

Accepted refereed manuscript of: Dobson R & Semple S (2018) “How do you know those particles are from cigarettes?”: An algorithm to help differentiate second-hand tobacco smoke from background sources of household fine particulate matter, *Environmental Research*, 166, pp. 344-347. DOI: <https://doi.org/10.1016/j.envres.2018.06.019>.

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1 *Report from the field*

2 **“How do you know those particles are from cigarettes?”: An algorithm to help**
3 **differentiate second-hand tobacco smoke from background sources of household fine**
4 **particulate matter**

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11 **FUNDING STATEMENT**

12 This research was carried out as part of a PhD study by one of the authors (RD) funded by a
13 staff-waiver programme at the University of Aberdeen.

14 **COMPETING INTERESTS STATEMENT**

15 The authors have no competing interests to declare.

16 **CONTRIBUTORSHIP STATEMENT**

17 Ruairaidh Dobson contributed to experimental design and planning, carried out fieldwork and
18 statistical analysis, drafted this paper and had final approval of the version to be published.

19 Sean Semple contributed to experimental design and planning, redrafting and critical
20 revision, and had final approval of the version to be published. Both authors are accountable
21 for all aspects of the work.

22 **KEYWORDS**

23 Second-hand smoke; tobacco smoke exposure; air quality monitoring; particulate matter

24

25 **ABSTRACT**

26 **Background**

27 Second-hand smoke (SHS) at home is a target for public health interventions, such as air
28 quality feedback interventions using low-cost particle monitors. However, these monitors
29 also detect fine particles generated from non-SHS sources.

30 The Dylos DC1700 reports particle counts in the coarse and fine size ranges. As tobacco
31 smoke produces far more fine particles than coarse ones, and tobacco is generally the greatest
32 source of particulate pollution in a smoking home, the ratio of coarse to fine particles may
33 provide a useful method to identify the presence of SHS in homes.

34 **Methods**

35 An algorithm was developed to differentiate smoking from smoke-free homes. Particle
36 concentration data from 116 smoking homes and 25 non-smoking homes were used to test
37 this algorithm.

38 **Results**

39 The algorithm correctly classified the smoking status of 135 of the 141 homes (96%),
40 comparing favourably with a test of mean mass concentration.

41 **Conclusions**

42 Applying this algorithm to Dylos particle count measurements may help identify the presence
43 of SHS in homes or other indoor environments. Future research should adapt it to detect
44 individual smoking periods within a 24h or longer measurement period.

45

46

47 INTRODUCTION

48 Second-hand smoke (SHS) is a serious cause of poor indoor air quality in homes. Around
49 40% of children are regularly exposed worldwide,(GTSS Collaborative Group, 2006) putting
50 them at risk of serious illness and impaired lung development(US Surgeon General, 2006).

51 For that reason interventions to promote smoke-free homes are of significant public health
52 interest. Several interventions have been developed using air quality monitoring to inform
53 parents of the impact of smoking on their indoor air quality, and the consequent effects on
54 their children.(Dobson et al., 2017; Klepeis et al., 2013; Rosen et al., 2015; Wilson et al.,
55 2013) A low-cost air quality monitor, the Dylos DC1700, has proved useful for monitoring
56 PM_{2.5} as a proxy for SHS in smokers' homes in these kinds of interventions.(Semple et al.,
57 2015, 2013) The Dylos is a small, portable monitor which provides comparable accuracy at a
58 considerably lower price than other widely used optical particle counters, such as the TSI
59 Sidepak.In addition to being approximately one-tenth of the cost of the Sidepak instrument,
60 the Dylos has several specific advantages in terms of low noise, simplicity of use and the
61 ability to determine particle size distribution in terms of fine and coarse particulate (Semple
62 et al., 2013)

63 PM_{2.5} has been widely used as a proxy to quantify indoor concentrations of SHS in many
64 settings including bars, homes and vehicles (Apelberg et al., 2013; Gorini et al., 2005) as
65 reliable measurements can be taken easily and affordably over time using optical particle
66 counters, in contrast to the high cost and complexity of more specific methods such as air
67 nicotine measurement. Other activities in these settings can generate PM_{2.5}. These can include
68 cooking emissions, combustion such as candle burning or the use of solid fuels for heating,
69 and aerosols such as deodorants and hair sprays.(He et al., 2004) These sources can produce
70 high concentrations of PM within a home which could be confused for SHS in interpretation.

71 Parents in previous intervention trials have been observed to deny and challenge messages
72 about the risk of SHS, (Passey et al., 2016) and if feedback wrongly identifies non-SHS
73 sources as being smoking activity this is likely to weaken the effectiveness of such
74 approaches and make the participant question the validity of the measurement method.
75 Developing reliable and accurate information on PM concentrations that are specifically
76 linked to SHS is therefore important in the development of effective interventions.

77 The particle size distribution of tobacco smoke is known to skew towards fine and ultrafine
78 particles. (Klepeis et al., 2003) The mean diameter of particles in tobacco smoke has been
79 measured as $0.27\mu\text{m}$ (in the case of mainstream smoke) and $0.09\mu\text{m}$ (for sidestream smoke);
80 smaller mean diameters than those associated with common household activities like frying,
81 cleaning and the movement of people, and other sources (Abt et al., 2000) while still
82 producing a sustained increase in particle mass concentration over time.(Semple and Latif,
83 2014)

84 The Dylos DC1700 provides data on both the fine and coarse fractions of particulate matter
85 in the form of particle counts for particles larger than $0.5\mu\text{m}$ and particles larger than $2.5\mu\text{m}$.
86 It may therefore be possible to use this particle size information to distinguish between
87 different sources of PM in a home, and potentially to classify homes as smoking or non-
88 smoking.

89 This research uses particle concentration data measured in homes to develop and test a rule-
90 based approach to determine whether tobacco was smoked in the home during the monitoring
91 period. This information could be useful in providing air quality data to support behavioural
92 interventions designed to encourage smokers to keep their homes smoke-free.

93 **MATERIALS AND METHODS**

94 **Measuring mass concentrations and particle counts in homes**

95 Previously reported methods (Semple et al., 2013) were used to assess PM_{2.5} concentrations
96 in homes. From previous work by our group (Semple, 2016), time resolved PM_{2.5} data were
97 already available from 116 smoking homes. Data from non-smoking homes were collected in
98 the course of this research. Minute-by-minute particle counts reported by the Dylos DC1700
99 monitor were converted to estimated PM_{2.5} concentrations using a previously developed
100 equation (Equation 1).

$$101 \quad PM_{2.5} = 0.65 + 4.16 \times 10^{-5}(\text{Dylos total particle count} - \text{large particle count}) \\ 102 \quad \quad \quad + 1.57 \times 10^{-11}(\text{Dylos total particle count} - \text{large particle count})^2$$

103 *Equation 1 - Conversion of Dylos particle counts to approximate mass concentration*
104 (Semple et al., 2013)

105 Also, the large particle percentage, consisting of the particles larger than 2.5µm as a
106 percentage of the total particles detected, was calculated for each minute for use in the
107 algorithm.

108 **Algorithm development**

109 A four-step algorithm was developed to classify homes as smoking or non-smoking based on
110 one day or more of Dylos-recorded data by excluding data points which were unlikely to be
111 related to smoking. This algorithm was designed to use the ratio of large to small particles
112 detected by the Dylos as a “signature” for the presence of SHS. Additional steps were
113 intended to reduce noise in the data caused by brief fluctuations in levels of PM.

114 For each home:

- 115 1. Remove data where PM_{2.5} concentration is below 5µg/m³. This step is intended to
116 account for low ambient concentrations of PM_{2.5} which are not related to SHS.
117 5µg/m³ was chosen as indoor PM_{2.5} has been shown to correlate to 79% of

118 ambient PM_{2.5} in similar conditions (Cyrus et al., 2004), while the average
119 ambient PM_{2.5} concentration in Scotland has been modelled at 6.6µg/m³.(Sykes,
120 2016) Previous research on smoke-free homes has shown

121 2. For each minute of data, calculate the percentage of the total detected particles
122 which are larger than 2.5µm in diameter. Remove data where the percentage of
123 large particles is greater than a threshold (described throughout as the ‘Large
124 Particle Threshold’ or LPT).

125 3. Remove data where a peak lasts for fewer than three minutes, to account for
126 random fluctuations compared to the sustained impact of SHS on indoor air
127 quality.(Semple and Latif, 2014)

128 4. Take the percentage of minutes in the log where data has not been removed in one
129 of the steps above. This can be used as an “SHS score” to classify the home as
130 smoking or non-smoking if the score is above a cut-off (determined
131 experimentally).

132 **Statistical analysis**

133 Use of the algorithm relies on two factors: the LPT which best indicates smoking, and the
134 best-performing cut-off value for the SHS score, over which a log can be classified as
135 smoking. Receiver operating characteristic curves were used to determine these factors.

136 ROC curves are a common method for determining the efficacy of a diagnostic test. (Bewick
137 et al., 2004) In an ROC curve, a test is carried out on a set of records, and its specificity and
138 selectivity are plotted. This allows comparison between different tests using the area under
139 the curve (AUC) of this plot – a mathematical representation of the overall effectiveness of
140 the test. Tests which classify records more successfully than random have AUC values
141 greater than 0.5, while a hypothetical perfect test would have a value of 1.0.

142 Variants of the algorithm using LPTs between 0.1% and 4.0% (stepped up in 0.1%
143 increments) were applied to the full dataset of logs and the categorisation results plotted on
144 an ROC curve using IBM SPSS v24.(IBM Corp., 2016) The LPT which resulted in the
145 highest AUC was selected, and the curve analysed to find the SHS score cut-off which
146 maximised selectivity and specificity. An ROC curve was also generated using the mean
147 PM_{2.5} measured in each household as a predictor of smoking status. Custom Python 2.7 scripts
148 were developed to apply the algorithm to Dylos data logs.

149 **Smoke-free homes data collection**

150 Participants working at three health charities in Scotland were recruited. Only people living
151 in homes where smoking or e-cigarette use was not permitted were eligible to participate in
152 the study. A target of 30 people was set as achievable with the time and resources available.

153 Participants were given a Dylos DC1700 monitor and an instruction sheet asking them to
154 install and run the monitor for 48 hours in their main living space, elevated above floor level
155 and away from doors and windows. This mirrored instructions given during previous studies
156 of personal exposure to SHS.(Semple et al., 2012) Participants were also asked to keep a
157 diary of events which could cause elevated PM in the home, including cooking and heating
158 use.

159 After the monitoring period, the Dylos was returned to the research team and data was
160 downloaded from it. A short report on air quality in the home was prepared for the participant
161 and emailed to them, along with any relevant information on reducing air pollution in their
162 home. The monitor's memory was then cleared prior to use with the next participant.

163 **Smoking homes data**

164 The pre-existing smoking homes dataset comprised minute-by-minute measurements from
165 116 homes, each spanning approximately 5 days, taken from the First Steps 2 Smoke-free

166 (FS2SF) study(Semple, 2016). Participants in that study self-reported that smoking took place
167 regularly within the home. No data on other events which could affect air quality was
168 available from these homes.

169 **Ethics**

170 Ethical approval for this study was given by the College Ethics Review Board of the College
171 of Life Sciences and Medicine at the University of Aberdeen.

172 **RESULTS**

173 **Estimated PM_{2.5} concentrations in smoking and smoke-free homes**

174 For the smoke-free home data collection part of the study 27 participants were recruited, with
175 25 of those completing the study. Homes were monitored for a mean of two days, eight hours
176 and six minutes (ranging from one day, 20 hours and 45 minutes to three days, 13 hours and
177 32 minutes). Two participants withdrew or were unable to provide 24h of data.

178 When compared to the existing data from 116 smoking homes the 25 smoke-free homes had
179 significantly lower concentrations of PM_{2.5}, with a geometric mean of 5.2µg/m³ (geometric
180 standard deviation (GSD) ±2.16), compared to 37.6µg/m³ (GSD ±3.0) (p<0.001, natural logs
181 compared with a one-tailed Student's t-test).

182 Mean large particle percentages were also significantly different, with a geometric mean in
183 smoke-free homes of 7.49% compared to 3.56% in smoking homes (p<0.001, natural logs
184 compared with Student's t-test).

185 **Classifying homes algorithmically**

186 Potential large particle percentages were selected based on previous research on the particle
187 size distribution of SHS.(Klepeis et al., 2003) The algorithm was applied to the whole dataset
188 using LPTs between 0.1% and 4.0%, incremented by 0.1%. The resulting output was plotted

189 as an ROC curve to determine the LPT which maximised AUC. An LPT of 1.8% was most
190 successful, with an AUC of 0.945.

191 **Comparison with classification by PM_{2.5} concentration**

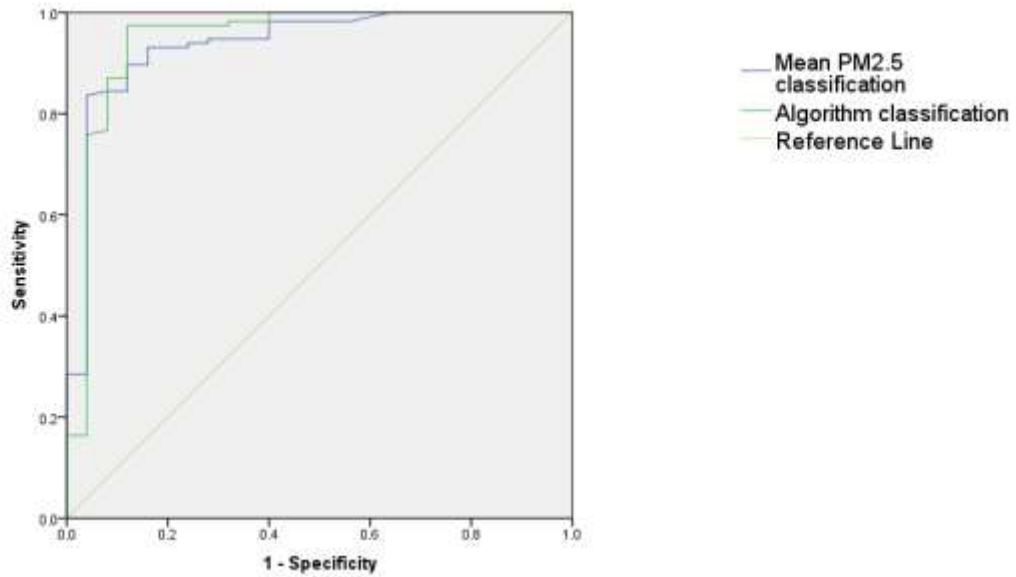
192 An ROC curve was plotted using the results of the algorithm along with the mean PM_{2.5}
193 concentrations of each home (Figure 1).

194 The AUC for selection using mean PM_{2.5} was 0.937, while the algorithm classification
195 attained 0.945. Both methods were highly successful in classifying homes, with the algorithm
196 more successful (although this was not statistically significant).

197 **Determining the SHS score classification cut-off**

198 Coordinates of the curve values were examined to determine the best-performing SHS score.

199 The value 1.455% maximised sensitivity (0.974) and specificity (0.88) and was therefore
200 selected. Using this value, the algorithm classified only 3/116 smoking and 3/25 non-smoking
201 homes incorrectly.



202

203 *Figure 1 – Receiver operating characteristic curve comparing home classification using the*
 204 *algorithm with home classification using mean PM_{2.5} in a home. Mean PM_{2.5} classification*
 205 *refers to the use of mean PM_{2.5} concentrations in isolation as a score to classify homes as*
 206 *smoking or smoke-free. Algorithm classification refers to the use of steps 1-3 of the algorithm*
 207 *to produce an SHS score which was used as a classifier. Curves approaching the upper left*
 208 *corner of the chart represent effective classifiers. Sensitivity refers to the number of true*
 209 *positive smoking homes identified, while 1 – specificity refers to the number of false positives*
 210 *identified. Coordinates of the curve were analysed separately to decide on an SHS score cut-*
 211 *off point which would best indicate a smoking home.*

212 **DISCUSSION**

213 It is possible to apply a simple algorithm to Dylos DC1700 particle number counts in order to
 214 predict with a high degree of certainty whether smoking occurred in a home during a multi-
 215 day monitoring period. While mean PM_{2.5} concentration in the homes measured is clearly
 216 linked to smoking status, the algorithm was able to characterise homes independently from
 217 that factor, suggesting that the additional steps linked to large particle percentage and
 218 removing data where low concentrations of PM_{2.5} are present are useful additions to the
 219 process of determining the presence of SHS in a home.

220 Previously, data from a similar monitor has been used to develop a logistic regression model
 221 to distinguish SHS from non-SHS sources of PM.(Dacunto et al., 2014) In this study, a large

222 particle threshold of 1% was identified as indicative of SHS, similar to the threshold
223 identified in this paper.

224 PM_{2.5} is a well-recognised marker for SHS(Gorini et al., 2005) which has been used in a
225 number of behavioural interventions.(Klepeis et al., 2013; Rosen et al., 2015; Wilson et al.,
226 2013) PM sensors are well-developed, easily portable and inexpensive, allowing them to be
227 used in a wide range of settings where it may be useful to measure SHS. This need not be
228 limited to homes – for instance, this technique could be used to promote smoke-free public
229 places laws.

230 **Limitations**

231 The limited number of measurements available from smoke-free homes made it impossible to
232 determine whether the algorithmic approach was statistically superior to an approach based
233 purely on the use of logistic regression analysis on the mean level of PM_{2.5}. A follow-up
234 study in further smoke-free homes may determine this.

235 Although the classification rate established by the algorithmic approach was high, one in
236 eight of the smoke-free homes tested was still mis-classified. These false positives could
237 cause intervention participants who have succeeded in keeping their homes smoke-free to be
238 told that they have not done so, potentially reducing their trust in the intervention.

239 Scotland has relatively low levels of outdoor particulate air pollution. The large particle
240 threshold and score values developed in these circumstances may not hold true in countries
241 with high levels of coarse particle pollution (including dust storms or other natural particulate
242 pollution).(Ahmed et al., 1987) Further research should be carried out in these conditions.

243 In step 1 of the algorithm we have assumed that 79% of ambient PM will infiltrate, leading to
244 an ambient PM_{2.5} concentration indoors of around 5µg/m³. Values below this concentration
245 are therefore excluded from the result. Infiltration of ambient PM varies greatly depending on

246 building ventilation and other factors, and so this assumption is unlikely to hold true
247 generally. Furthermore, measurements in settings where ambient PM is significantly higher
248 than $6.6\mu\text{g}/\text{m}^3$ may cause few data points to be excluded at step 1, affecting the results of the
249 algorithm. Further research is most likely necessary to test the algorithm in a variety of other
250 settings, and to test the assumptions implicit in step 1. It may be beneficial to generate a
251 specific “ambient $\text{PM}_{2.5}$ ” value for the time periods in which measurement takes place.

252 The results of this research can only be applied directly to the Dylos DC1700, with its two
253 size bins. It may be possible to adapt the algorithm to other optical particle counters with
254 multiple size bins, but research would be needed to measure their agreement with the size
255 classifications made by the Dylos.

256 In general, optical particle counters are limited instruments compared to more labour- and
257 time-intensive methods of detecting and quantifying PM, such as gravimetric methods. A
258 wide range of factors can affect their results, including relative humidity, (Ruprecht et al.,
259 2011) aerosol composition and the age of cigarette smoke in the air.(Dacunto et al., 2015)

260 The particle number to mass concentration equation used in this study has been developed
261 with reference to SHS aerosol only, so mass concentrations calculated by this method should
262 be considered as estimates or approximations of exposure.

263 The effectiveness of the algorithm may be impeded in settings where there are other
264 significant sources of $\text{PM}_{2.5}$, such as open flames. Similarly, high concentrations of PM_{10} in
265 outdoor air could impede the effectiveness of the algorithm, raising the percentage of large
266 particles measured by the monitor. This would be a particular concern in countries with high
267 levels of outdoor air pollution.

268 **Implications**

269 Due to the well-known health implications of PM_{2.5} in air and of SHS, particularly for
270 children, interventions to reduce the number of homes in which smoking takes place are of
271 importance in improving public health, with several recent studies describing the use of the
272 Dylos DC1700 monitor.(Klepeis et al., 2013; Rosen et al., 2015; Semple et al., 2013)

273 While most people are well aware that SHS is harmful, many smokers blame other factors
274 such as outdoor air pollution when presented with evidence of poor air quality in their homes.
275 Researchers developing air quality feedback interventions for smoke-free homes or smoking
276 cessation should consider incorporating this classification method to reinforce the specific
277 danger of SHS.

278 Although this study took place solely in homes, the algorithm could be used to detect SHS in
279 other indoor environments such as bars, casinos and other workplaces. This could be useful in
280 assessing occupational exposure to SHS, and in providing evidence for advocacy for
281 comprehensive smoke-free legislation.

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