

Practical retention index models of OV-101, DB-1, DB-5, and DB-Wax for flavor and fragrance compounds[☆]

K.L. Goodner*

USDA, ARS, Citrus & Subtropical Products Lab, Winter Haven, FL 33884, USA

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Abstract

High-quality regression models of gas chromatographic retention indices were generated for OV-101 ($R = 0.997$), DB-1 ($R = 0.998$), DB-5 ($R = 0.997$), and DB-Wax ($R = 0.982$) using 91, 57, 94, and 102 compounds, respectively. The models were generated using a second-order equation including the cross product utilizing two easily obtained variables, boiling point and the log octanol-water coefficient. Additionally, a method for determining outlier data (the Goodner Outlier Determination (GOOD) method) is presented, which is a combination of several outlier tests and is less prone to discarding legitimate data.

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1. Introduction

Determination of unknowns in gas chromatography (GC) requires two independent forms of identification such as the retention time on two different chromatographic columns, retention time and mass spectral match, or retention time and aromatic match (Harris, 1987). Because retention times vary depending on the temperature programming of the GC, Kovat introduced a relative retention index scheme (Kovats, 1958). A relative retention index uses a series of standards, often n -alkanes, with other compounds referenced against the standards using the equation

$$I = 100 \left[n + (N - n) \frac{\log t'_r(\text{unknown}) - \log t'_r(n)}{\log t'_r(N) - \log t'_r(n)} \right],$$

where n is the number of carbon atoms in the smaller alkane, N the number of carbon atoms in the larger alkane, $t'_r(n)$ the adjust retention time of the smaller alkane, and

$t'_r(N)$ is the adjusted retention time of the larger alkane (Harris, 1987).

There are compilations of retention indices on different stationary phase columns for many compounds, which are useful for identifying unknown compounds. However, these compilations are not complete and situations arise where one has a potential identification from a mass spectral match, but no information on retention index. Unless the compound is available or readily synthesized, it is unlikely that a positive identification using a standard can be determined. Another common situation is determining if co-eluting compounds on one type of column phase will be chromatographically separated on a different phase where the retention indices are not known. Additionally, knowing the retention indices of two target analytes a priori would ease method development. One potential aid to the researcher is a mathematical model of retention indices for the column stationary phase they are using.

There have been numerous mathematical models of GC retention indices on various stationary phases (Anker, Jurs, & Edwards, 1990; Bermejo & Guillén, 1987; Buydens & Massart, 1983; Gerasimenko & Nabivach, 1990; Hale et al., 1985; Hasan & Jurs, 1988; Héberger, Görgényi, & Sjöström, 2000; Jalali-Heravi & Fatemi, 2001; Ośmiałowski, Halkiewicz, & Kaliszan, 1986; Ośmiałowski, Halkiewicz, Radecki, & Kaliszan, 1985; Raymer, Wiesler, & Novotny, 1985; Robbat & Kalogeropoulos, 1990; Rohrbach & Jurs,

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*Tel.: +1 863 293 4133; fax: +1 863 299 8678.

E-mail address: goodner@citrus.usda.gov

1985; Sabljic, 1985; Stanton & Jurs, 1989; Whalen-Pedersen & Jurs, 1981). One study used artificial neural networks to model retention indices on a Carbowax 20M stationary phase (Jalali-Heravi & Fatemi, 2001). There were 35 descriptors used in the neural network model that were based on electronic, geometric, topological, and a single physicochemical property resulting in a regression coefficient of the calculated and experimental indices of $R = 0.984$. Jurs and coworkers have used their in-house created ADAPT platform to generate descriptors for modeling retention indices (Anker et al., 1990; Hasan & Jurs, 1988; Rohrbach & Jurs, 1985; Stanton & Jurs, 1989; Whalen-Pedersen & Jurs, 1981) with good results (generally $R > 0.99$).

Héberger et al. (2000) used a partial least-squares model of several physical properties to determine retention index and classify compounds as either ketones or aldehydes. The researchers used five terms and achieved good results, but were unable to classify compounds based solely on their retention data.

Many of these retention index models are quite good, providing excellent models with good predictive power. However, the drawback for the typical laboratory worker is their complexity. This report covers a series of models based on boiling point (T_B) and log of the octanol–water partition coefficient ($\log K_{ow}$, also called $\log P$) which are both easily obtained via reference books, the internet, and/or free programs. Additionally, a new algorithm for determining outlier data is presented and utilized in the analysis.

2. Materials and methods

2.1. Data collection

The data used in this report were collected from numerous sources. The Kovat's retention indices were collected from Acree's Flavornet (Acree, 2006), Rouseff's database (Rouseff, 2006), Adam's book (Adams, 1995), Kondjoyan and Berdagué's compilation (Kondjoyan & Berdagué, 1996), the NIST MS library (Stein et al., 1998), and/or Flavorworks (Flavometrics, NJ) for OV-101, DB-1, DB-5, and Carbowax. The boiling point (T_B) data was taken from the Handbook of Chemistry and Physics (Anonymous, 1990) and/or from internet searches. Retention indices and boiling points were averaged if available from multiple sources. $\log K_{ow}$ was determined using the Kowwin module in the Estimation Program Interface (EPI) suite (Anonymous, 2000). The data used for this study are provided in Table 1.

2.2. Data modeling

The data were then modeled in Statistica version 7 (Statsoft, Tulsa, OK) using the general linear model module and using T_B , $\log K_{ow}$, T_B^2 , $(\log K_{ow})^2$, and $T_B \log K_{ow}$ for a second-order model with a cross product

term. The residuals were examined for Potential outliers using the GOOD Outlier Determination (GOOD) Method, detailed below, and re-ran with outliers removed.

2.3. Outlier analysis

The data (both input data and results) were analyzed for outliers using the GOOD method which was programmed as a Microsoft Excel add-in (Microsoft, Redmond, WA) and is available from the author. This method is a combination of the Grubb's test, the Dixon's Q -test, and a modified "huge" rule. The Grubb's test is the basis for the ASTM E-178-02 (Anonymous, 2002) and is calculated by

$$T_1 = \frac{\bar{x} - x_1}{s}, \quad T_n = \frac{x_n - \bar{x}}{s},$$

where the datapoints are arranged in increasing order from the smallest x_1 to the largest x_n . T_1 or T_n is the data point in question (possible outlier) depending if the questionable data point is the smallest or largest value, \bar{x} is the mean of all samples, and s is the standard deviation of the data set. The calculated T -value is compared to a table of critical values and if the calculated statistic is larger than the critical value, then the data point is considered an outlier.

When you have a possible outlier, usually you have a cluster of data points along with an isolated (outlying) point. Dixon's Q -test relies on determining the ratio of the "gap" (distance from "possible outlier" to the main cluster of data) to the range and is dependent upon the number of data points in the sample (Dixon, 1951).

$$r = \frac{\text{gap}}{\text{range}},$$

If $3 \leq n \leq 7$

$$r_{10} = \frac{x_2 - x_1}{x_n - x_1} \text{ if smallest value is suspected}$$

$$r_{10} = \frac{x_n - x_{n-1}}{x_n - x_1} \text{ if largest value is suspected}$$

If $8 \leq n \leq 10$

$$r_{11} = \frac{x_2 - x_1}{x_{n-1} - x_1} \text{ if smallest value is suspected}$$

$$r_{11} = \frac{x_n - x_{n-1}}{x_n - x_2} \text{ if largest value is suspected}$$

If $11 \leq n \leq 13$

$$r_{21} = \frac{x_3 - x_1}{x_{n-1} - x_1} \text{ if smallest value is suspected}$$

$$r_{21} = \frac{x_n - x_{n-2}}{x_n - x_2} \text{ if largest value is suspected}$$

If $14 \leq n \leq 30$

$$r_{22} = \frac{x_3 - x_1}{x_{n-2} - x_1} \text{ if smallest value is suspected}$$

$$r_{22} = \frac{x_n - x_{n-2}}{x_n - x_3} \text{ if largest value is suspected}$$

Table 1
 Linear retention indices for OV-101, DB-1, DB-5, Wax columns along with boiling point (T_B) and $\log K_{ow}$

Compound	CAS	OV-101	DB-1	DB-5	Wax	T_B	$\log K_{ow}$
Pentane	109-66-0	500	500	500	500	35.5	2.80
Hexane	110-54-3	600	600	600	600	69	3.29
Heptane	142-82-5	700	700	700	700	98	3.78
Octane	111-65-9	800	800	800	800	125	4.27
Nonane	111-84-2	900	900	900	900	151	4.76
Decane	124-18-5	1000	1000	1000	1000	174	5.25
Undecane	1120-21-4	1100	1100	1100	1100	196	5.74
Dodecane	112-40-3	1200	1200	1200	1200	216	6.23
Tridecane	629-50-5	1300	1300	1300	1300	234	6.73
Tetradecane	629-59-4	1400	1400	1400	1400	253	7.22
Pentadecane	629-62-9	1500	1500	1500	1500	269	7.71
Hexadecane	544-76-3	1600	1600	1600	1600	287	8.20
Heptadecane	629-78-7	1700	1700	1700	1700	302	8.49
Octadecane	593-45-3	1800	1800	1800	1800	317	9.18
Nonadecane	629-92-5	1900	1900	1900	1900	330	9.67
Eicosane	112-95-8	2000	2000	2000	2000	343	10.16
Methanethiol	74-93-1	483			683	6	0.78
Acetaldehyde	75-07-0	418			706	21	-0.17
Dimethyl sulfide	75-18-3	527		510	734	38	0.92
(E)-2hexenal	6789-80-6	870	828	854	1148	148	1.58
Butanal	123-72-8			596	822	75	0.82
Ethyl acetate	141-78-6	595	600	614	898	77	0.86
Ethanol	64-17-5	500			928	78	-0.14
Butane-2,3-dione	431-03-8			596		88	-1.34
Ethyl propanoate	105-37-3	691		714	950	99	1.36
Methyl butanoate	623-42-7	705		724	990	102	1.36
2-methyl-1-propanol	78-83-1	616		647	1103	108	0.77
Dimethyl disulfide	624-92-0	725		744	1078	110	1.87
Methylbenzene	108-88-3	756		769	1038	110	2.54
Ethyl isobutanoate	97-62-1	746		754	964	112	1.77
1-butanol	71-36-3	655		675	1142	117	0.84
Ethyl butanoate	105-54-4	705	797	800	1038	121	1.85
3-Methylbutanol	123-51-3	736	720	738	1208	130	1.26
2-Methylbutanol	137-32-6	738		755	1208	128	1.26
Hexanal	66-25-1	780	792	800	1088	130	1.80
Ethyl 2-methylbutanoate	7452-79-1	837	835	846	1056	133	2.26
1-Pentanol	71-41-0	756		768	1244	137	1.33
3-Methyl-2-buten-1-ol	556-82-1	762		778	1127	140	1.17
Ethyl pentanoate	539-82-2	884	875	899	1138	144	2.34
Heptanal	111-71-7	883		901	1184	153	2.29
α -Pinene	80-56-8	926	929	939	1035	156	4.27
1-Hexanol	111-27-3	858	846	865	1362	156	1.82
(Z)-3-hexen-1-ol	928-96-1	844		858	1392	156	1.61
Camphene	79-92-5	957	955	953	1080	159	4.35
Furfural	98-01-1	800	798	852	1432	162	0.83
β -Pinene	127-91-3	985	983	980	1118	164	4.35
Methional	3268-49-3	864	867	911	1468	166	0.41
β -Myrcene	123-35-3	990	991	990	1158	167	4.88
Ethyl hexanoate	123-66-0	983	982	1002	1231	168	2.83
Hexyl acetate	142-92-7	1012	994	1011	1268	169	2.83
Octanal	124-13-0	985	985	1004	1291	171	2.78
α -Terpinene	99-86-5	990	999	1015	1184	174	4.75
1,8-Cineole	470-82-6	1015	1009	1031	1222	176	3.13
Limonene	5989-27-5	1013	1022	1030	1208	176	4.83
<i>p</i> -Cymene	99-87-6	1025		1026	1274	177	4.00
Ibenzaldehyde	100-52-7	943		964	1525	178	1.71
γ -Terpinene	99-85-4	1058	1022	1072	1249	182	4.75
Ethyl heptanoate	106-30-9	1083		1098	1397	188	3.32
Phenylacetaldehyde	122-78-1	1004		1047	1650	195	1.54
1-Octanol	111-87-5	1061	1051	1071	1558	196	2.81
<i>p</i> -Cresol	106-44-5	1058		1074		202	2.06
Benzyl alcohol	100-51-6		1003		1879	204	1.08
Guaiacol	90-05-1	1056		1088	1872	205	1.34

Table 1 (continued)

Compound	CAS	OV-101	DB-1	DB-5	Wax	T_B	$\log K_{ow}$
Citronellal	106-23-0	1134	1138	1157	1492	207	3.53
Ethyl octanoate	106-32-1	1185		1198	1497	207	3.81
Decanal	112-31-2	1188		1207	1500	208	3.76
Octyl acetate	112-14-1		1137	1212	1478	211	3.81
Terpinen-4-ol	2438-10-0	1182	1160	1180	1606	212	3.33
Nonyl acetate	143-13-5				1583	212	4.30
1-Nonanol	143-08-8	1161	1155	1162	1654	215	3.30
α -Terpineol	10482-56-1		1184	1192	1700	218	3.33
Phenethyl mercaptan	4410-99-5			1182	1688	218	2.98
Naphthalene	91-20-3	1197		1196	1718	218	3.17
Linalyl acetate	115-95-7	1244		1259	1566	220	4.39
α -Terpinyl acetate	80-26-2				1681	220	4.34
Citronellol	106-22-9	1229	1225	1235	1768	225	3.56
4-Methylacetophenone	122-00-9	1174		1186		226	2.22
Ethyl phenylacetate	101-97-3	1235	1213	1248	1785	229	2.57
Carvone	99-49-0	1236	1208	1248	1765	229	3.07
Geraniol	106-24-1	1258	1238	1266	1852	229	3.47
1-Decanol	112-30-1	1263		1268	1767	231	3.79
2-Undecanone	112-12-9	1276		1294		232	3.69
Citronellyl acetate	150-84-5	1335		1356	1639	240	4.56
Ethyl decanoate	110-38-3	1379		1396	1636	245	4.79
α -Cubebene	17699-14-8	1328	1360	1348	1472	246	6.73
Eugenol	97-53-0	1381	1335	1360	2164	254	2.73
Methyleugenol	93-15-2	1390		1404		254	3.03
Geranyl acetone	3796-70-1	1431		1416	1840	256	4.36
α -Farnesene	502-61-4	1518	1456	1504		260	7.10
α -Ionone	127-41-3	1408		1424	1840	261	4.29
Valencene	4630-07-3		1497	1490	1746	274	6.30
Tetradecanol	112-72-1			1676	2177	289	5.75
2-Octanol	123-96-6	988		990	1332	179	2.73
1,4-Cineole	470-67-7	1001	994	1017	1188	173	3.13
Linalool	78-70-6	1085	1098	1100	1544	199	3.38
Nerol	106-25-2	1234	1212	1230	1792	225	3.47
Nonanal	124-19-6	1087	1091	1106	1397	195	3.27
α -Phellandrene	99-83-2	1009		1006	1170	172	4.62
Sabinene	3387-41-5	970		974	1125	164	4.69
β -Phellandrene	555-10-2	1035	985	1042	1245	172	4.70
Acetic acid	64-19-7	710				118	0.09
Propanoic acid	79-09-4				1525	141	0.58
1-Butanoic acid	107-92-6				1628	162	1.07
Pentanoic acid	539-82-2				1698	186	1.56
Hexanoic acid	142-62-1				1797	203	2.05
Heptanoic acid	111-14-8				1900	223	2.54
Octanoic acid	124-07-2				2065	237	3.03
Nonanoic acid	112-05-0				2185	268	3.52
2-Methylbutanoic acid	116-53-0				1672	176	1.49

The calculated “ r ” value is compared to a table of critical values and if the calculated statistic is larger than the table value, the data point is considered an outlier.

The huge rule (Marascuilo, 1971) is determined by calculating the mean and standard deviation of the data set with the questionable data point excluded and determining how many standard deviations the questionable data point would be using

$$M = \frac{(|x_i - \bar{X}'|)}{S'}$$

where \bar{X}' and S' are the mean and standard deviation calculated excluding the data point in question, x_i . The rule

is that if the data point is more than four standard deviations away from the reduced data set, then it is an outlier. It is extremely unlikely ($p < 0.00005$) that data points would be more than four standard deviations away from the mean assuming a normal distribution. The GOOD method uses a modified test using the t -distribution (using an $\alpha/10$ confidence level) instead of the normal distribution and adds confidence levels. The calculation is performed similarly, but the critical value, C_t , is no longer 4, but rather determined by calculating the t -value at $n-1$ degrees of freedom for the confidence level desired.

$$C_t = t_{\alpha/10}$$

The GOOD method performs all three outlier tests and determines the data point to be an outlier only if all three of the tests return a positive result. This results in a more conservative test than the three individually. As is noted in ASTM-E178, repeated application of outlier tests reduces the significance level and one would use α/k for k tests to approximate an overall significance level of α . However, by requiring that at all three of the tests return a positive value, the overall significance level of the GOOD method is less than α . While this is a laborious technique for determining if datasets have possible outliers, the Excel add-in introduces a new function that performs all three tests and returns a “yes”/“no” answer making the method readily usable to test all data sets.

The GOOD method was analyzed as compared to its constituent tests using randomly generated Gaussian data sets. Eight thousand 15-point data set was generated in Statistica and analyzed in Excel. The data set was analyzed as both a 15 datapoint set and as 3 individual data sets of 5 points each were analyzed. The results are tabulated in Table 2.

Results and discussion

The resulting equations from the regression modeling are

$$RI_{OV-101} = 1.1623T_B + 0.0064T_B^2 + 35.2861K_{OW} - 9.0068K_{OW}^2 + 0.2756T_BK_{OW} + 421.4386,$$

$$RI_{DB-1} = 1.5901T_B + 0.0040T_B^2 + 14.0606K_{OW} - 7.7975K_{OW}^2 + 0.3396T_BK_{OW} + 436.2845,$$

$$RI_{DB-5} = 1.7273T_B + 0.0049T_B^2 + 17.2140K_{OW} - 7.0459K_{OW}^2 + 0.2663T_BK_{OW} + 422.8297,$$

$$RI_{DB-Wax} = 2.8662T_B + 0.0199T_B^2 - 58.2317K_{OW} + 3.0049K_{OW}^2 - 0.4975T_BK_{OW} + 630.7004.$$

The regression results for the four column stationary phases is presented in Table 3. The models include the cross product of T_B and $\log K_{OW}$, which has not previously been used. The multiple R , which is a measure of how well the model fits the data set, is excellent for the OV-101, DB-1, and DB-5 stationary phases with $R \geq 0.997$ and the DB-Wax multiple R was 0.982. Additionally, various quality measures are provided such as the average percent error and the percentage of the samples that are within 3% and 5% of the model. Also provided is the percentage from the model needed to account for 75% and 95% of the data set. For example, 95% of the data set for DB-5 are within 5.7% of the model. Examining Table 2, one can see that approximately about 80% of the cases were within 3%

Table 3
Regression models for different phase columns

Model term	Column phase			
	OV-101	DB-1	DB-5	DB-Wax
Intercept	421.4386	436.2845	422.8297	630.7004
T_B	1.1623	1.5901	1.7273	2.8662
T_B^2	0.0064	0.0040	0.0049	0.0199
K_{OW}	35.2861	14.0606	17.2140	-58.2317
K_{OW}^2	-9.0068	-7.7975	-7.0459	3.0049
$T_B \times K_{OW}$	0.2756	0.3396	0.2663	-0.4975
Multiple R	0.997	0.998	0.997	0.982
n	91	57	94	102
Average % error	2.11	1.41	1.90	4.41
±3%	74.7	89.5	79.8	38.2
±5%	91.2	96.5	94.7	63.7
75% cases ±	3.3	2.0	2.7	6.2
95% cases ±	6.5	4.4	5.7	11.2

Note: The table is interpreted as follows for OV-101: 74.7% of the cases are with 3% of the reported values and 75% of the cases are within 3.3% of reported values.

Table 2
Performance of the GOOD method for determining outlying data points as compared to its constituent tests

Dataset size	Number of datasets	Confidence level	Datapoint in question	Outlier method			
				ASTM	Q-test	“Huge”	GOOD method
15	8000	95%	Maximum	388	323	397	241
			Minimum	430	326	439	230
		99%	Maximum	69	72	80	31
			Minimum	69	62	75	32
		99.5%	Maximum	27	39	33	19
			Minimum	34	32	38	13
5	24000	95%	Maximum	1217	1227	940	939
			Minimum	1199	1200	919	916
		99%	Maximum	234	280	281	227
			Minimum	214	268	254	212
		99.5%	Maximum	116	125	160	111
			Minimum	114	117	151	110

error and about 95% are within 5%. Thus, 3% and 5% were chosen as reasonable limits based on variations of reported retention indices. OV-101 and DB-1 are very similar stationary phases, 100% polydimethylsiloxane, but the DB-1 is bonded and crosslinked, which apparently led to differences in retention indices reported for numerous compounds with the average difference being 1.7%.

The models for OV-101 and wax stationary phases were tested by comparing the results of these models with those previously published by Anker et al. (1990). In this paper, approximately 115 compounds were modeled using a linear regression of 7 variables. The average absolute percent error was 0.98% and 1.16% for OV-101 and Wax stationary phases, respectively. The models presented here and applied to the data presented in Anker's paper showed a 2.9% and 3.6% average absolute error for OV-101 and Wax stationary phases, respectively. However, it was noted that there was a systematic overestimation for both data sets. Applying a correction factor reduced the average absolute error to 1.9% and 2.7%, respectively.

Fig. 1 is a multiple plot of the observed versus predicted retention indices. The line indicates a theoretical perfect fit. The difference between the predicted value and the actual value is the residual. The residuals were analyzed for potential outliers using the GOOD method. These potential outliers were inspected to determine if there was a logical reason to exclude from the model. Some compounds had suspicious input parameters such as a highly unlikely reported boiling point (e.g., a reduced pressure T_B reported as an atmospheric T_B). A few potential outliers were merely transcription errors (e.g., inputting 218 °C instead of 128 °C as the T_B) which were included in the model after correction. Some systematic compounds were removed from the models. For example, carboxylic acids performed very poorly on the non-wax columns and were excluded from the models. This is not unexpected as carboxylic acids often perform poorly on non-polar columns, resulting in poor peak shape with severe tailing.

Table 4 is a comparison of this work with other similar reports from the literature. While some of the models appear to perform better than the one presented here, none

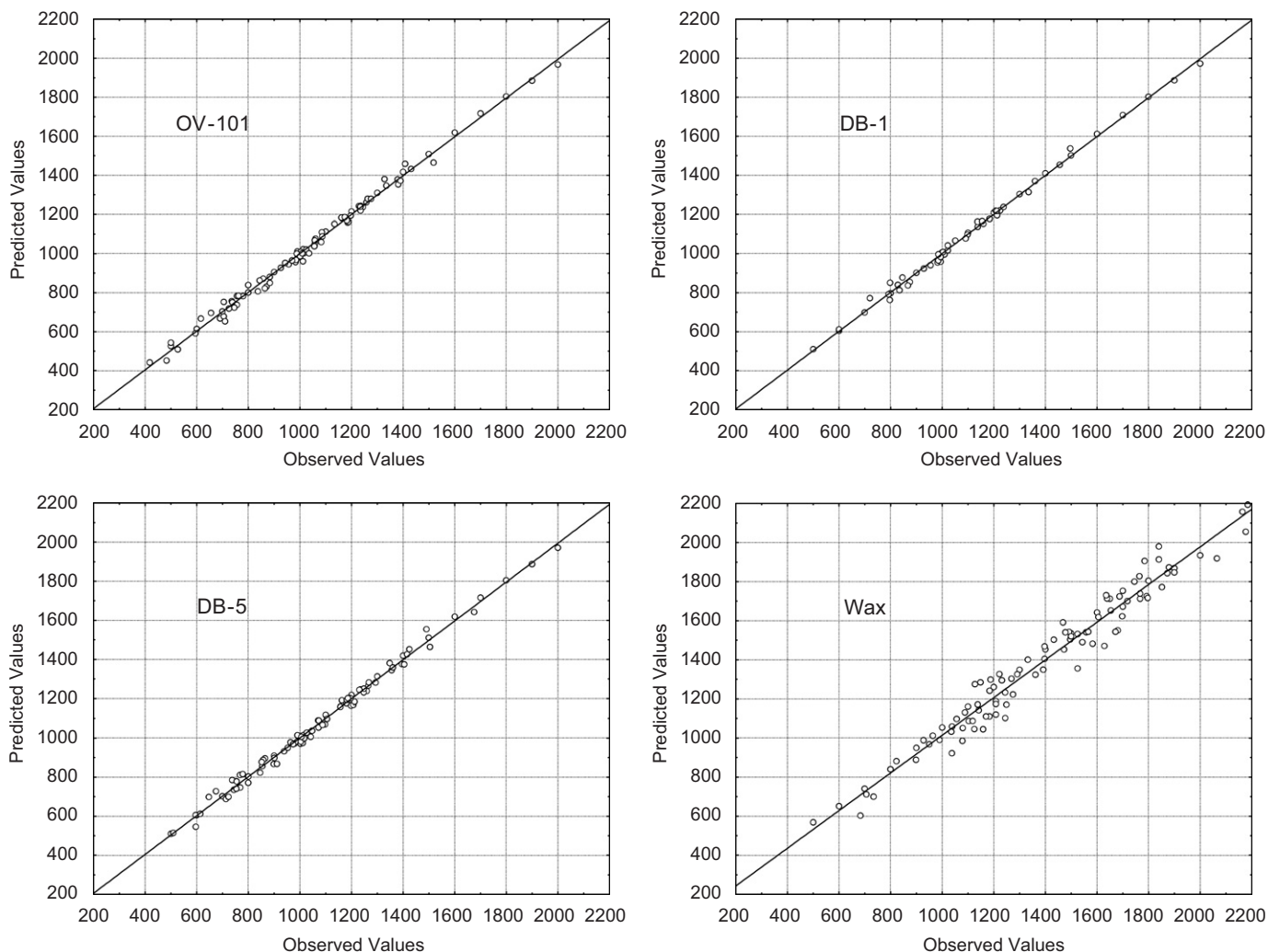


Fig. 1. Graphical plots of observed versus predicted retention indices for the (a) OV-101, (b) DB-1, (c) DB-5, and (d) DB-Wax column types.

Table 4
A comparison of various models from literature

Reference	Phases	Number of variables	Variables	R-range
Héberger et al. (2000)	HP-1, HP-50, DB-210, HP-Wax	5	$T_B, V_M, W_m, R_m, \log K_{ow}$	0.980–0.995
Stanton and Jurs (1989)	OV-101, Wax	6	ADAPT	0.993–0.997
Rohrbagh and Jurs (1985)	PONA, DB-1, DB-5	2–4	$T_B, 1/R_m, \log K_{ow}, I_m, W_m$	0.996–0.998
Anker et al. (1990)	OV-101, Wax	7	ADAPT	0.997–0.999
Bermejo and Guillén (1987)	SE-30, Dioctyl Phthlate, Oronite Niw, Pluronic F88, Carbowax 1000	7	$T_B, V_M, R_m, V_W, D, N_c, {}^1X$	0.994–0.999
Raymer et al. (1985)	SE-30	1–3	X	0.946–0.988
Gerasimenko and Nabivach (1990)	HPE, OV-101, SE-30	4	V_W, X, T_B, R_M, V_M	0.997–1.000
Ośmiałowski et al. (1985)	OV-101	2–3	E_T, Δ, E_{HOMO}	0.93–0.96
This report	OV-101, DB-1, DB-5, Wax	2	$T_B, \log K_{ow}$	0.982–0.998

T_B , boiling temperature; V_M , molar volume; W_m , molecular weight; R_m , molar refraction; I_m , moment of inertia; $\log K_{ow}$, log of octanol–water partition coefficient; ADAPT, various variables from modeling program; X , molar connectivity; V_W , Van der Waals' volume; E_T , total energy; Δ , polarity parameter; E_{HOMO} , energy of HOMO.

combine the simplicity and easily accessible input data. From the table it is clear that several descriptors are fairly common in the modeling of retention indices. Boiling point, molar refraction, $\log K_{ow}$, and molar volume seem to be some fairly common descriptors used. Of those, boiling point, $\log K_{ow}$, and molar volume are likely the easiest to be found in literature. From a user's perspective, the fewer number of descriptors needed, coupled with the ease of finding or determining the values of the descriptors, is ideal. Boiling point is readily available from numerous resources, including the CRC Handbook of Chemistry and Physics, material safety data sheets (MSDS), and internet searches. $\log K_{ow}$ is also easily obtainable from several sources. One source is by using the EPI Suite software, which is currently freely downloadable from the Environmental Protection Agency (<http://www.epa.gov/opptintr/exposure/pubs/episutedl.htm>), and also available through some internet webpages (<http://www.logp.com>, <http://146.107.217.178/lab/alogsps/start.html>, and http://www.syrres.com/esc/est_kowdemo.htm).

As an example of using these models in the lab consider DB-Wax co-eluting compounds ethyl butanoate and isopropyl butanoate. If the retention indices were not known for these two compounds, or one of them, then this method could indicate whether they would be co-eluting on a different column phase. The boiling points and $\log K_{ow}$ for ethyl butanoate and isopropyl butanoate are 121 °C, 1.85 and 131 °C, 2.26, respectively. Using the equations above the retention indices for ethyl butanoate and isopropyl butanoate are 753 and 800 for OV-101, 763 and 806 for DB-1, and 771 and 815 for DB-5. These average 45 unit separation with errors of reported values of 3.5%. These values indicate that you could use any of those columns to achieve separation of the compounds.

By using the models presented here, one would be able to narrow a list of potential unknown identifications quickly and easily to a more manageable list for further analysis, which would be beneficial to many researchers around the

world who have limited funds for purchasing standards or access to synthesis equipment. One could also determine a priori if co-eluting compounds would be resolved on a different stationary phase, aid in determining which column phase would be best suited for separating analytes of interest, and aid in the selection of internal standards. The GOOD method is a general purpose algorithm which can be used for determining outliers for normally distributed data sets.

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