

LDM is a geometric and size-dependent model. It assumes that the most probable nanoparticle shape is a sphere. Based on this assumption, the number of elementary particles in a nanoaggregate is defined as follows (eq 3):

$$n = \left(\frac{r_0}{4\pi}\right)^3 \quad (3)$$

where r_0 = the mean radius of a nanoparticle.

Further transformations of eq 3 allow calculation of the nanoparticle surface area, the number of nanoparticles present on the surface, F (eq 4), and the surface-area-to-volume ratio, SV (eq 5).

$$F = 4n^{-1/3} \quad (4)$$

$$\mathrm{SV} = \frac{F}{1-F} = \left(\frac{\text{surface molecules}}{\text{molecules in volume}}\right) \quad (5)$$

In this work, we have calculated LDM descriptors for all 23 studied nanofluid systems. Values of the particular descriptors are provided in the Supporting Information.

Model Development and Validation Procedures. After calculation, the LDM-based descriptors were standardized. The Random Forest (RF) approach using Breiman's algorithm was employed for the purposes of QSAR model development.[37] RF is a simple, stepwise nonparametric regression approach. The final RF model represents an ensemble of different decision trees, wherein a particular tree is not influenced by other ones when constructed. An essential feature of Breiman's algorithm is the variable importance calculation. For each chosen descriptor, the importance (raw score) indicates how much that structural feature influences the modeled end point.[38] To accomplish this, at the first step, the "untouched correct count" is computed. This value is defined as the number of correct classifications using "bagging", using "out-of-bag" (temporarily excluded) data points as its validation set. Bagging is close to the well-known "leave-one-out" validation in classical regression modeling.[38] The initial data set, after bagging, is then tested for the correctness of classification. This step is performed for each regression tree. The average of this number over all trees in the forest is the raw importance score for the studied descriptor (eq 6):

$$\text{raw importance}(x) = \frac{\text{untouched count} - \text{variable } x \text{ count}}{\text{number of trees}} \quad (6)$$

A positive importance score indicates that the given variable is important for correct classification.[37,39] For readers interested in a detailed description of Random Forest modeling, Breiman's original paper is strongly recommended.[37]

The statistical fit of nano-QSPR models was assessed by the correlation coefficient, R^2 (eq 7), and the root-mean-square error, RMSE (eq 8),to evaluate the model quality for bagging, test, and training sets.

$$R^2 = \frac{m\sum_{i=2}^{m} y_i\hat{y}_i - \sum_{i=2}^{m} y_i \cdot \sum_{i=2}^{m} \hat{y}_i}{\sqrt{m\sum_{i=2}^{m} y_i^2 - \left(\sum_{i=2}^{m} \hat{y}_i\right)^2}\sqrt{m\sum_{i=2}^{m} \hat{y}_i^2 - \left(\sum_{i=2}^{m} y_i\right)^2}} \quad (7)$$

where m = the number of nanofluids in the data set, y_i = the observed values of the investigated property (here, the thermal conductivity enhancement, k_{obs}), $\hat{y}_i$ = the predicted values of the investigated property (here, the thermal conductivity enhancement, k_{pred}).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{m-1}} \quad (8)$$

For model development, standalone tool Random Forest software (CF) was used.[40,41]

RESULTS AND DISCUSSION

Model Development and Validation. The collected data (Table 1) consisted of nanofluids of both metal (Cu, Fe) and metal oxide (Al_2O_3, TiO_2, ZrO_2) nanoparticles. The data were split randomly into the training (18 nanofluids) and test set (5 nanofluids; bold font in Table 2 indicates nanofluids from the test set). The training set nanofluids were structurally diverse enough to cover the whole descriptor space of the overall data set.[42] Moreover, chemical diversity of nanofluids in the training and test sets was similar.

The developed model consists of 10 trees with 5 descriptors in each. The models is characterized by R^2 = 0.93 and RMSE = 0.07 for the training set and R^2 = 0.77 and RMSE = 0.06 for the test set. RMSE after the bagging procedure was higher (RMSE = 0.13). Relatively high values of the correlation coefficients and low values of the prediction errors confirm not only the accuracy of fitting but also high predictive ability of the model. This can be also noticed after a visual inspection of the correlation plot (Figure 3). The experimental (observed), predicted and residual values are listed in Table 2.

Physical–Chemical Interpretation of the Model. The model developed within our study represents the thermal conductivity enhancement as a function of the experimentally measured and calculated LDM-derived descriptors (Table 3).

Chandrasekar et al.[9] have reviewed and systemized findings from experimental work on the thermal conductivity of various nanofluids. The authors[9] concluded that the increase in

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J. Phys. Chem. C XXXX, XXX, XXX−XXX

Table 2. Experimental and Predicted Values of the Thermal Conductivity Enhancement

no.	nanofluid	k_{obs}	k_{pred}	residual value
1	Cu−water	1.180	1.210	−0.030
2	Cu−water	1.085	1.096	−0.011
3	**Cu−water**	**1.240**	**1.222**	+0.018
4	Cu−water	1.238	1.217	+0.021
5	Cu−water	1.480	1.387	+0.093
6	Cu−water	1.097	1.185	−0.088
7	Cu−water	1.750	1.500	+0.250
8	Fe−water	1.130	1.145	−0.015
9	**Fe−water**	**1.155**	**1.223**	−0.068
10	Fe−water	1.170	1.165	+0.005
11	Fe−water	1.180	1.171	+0.009
12	Al_2O_3−water	1.002	1.014	−0.012
13	Al_2O_3−water	1.002	1.014	−0.012
14	**Al_2O_3−water**	**1.004**	**1.025**	−0.021
15	Al_2O_3−water	1.010	1.029	−0.019
16	**Al_2O_3−water**	**1.014**	**1.112**	−0.098
17	Fe_2O_3−water	1.170	1.119	+0.051
18	**TiO_2−water**	**1.040**	**1.080**	−0.040
19	TiO_2−water	1.090	1.089	+0.001
20	TiO_2−water	1.100	1.106	−0.006
21	TiO_2−water	1.110	1.178	−0.068
22	ZrO_2−water	1.110	1.121	−0.011
23	ZrO_2−water	1.140	1.138	+0.002

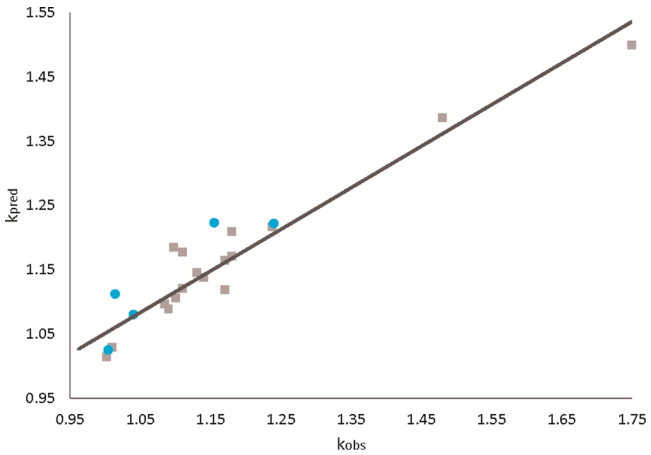

Figure 3. Observed (experimental) vs predicted values of the thermal conductivity enhancement. Dots represent test set; squares represent training set.

Table 3. Relative Variable Importance Values for Descriptors

descriptor	symbol	descriptor type	raw score
average nanoparticle size	S_A	experimental	0.028
volume fraction of nanoparticles in base fluid	φ_i	experimental	0.011
density	ρ	LDM	0.039
Wigner−Seitz radius	r_w	LDM	0.054
number of elementary particles in a nanoaggregate	n	LDM	0.008
surface-to-volume ratio	SV	LDM	0.003
number of nanoparticles present on the surface	F	LDM	0.001

conductivity is a function of size, volume fraction, and the thermal properties of the solid suspension. Almost all these findings are in agreement with our nano-QSPR model. The highest raw score in our nano-QSPR model was assigned to the volume fraction, φ_i (Table 3). Chandrasekar et al.[9] reported a nonlinear increase in thermal conductivity attributed to the increase in specific surface area in nanoparticles. In the case of our model, this conclusion is supported by the importance of two LDM-based descriptors, namely, surface-area-to-volume ratio (SV) and Wigner−Seitz radius (r_w).

Chandrasekar et al.[9] also mentioned that the geometrical structure of nanoparticles might affect the thermal conductivity enhancement as well. This factor, however, limits the application of our model, since the LDM approach assumes that the particles are spherical. That is the reason we have collected data only for nanoliquids containing spherical nanoparticles and then used them for developing the model. As such, the applicability domain of the developed QSPR model has been restricted only to spherical and near-spherical nanoparticles. In future investigations, we are planning to develop a more generalized equation that will describe and take into account the shape of nanoparticles. However, in such a case, additional structural descriptors must be developed first.

The presence of the average nanoparticle size, S_A, on the list of important descriptors is also in agreement with results of Beck et al.[10] The authors found that nanofluid thermal conductivity should emphasize the size dependence of the thermal conductivity of the solid nanoparticles.

Although the developed nano-QSPR model is rather "local" (developed based on a relatively small data set), it is descriptive and suitable for the modeled nanofluids. With this work, we have confirmed the usefulness of nano-QSPR methodology for predicting physical−chemical properties of nanofluids. This should be considered as the first but the most important, step. Further development of the model should include (1) expanding the data set for nanoparticles of different shapes and chemical composition, (2) developing new descriptors capable of sufficiently expressing different shapes, and (3) expanding the range of volume fractions. Moreover, a series of models can be built for different base fluids, different experimental conditions, and of course different physical−chemical properties of nanofluids (e.g., viscosity). However, development of better and "wider" nano-QSPR models requires more experimental observations. We believe the present contribution will stimulate further work in this area and nano-QSPR modeling would become an important tool in designing novel chemicals and materials in near future.

CONCLUSIONS

In the present study, we have successfully applied quantitative structure−property relationship (QSAR) technique to model the thermal conductivity enhancement of nanoliquids. This property was modeled as a function of nanoparticle volume fraction and size and calculated size-dependent nanostructural descriptors. This model employed "liquid drop" model (LDM) theoretical descriptors and descriptors derived experimentally. Although the applicability of the model is limited only to spherical nanoparticles in water (volume fraction <1%) at 21−25 °C, we believe this is the most important first step and the proof-of-the-concept for the use of nano-QSPR models in predicting properties of newly designed nanoliquids. In the future, we expect to develop a set of models that simultaneously will characterize different shapes of nanoparticles and basic physicochemical properties of nanofluids at different conditions.

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J. Phys. Chem. C XXXX, XXX, XXX−XXX

■ ASSOCIATED CONTENT

Supporting Information

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Values of the particular experimental descriptors and descriptors calculated within LDM model (XLSX)

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Author Contributions

N.S. and T.P. planned the experiment and analyzed the results. N.S. carried out all experiments and processed the data. N.S. and K.J. drafted and revised the manuscript. J.L. and T.P. supervised the research, coordinated the study, and revised the manuscript. All authors have read and have given approval to the final version of the manuscript.

Notes

The authors declare no competing financial interest.

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■ ABBREVIATIONS

LDM "liquid drop" model; QSAR quantitative structure−activity relationships; QSPR quantitative structure−property relationships; RMSE the root-mean-square error

■ REFERENCES

(1) Kroll, A.; Pillukat, M.; Hahn, D.; Schnekenburger, J. Interference of engineered nanoparticles with in vitro toxicity assays. *Arch. Toxicol.* **2012**, *86*, 1123−1136.

(2) Puzyn, T.; Leszczynska, D.; Leszczynski, J. Toward the development of "Nano-QSARs": Advances and challenges. *Small* **2009**, *5*, 2494−2509.

(3) Kleinstreuer, C.; Feng, Y. Experimental and theoretical studies of nanofluid thermal conductivity enhancement: a review. *Nanoscale Res. Lett.* **2011**, *6*, 439.

(4) Yu, W.; Choi, S. U. S. The role of interfacial layers in the enhanced thermal conductivity of nanofluids: a renovated Maxwell model. *J. Nanopart. Res.* **2003**, *5*, 167−171.

(5) Hamilton, R. L.; Crosser, O. K. Thermal conductivity of heterogeneous two-component systems. *Ind. Eng. Chem. Fundam.* **1962**, *1*, 187−191.

(6) Wei, W.; et al. A Comprehensive model for the enhanced thermal conductivity of nanofluids. *J. Adv. Res. Phys.* **2012**, *3* (2), 021209.

(7) Ghosh, M. M.; Roy, S.; Pabi, S. K.; Ghosh, S. A molecular dynamics-stochastic model for thermal conductivity of nanofluids and its experimental validation. *J. Nanosci. Nanotechnol.* **2011**, *11*, 2196−2207.

(8) Koo, J.; Kleinstreuer, C. A new thermal conductivity model for nanofluids. *J. Nanopart. Res.* **2004**, *6*, 577−588.

(9) Chandrasekar, M.; Suresh, S.; Senthilkumar, T. Mechanisms proposed through experimental investigations on thermophysical properties and forced convective heat transfer characteristics of various nanofluids − A review. *Renewable Sustainable Energy Rev.* **2012**, *16*, 3917−3938.

(10) Beck, M.; Yuan, Y.; Warrier, P.; Teja, A. The effect of particle size on the thermal conductivity of alumina nanofluids. *J. Nanopart. Res.* **2009**, *11*, 1129−1136.

(11) Kumar, M. P.; Kumar, J.; Tamilarasan, R.; Sendhilnathan, S.; Suresh, S. Review on nanofluids theoretical thermal conductivity models. *Engineer. J.* **2015**, *19* (1), 67−83.

(12) Younes, H.; Christensen, G.; Li, D.; Hong, H.; Ghaferi, A. Thermal Conductivity of Nanofluids: Review. *J. Nanofluids* **2015**, *4*, 107−132.

(13) Aybar, H.; Sharifpur, M.; Azizian, R.; Mehrabi, M.; Meyer, J. A Review of thermal conductivity models for nanofluids. *Heat Transfer Eng.* **2015**, *36*, 1085−1110.

(14) Lipnick, R. L. Computational chemistry in environmental toxicology QSAR. *SAR and QSAR Environ. Res.* **1995**, *4*, 125−130.

(15) Puzyn, T.; Rasulev, B.; Gajewicz, A.; Hu, X.; Dasari, T. P.; Michalkova, A.; Hwang, H.-M.; Toropov, A.; Leszczynska, D.; Leszczynski, J. Using nano-QSAR to predict the cytotoxicity of metal oxide nanoparticles. *Nat. Nanotechnol.* **2011**, *6*, 175−178.

(16) Fourches, D.; Pu, D.; Tassa, C.; Weissleder, R.; Shaw, S. Y.; Mumper, R. J.; Tropsha, A. Quantitative nanostructure−activity relationship modeling. *ACS Nano* **2010**, *4*, 5703−5712.

(17) Kar, S.; Gajewicz, A.; Puzyn, T.; Roy, K. Nano-quantitative structure−activity relationship modeling using easily computable and interpretable descriptors for uptake of magnetofluorescent engineered nanoparticles in pancreatic cancer cells. *Toxicol. In Vitro* **2014**, *28*, 600−606.

(18) Toropova, A.; Toropov, A.; Benfenati, E.; Leszczynska, D.; Leszczynski, J. QSAR modeling of measured binding affinity for fullerene-based HIV-1 PR inhibitors by CORAL. *J. Math. Chem.* **2010**, *48*, 959−987.

(19) Zhang, H.; Ji, Z.; Xia, T.; Meng, H.; Low-Kam, C.; Liu, R.; Pokhrel, S.; Lin, S.; Wang, X.; Liao, Y.-P.; et al. Use of metal oxide nanoparticle band gap to develop a predictive paradigm for oxidative stress and acute pulmonary inflammation. *ACS Nano* **2012**, *6*, 4349−4368.

(20) Kar, S.; Gajewicz, A.; Puzyn, T.; Roy, K.; Leszczynski, J. Periodic table-based descriptors to encode cytotoxicity profile of metal oxide nanoparticles: A mechanistic QSTR approach. *Ecotoxicol. Environ. Saf.* **2014**, *107*, 162−169.

(21) Sizochenko, N.; Rasulev, B.; Gajewicz, A.; Kuz'min, V.; Puzyn, T.; Leszczynski, J. From basic physics to mechanisms of toxicity: the "liquid drop" approach applied to develop predictive classification models for toxicity of metal oxide nanoparticles. *Nanoscale* **2014**, *6*, 13986−13993.

(22) Sizochenko, N.; Rasulev, B.; Puzyn, T.; Leszczynski, J. Genotoxicity of metal oxide nanoparticles: classification, clustering and causality. Presented at 12th Annual MCBIOS Conference, Little Rock, AR, USA, 2015.

(23) Golbamaki, N.; Rasulev, B.; Benfenati, E.; Cronin, M.; Leszczynski, J. Quantum-chemical and (Q)SAR modeling of metal oxide nanoparticles genotoxicity. Presented at 22nd Conference on Current Trends in Computational Chemistry, Jackson, MS, USA, 2013.

(24) Toropov, A. A.; Leszczynski, J. A new approach to the characterization of nanomaterials: Predicting Young's modulus by correlation weighting of nanomaterials codes. *Chem. Phys. Lett.* **2006**, *433*, 125−129.

(25) Toropov, A. A.; Leszczynska, D.; Leszczynski, J. Predicting thermal conductivity of nanomaterials by correlation weighting technological attributes codes. *Mater. Lett.* **2007**, *61*, 4777−4780.

(26) Mikolajczyk, A.; Gajewicz, A.; Rasulev, B.; Schaeublin, N.; Maurer-Gardner, E.; Hussain, S.; Leszczynski, J.; Puzyn, T. Zeta potential for metal oxide nanoparticles: a predictive model developed by a nano-quantitative structure−property relationship approach. *Chem. Mater.* **2015**, *27*, 2400−2407.

(27) Özerinç, S.; Kakaç, S.; Yazıcıoğlu, A. Enhanced thermal conductivity of nanofluids: a state-of-the-art review. *Microfluid. Nanofluid.* **2010**, *8*, 145−170.

DOI: 10.1021/acs.jpcc.5b05759
J. Phys. Chem. C XXXX, XXX, XXX−XXX

(28) Timofeeva, E.; Routbort, J.; Singh, D. Particle shape effects on thermophysical properties of alumina nanofluids. *J. Appl. Phys.* **2009**, *106*, 014304.
(29) Jana, S.; Salehi-Khojin, A.; Zhong, W.-H. Enhancement of fluid thermal conductivity by the addition of single and hybrid nano-additives. *Thermochim. Acta* **2007**, *462*, 45−55.
(30) Liu, M.-S.; Lin, M.; Tsai, C.; Wang, C. Enhancement of thermal conductivity with Cu for nanofluids using chemical reduction method. *Int. J. Heat Mass Transfer* **2006**, *49*, 3028−3033.
(31) Hong, T.; Yang, H. Nanoparticle-dispersion-dependent thermal conductivity in nanofluids. *J. Korean Phys. Soc.* **2005**, *47*, 321−324.
(32) Lee, J.; Hwang, K.; Jang, S.; Lee, B.; Kim, J.; Choi, S.; Choi, C. J. Effective viscosities and thermal conductivities of aqueous nanofluids containing low volume concentrations of Al2O3 nanoparticles. *Int. J. Heat Mass Transfer* **2008**, *51*, 2651−2656.
(33) Zhu, H.; Zhang, C.; Liu, S.; Tang, Y.; Yin, Y. Effects of nanoparticle clustering and alignment on thermal conductivities of Fe3O4 aqueous nanofluids. *Appl. Phys. Lett.* **2006**, *89*, 023123.
(34) Paul, G.; Chopkar, M.; Manna, I.; Das, P. K. Techniques for measuring the thermal conductivity of nanofluids: a review. *Renewable Sustainable Energy Rev.* **2010**, *14*, 1913−1924.
(35) Lubinski, L.; Urbaszek, P.; Gajewicz, A.; Cronin, M.; Enoch, S. J.; Madden, J. C.; Leszczynska, D.; Leszczynski, J.; Puzyn, T. Evaluation criteria for the quality of published experimental data on nanomaterials and their usefulness for QSAR modelling. *SAR QSAR Environ. Res.* **2013**, *24* (12), 995−1008.
(36) Smirnov, B. M. Processes involving clusters and small particles in a buffer gas. *Phys.-Usp.* **2011**, *54*, 691−721.
(37) Breiman, L. Random forests. *Machine Learning* **2001**, *45*, 5−32.
(38) Strobl, C.; Malley, J.; Tutz, G. An introduction to recursive partitioning: rationale, application and characteristics of classification and regression trees, bagging and random forests. *Psych. Met.* **2009**, *14*, 323−348.
(39) Livingston, F. Implementation of Breiman's Random Forest Machine Learning Algorithm. *ECE591Q Mach. Learn. J. Pap.* **2005**, 1.
(40) Polishchuk, P.; Muratov, N.; Artemenko, A.; Kolumbin, O.; Muratov, N.; Kuz'min, V. Application of Random Forest Approach to QSAR Prediction of Aquatic Toxicity. *J. Chem. Inf. Model.* **2009**, *49*, 2481−2488.
(41) QSAR4U: A.V. Bogatsky Physico-Chemical Institute of National Academy of Sciences of Ukraine. http://www.qsar4u.com/pages/rf.php (accessed Sep 3, 2015), Random Forest tool.
(42) OECD. *Guidance Document on the Validation of (Quantitative) Structure-Activity Relationship [(Q)SAR] Models*; OECD Publishing: Paris, 2007.

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J. Phys. Chem. C XXXX, XXX, XXX−XXX