

From big data to speed and safety: A review of surrogate safety measures based on speeds from floating car data

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Abstract

In order to overcome biases of crash-based safety analyses, research is looking for surrogate safety measures. A candidate are speeds derived from floating car data (FCD, or probe vehicle data). The goal of the review is to identify challenges and opportunities regarding using FCD speeds to develop surrogate safety measures. Specific points focused on the questions of sampling rate, study size, free-flow speed determination, reliability and validity. The review indicated several remaining knowledge gaps in relation to reliability of different FCD speed sources, sampling design, or estimation of free-flow speeds. Many of these gaps are likely to be quickly resolved at the current rate of research. The main conclusion is that benefits, limitations and nature of different FCD sources need to be carefully understood and considered before adopting FCD speeds as a surrogate safety measure. Further research and development opportunities exist in the subject area.

Introduction

Traffic speeds are one of the most significant factors in road safety performance. With increasing speed on roads both the likelihood and severity of crashes increase. These basic facts have been demonstrated within and across a number of methodological paradigms (Johnston, 2004; Jurewicz, Tofler, & Makwasha, 2015); however, speed-related crashes still occur. This calls for specific measurement and deeper understanding of various aspects of traffic speed in safety context. Such understanding will assist in development and implementation of effective road safety strategies and countermeasures.

Traditional crash-based safety analyses have several limitations, including their reactive nature, and statistically low occurrence of crashes. Surrogate safety measures provide a valuable alternative. For example, the Power Model (Nilsson, 2004) relates the effects of mean speed changes to the number of crashes of different severity, and was validated in various road environments (Elvik, 2009, 2013). However, not all surrogate safety measures proved to have reliable relationship with crashes; Tarko, Davis, Saunier, Sayed, & Washington (2009) noted that using speed as a standalone surrogate measure may be difficult due to the complexity of the speed-safety relationship.

In this context, speeds derived from emerging sources of floating car data (FCD, also known as probe vehicle data) provide an interesting alternative. This approach to speed measurement is based on big data, sampled from vehicle fleets (data “collected by the vehicles themselves”; Bessler & Paulin, 2013).

The goal of this paper is to identify opportunities and challenges regarding using FCD speeds to develop surrogate safety measures. This new use of FCD data could enhance research on speed and safety. Some examples of recent and emerging research explored in the paper include:

- a. using speed or speeding as a safety performance indicator, collected in a representative network of sites, for example to evaluate measures (national speed limit changes, campaigns, enforcement, etc.) and observe long-term national safety trends
- b. using speeding or harsh braking to identify dangerous events or assess driving behaviour
- c. using speed (or derived indicators) to identify and assess high-risk sites, as well as safety variations, for example due to the impact of curve radii on driving behaviour, effect of

45 changing road width, or traffic calming measures (both before-after and cross-sectional
46 studies), for example to provide background for revision of local speed limits.

47 Note that in this review, speeding is understood as driving in excess of posted speed limit.

48 Compared to the previous reviews, which focused mainly on uses of on GSM (Global System for
49 Mobile Communications) and FCD for traffic monitoring (e.g. Bessler & Paulin, 2013; Leduc,
50 2008; Rose, 2006), the presented review focuses primarily on the safety perspective.

51 **Background**

52 Traditionally data for speed studies have been collected using a mix of methods: hand-held radar
53 guns, roadside traffic counters, or fixed loops or tube counters. The common characteristic of these
54 approaches is their spot character: the obtained speeds come from fixed points, which may not be
55 representative of the rest of the entire studied road segment or location. Therefore, using
56 conventional approaches to collect network-wide data is not likely to be feasible.

57 Compared to traditional speed measurement techniques, FCD has two main benefits:

- 58 • Coverage is not limited in space (suitable for network-wide speed surveys)
- 59 • Availability of historical FCD data (ideal source for before-after studies)

60 The vehicles (probes) are located through:

- 61 • mobile phone triangulation (so called GSM data or cellular FCD), or
- 62 • GPS navigation devices, registering GPS position and time of a vehicle along a known route
63 enables calculation of average vehicle speed (this being the more accurate of the two;
64 Bessler & Paulin, 2013)

65 GPS signals may be registered by a portable device (smartphone or satellite navigation), or an in-
66 vehicle data recorder (IVDR). Both may also contain additional sensors (e.g. accelerometer,
67 gyroscope) or a connection to a Controller Area Network (CAN bus), which enables recording data
68 from other car sensors (odometer, fuel consumption, engine performance, etc. – such enhanced data
69 are also called extended floating car data, xFCD; Bessler & Paulin, 2013). In the review, the term
70 FCD will cover subset of data, mainly speed (from GPS) and acceleration (from accelerometer),
71 which are clearly related to safety.

72 Despite the mentioned benefits, it should be remembered that FCD was originally serving different
73 purposes (navigation, traffic monitoring). In order to make sure that FCD may be confidently used
74 in road safety research, the differences between the original purposes and mentioned research
75 approaches and their implications will be made clear in the following parts:

- 76 • Sampling rate
- 77 • Study size
- 78 • Free-flow speed determination
- 79 • Reliability and validity

80 **Method**

81 This paper undertook a review of available literature from across a range of subjects and different
82 study types pertaining to FCD speeds. Given the exploratory nature of this review, only sources
83 with unclear methodology and FCD data sources were set aside. All other studies were considered
84 in high-level reporting used in this review. Full manuscripts were reviewed to extract qualitative
85 and quantitative information.

86 The review parameters included:

- 87 • Retrieved sources:

- 88 ○ papers from Web of Science, Scopus and TRID databases, including their references
 89 (snowballing)
 90 ○ “grey literature”: ARRB Knowledge Base, institute reports, naturalistic driving
 91 studies/field operational test (NDS/FOT) project deliverables
 92 ○ proprietary data specification sources.
 93 ● Keywords: floating car data, speed, safety
 94 ● Language: English
 95 ● Time frame restriction: none

96 The review findings were organised into logical subject areas pertaining to FCD data, its speed
 97 aspects, and its potential use to develop surrogate safety measures. These were then synthesised into
 98 general conclusions about opportunities and challenges. These subject areas were as follows:

- 99 ● Sampling rate
 100 ● Study size
 101 ● Free-flow speed determination
 102 ● Reliability
 103 ● Validity
 104 ● Relevance to road safety

105 **Review results**

106 *Sampling rate*

107 Typical FCD studies are conducted for traffic analyses (providing real-time traffic information,
 108 travel time predictions, etc.) based on GPS signals from vehicle fleets (taxis, commercial vehicles,
 109 but also private vehicles using mobile phones or satellite navigation). For these purposes, GPS
 110 signal sampling rate in order of seconds or minutes is common, see examples in Table 1.

111 **Table 1. FCD studies and their characteristics (sorted by sampling rate)**

Reference	Data provider (fleet, location)	Sampling rate
Berntsen, Molnár, & Zďenek (2016)	Telemotix (544 vehicles, Norway)	5 sec
Wang et al. (2015, 2016)	YOOTU (15,000 taxis in Shanghai)	10 – 15 sec
Jurewicz et al. (2017)	HERE and TomTom (Australia)	10 – 30 sec
Bekhor, Lotan, Gitelman, & Morik (2013)	Decell (> 100,000 vehicles in Israel)	30 sec
Hrubeš & Blümelová (2015)	RODOS (> 100,000 vehicles, Czech Republic)	1 min
Pascale et al. (2015)	WAY (13,000 trucks in Italy)	20 sec – 3 min
Aarts, Bijleveld, & Stipdonk (2015)	TomTom (the Netherlands)	5 min

112 Sampling rates have a direct impact on available level of detail of obtained data. For example, 1
 113 second (i.e. 1 Hz) corresponds to approx. 14 and 25 metres driven, at typical urban/rural speed
 114 limits 50 and 90 km/h, respectively. This is why frequencies below 1 Hz (i.e. one or more records
 115 per second), are necessary for detailed studies. FESTA Handbook (Barnard, 2017) for FOTs
 116 explicitly states that “vehicle speed must be recorded in at least 10 Hz”. In addition, not only speed
 117 is interesting for safety studies. Acceleration data (or jerk, i.e. derivative of acceleration) is
 118 collected from accelerometer, usually at higher frequencies, compared to speed. The question is
 119 what frequency should be set.

120 Current FCD data market offers various sensors, which are capable of providing instant data at rates
 121 of up to 1000 Hz – however, the choice influences the sample size, representativeness of the data,

122 the price of purchase, data storage and processing. Ideally, data collection requirements should be
 123 planned according to the observed phenomenon. For example, in a naturalistic driving studies of
 124 motorcycle riders (Laporte, 2010), based on typical riders' reaction time 0.3 – 0.4 s and requirement
 125 of at least 15 signal samples for adequate instrumental description of the reactions, sampling
 126 frequency was set at 100 Hz. However, most naturalistic driving studies are not as strict: a review of
 127 such studies (Backer-Grøndahl, Phillips, Sagberg, Touliou, & Gatscha, 2009) listed typical values
 128 between 10 and 30 Hz; another summary (Welsh, Reed, Talbot, & Morris, 2010) recommended 50
 129 Hz as sufficient acceleration data sampling frequency. In general, 10 Hz seems to be typical
 130 sampling rate for large NDS/FOT (e.g. 100-Car NDS, SHRP2 NDS, euroFOT, SeMiFOT).

131 On the other hand, for routinely collected data (not specifically planned for research), lower rates
 132 could suffice. For example, Bärghman (2015) distinguishes research data (often collected at 10 Hz or
 133 higher) and commercially collected data (usually with lower sample frequency, such as 4 Hz) –
 134 these may involve fleet monitoring or car insurers.

135 In general, usefulness of data depends on the purpose of safety research. These may comprise
 136 monitoring speed trends, informing strategy and doing evaluations at road segment level, as well as
 137 more detailed studies, using acceleration/jerks. For selected examples of research studies, based on
 138 both data sources, see Table 2.

139 **Table 2. Research-oriented FCD studies and their characteristics (sorted by rate)**

Reference	Location, fleet	Sampling rate
<i>Naturalistic driving studies with dedicated data collection</i>		
Reinau, Andersen, & Agerholm (2016)	Denmark (ITS Platform)	speed 1 Hz acceleration 10 Hz
Pande et al. (2017)	US (33 drivers)	jerk 3 Hz
Ryder, Gahr, Egolf, Dahlinger, & Wortmann (2017)	Switzerland (57 drivers)	speed 30 Hz
Toledo, Musicant, & Lotan (2008)	Israel (GreenBox)	acceleration 40 Hz
Naude et al. (2017)	France (51 drivers)	acceleration 100 Hz
<i>Studies which used data collected for other purposes</i>		
Ambros et al. (2017)	Czech Republic (Princip)	speed 4 Hz acceleration 32 Hz
Bagdadi & Várhelyi (2011)	Sweden (Lund ISA trial)	jerk 5 Hz
Punzo, Borzacchiello, & Ciuffo (2011)	US (NGSIM program)	jerk 10 Hz
Joubert, de Beer, & de Koker (2016)	South Africa (Digicore)	acceleration 50 Hz

140 Apart from the mentioned GPS and accelerometers, there are instrumented vehicles, which involve
 141 for example cameras, VBOX sensors, Mobileye or LIDAR (see reviews by Carsten, Kircher, &
 142 Jamson, 2013; Valero-Mora et al., 2013). While they present excellent data acquisition systems for
 143 safety research, they are not likely to be feasible for large fleets due to their high cost. Large FCD
 144 fleets are necessary to provide large speed data sources for consideration.

145 **Study size**

146 Conventional sampling theory calculates minimum sample size based on allowable error and
 147 sample standard deviation of measured speeds. Traditional recommendation was measuring at least
 148 30, ideally 100 – 200 vehicles (e.g. Kraft, Homburger, & Pline, 2009; Narasimha Murthy & Mohle,
 149 2001; PIARC, 2003). Also TRB synthesis (TRB, 2011) of operating speed studies reports typical
 150 requirement “at least 100 per site.”

151 However, Smith, Zhang, Fontaine, & Green (2003) noted that this traditional approach is not fully
152 transferable to FCD studies, where the conditions of sampling theory (data within each
153 measurement interval is stationary, and variance does not change) do not hold. On the contrary,
154 FCD depends on non-constant penetration rate (how large fleet sample should be equipped by FCD
155 sensors, in order to make its data representative of total flow). Reviews summarized that in the
156 highway environment penetration rates up to 3 % are sufficient (Vandenberghe, Vanhauwaert,
157 Verbrugge, Moerman, & Demeester, 2012); in urban areas rates up to 5 % were recommended
158 (Bessler & Paulin, 2013).

159 In addition, on roads with lower volumes lack of data may be expected. Srinivasan & Jovanis
160 (1996) argued that “probes cannot be used as a stand-alone source of travel time information,
161 especially during off-peak periods and on lightly travelled corridors and low-speed roads, such as
162 local and collector streets and minor arterials”. Nevertheless, recent expansion of FCD is changing
163 this situation. Jurewicz et al. (2017) studied FCD on lower-volume roads and provided some
164 guidance on necessary data collection periods (in numbers of months, based on the level of traffic
165 volume).

166 To produce national/state safety performance indicators, the speed data should come from the
167 widest possible spectrum of locations to make it representative of the entire road network (or from
168 the entire road network). EU SafetyNet project (Hakkert & Gitelman, 2007) developed detailed
169 manual to this process. As a minimum, the sites should be sampled from sub-groups based on
170 different road types, speed limits or number of lanes (approx. 30 sites per group). This could also
171 serve as a minimum requirement for FCD speeds, if necessary.

172 *Free-flow speed determination*

173 In traffic engineering, there is an important concept of free-flow speed, as a standard measure,
174 comparable across different sites and representing speed of vehicles under low volume conditions,
175 unhindered by traffic control devices.

176 Spot-speed studies are done either collected automatically or manually. In the latter approach, free-
177 flowing vehicles are selected individually by an observer. Another, more objective approach is
178 based on gaps between vehicles – various headway or gap thresholds are used to distinguish
179 between vehicles following others or travelling freely. However, many different values have been
180 used in international guidance, ranging from 3 to 12 s. Other thresholds have been even more
181 pragmatic: for example in terms of hourly number of vehicles (ranging between studies from 200 to
182 1000 veh/hr) (for a review see Ambros & Kysely, 2016).

183 Nevertheless, none of these approaches is feasible for FCD, which is collected from individual
184 vehicles only, without being able to check whether they are influenced by other vehicles or not.
185 Popular approach is thus restricting data collection to off-peak hours (Bekhor et al., 2013; Pline,
186 1992; Wang et al., 2006), or night time (TomTom, 2016). However, this practice is likely to
187 severely reduce the sample, especially in case of commercial vehicles, which usually travel during
188 daytime.

189 One could also ask whether night time speeds are representative of typical driver behaviour, as
190 these speeds may be influenced by darkness, fleet composition, presence/absence of street lighting,
191 and potentially increased speeding (Jurewicz et al., 2017). The question could be even more
192 general: if we aim to study ‘unsafety’, then should we focus on speed data from the times and
193 conditions when crashes happen most? If so, then why do we typically study free-flow conditions,
194 where vehicles are not affected by presence of others?

195 In general, free-flow speed issues have not been studied much in FCD literature. For example,
196 Diependaele, Riguelle, & Temmerman (2016) attempted modelling the free-flow speeds with

197 probabilistic approach; Ambros et al. (2017) applied cluster analysis to separate free-flow speeds
 198 from all-vehicle speed data. For practical purposes, FCD speeds from off-peak periods may be
 199 assumed to be an estimate of free-flow speeds. The specific selection of these periods may need to
 200 be judgement-based.

201 In case of FCD speeds it is important to make sure that speeds are:

- 202 1. reliable when compared between various providers
- 203 2. valid when compared to “ground truth” (traditional speed measurement methods)
- 204 3. relevant to road safety

205 **Reliability**

206 Spasovic, Dimitrijevic, & Kim (2013) reported a US validation study for the FCD speeds provided
 207 by three commercial traffic data providers (INRIX, NAVTEQ, TrafficCast Dynaflow), using data
 208 from 4 roadways in New Jersey and New York. All three technologies were mostly within the
 209 acceptance limits for the average absolute speed error (≤ 16 km/h) and the speed error bias (≤ 8
 210 km/h). All of the studied technologies consistently overestimated the speed in the lowest speed bin
 211 (0 – 50 km/h), and consistently underestimated the speed in the highest speed bin (> 100 km/h).

212 Another US study (Rapolu & Kumar, 2015) investigated whether there is a relationship between
 213 HERE, INRIX and Bluetooth speed data. Model free-flow speeds were found on an average 10 %
 214 higher than the observed Bluetooth speeds; Bluetooth and HERE travel speeds were in general 8 to
 215 16 km/h lower than INRIX speeds during the day.

216 **Validity**

217 Several comparative studies investigated quality of FCD-based travel times and speeds; see Table 3.
 218 Due to the wide range of study types, FCD sources, and differences in their robustness, only high-
 219 level findings are provided in Table 3 to provide a general overview of validity

220 **Table 3. FCD-based comparative studies and their characteristics (sorted by study date)**

Reference	Data description	High-level findings
<i>Travel time studies</i>		
Brockfeld, Lorkowski, Mieth, & Wagner (2007)	4 days of data from 500-taxi FCD fleet in Nuremberg (Germany) vs. automated license plate recognition (ALPR)	“travel times calculated by the system deliver valuable data”
de Boer & Krootjes (2012)	9 routes in Eindhoven (the Netherlands), penetration > 2 %, TomTom historic travel times vs. ALPR	“FCD is accurate”
Clergue & Buttignol (2014)	4 routes in France (penetration 0.7 – 4.3 %), TomTom vs. ALPR	“differences are insignificant”
<i>Speed studies</i>		
Yim (2003)	cellular phone-based speeds vs. loop speeds over 1 month (four French freeways)	cellular data speeds about 10 % lower on intercity freeways, higher (24 – 32 %) on an urban freeway
Smith et al. (2003)	cellular FCD (10-minute intervals) vs. point video	FCD on average by 10 – 15 km/h higher
Bar-Gera (2007)	cellular FCD vs. dual magnetic loop detectors (Israeli freeway)	“a good match between the two measurement methods”
Lattimer &	INRIX FCD vs. ALPR data on 4	INRIX speeds on average 10 km/h

Glotzbach (2012)	Florida freeways	<i>higher</i>
Espada & Bennett (2015)	EastLink in Melbourne, HERE travel speeds every 5 minutes vs. e-tag gate crossings	probe travel speed estimates on average by 9 km/h <i>lower</i>
Hrubeš & Blümelová (2015)	Prague ring road (Czech Republic), 2% penetration, FCD vs. loops	“reasonable estimate of speed”, shown to be generally <i>lower</i>
INRIX (2016)	“The World’s Largest Independent Traffic Data Validation” (I-95 VPP)	accurate within 16 km/h of actual traffic speeds on average
Diependaele et al., 2016	Belgian rural roads, FCD vs. loops	FCD-speed almost by 10 km/h <i>higher</i> than free-flow loop-speed
Ambros et al. (2017)	Czech rural roads, FCD vs. radar	FCD-speed on average by 2 km/h <i>higher</i>

221 Some of the mentioned studies found FCD speeds *higher* than radar speeds; other studies (Aarts et
 222 al., 2015; Jurewicz et al., 2017) found an opposite tendency (FCD-speed *lower* than radar-speed).
 223 An explanation was given that FCD average speed relates to a whole road segment (i.e. including
 224 turning at intersections), while the traditional spot-speed relates to a single spot only (typically
 225 collected away from intersections; Aarts et al., 2015). Also, different FCD sources were used in the
 226 studies leading to different outcomes. It is thus important to understand the specifications of each
 227 FCD source and to sense-check (or calibrate) its speed outputs against a trusted ground truth source.

228 To sum up, many studies concluded that FCD speed is reliable (not more than by 16 km/h different
 229 compared to ground truth or other providers’ data). For research purposes, this difference may be
 230 too large; if the differences are systematic, calibration may be a solution.

231 ***Relevance to road safety***

232 Information, distilled from FCD studies, has a potential to enhance and improve the quality and
 233 coverage of speed and safety studies. In terms of the applications, which were outlined in the
 234 introduction:

235 *a. FCD-speeds may be used network-wide as a safety performance indicator*

236 This was an idea of a Dutch analysis reported by Aarts et al. (2015). After investigating
 237 performance of TomTom data, the source was found feasible for providing information for safety
 238 performance indicators (specifically speed levels). The study noted some limitations of FCD, for
 239 example that they do not provide information about speed differences between individual vehicles;
 240 privacy issues also limit analyses related to vehicle types or driver age/gender.

241 Recent Australian studies are more positive. Jurewicz et al. (2017) found that FCD can be
 242 potentially translated to spot-speed equivalent using calibration models; the authors also provided
 243 an example of using FCD speeds for before-after evaluation of a speed limit change. A follow-up
 244 study (Jurewicz, Han, & Espada, 2018) used TomTom and HERE data, which can be proportionally
 245 split by vehicle type to test matching with actual fleet composition; this would help in estimating
 246 speeding and speed percentiles.

247 *b. FCD may be used to derive speeding or harsh braking/accelerating to identify dangerous* 248 *events and assess driving styles*

249 There is clear evidence that some indicators, for example, related to speed and acceleration, are
 250 predictive of crash involvement risk (Sagberg, Selpi, Piccinini, & Engström, 2015). In this regard,
 251 FCD, which is linked to specific drivers, is a valuable source for assessing driving performance and
 252 driving styles (for example defensive/aggressive/inattentive), as well as driving exposure. This data

253 may then be compiled and used for so called usage-based insurance systems (Tselentis, Yannis, &
 254 Vlahogianni, 2017). For example, Feng et al. (2017), using criteria based on jerk metrics,
 255 successfully identified aggressive drivers. However, large amounts of collected data need to be
 256 analysed; Ellison, Greaves, & Bliemer (2015) mention various approaches, such as using pattern
 257 matching algorithms to identify patterns that are of interest and to focus analysis on these portions
 258 of the data, including verification through additional video footage. In addition, FCD were found
 259 influenced by exogenous factors, such congestion, construction, traffic light timings and other
 260 vehicles. The use of video cameras may reduce these influences, but requires a labour intensive
 261 manual processing.

262 Fortunately, there are approaches to recognize conflicts within FCD without manually reviewing all
 263 video streams. A common approach is to analyse kinematic vehicle data to detect safety-critical
 264 events such as emergency braking or sudden steering. However, critical values (thresholds) of these
 265 “event triggers” vary significantly in the literature (Aichinger, Nitsche, Stütz, & Harnisch, 2016),
 266 for example:

- 267 • longitudinal deceleration range from approx. 0.1 to 0.7 g (Johnson & Trivedi, 2011;
 268 Paefgen, Kehr, Zhai, & Michahelles, 2012)
- 269 • critical jerks vary between 0.06 and 2 g/sec (Naude et al., 2017; Pande et al., 2017)

270 Combined criteria were also used (Naude et al., 2017). Alternative approach is analysing all the
 271 collected data (so called risk space; Joubert et al., 2016).

272 Note that smartphones are often used for collecting data for driver assessment. However, studies
 273 indicated they may not be fully suitable, compared to in-vehicle data recording. Paefgen et al.
 274 (2012) found smartphone FCD as overestimating critical driving events; Händel et al. (2014)
 275 reported that they are lacking reliability.

276 *c. FCD may be used to obtain speed and other indicators to identify and assess safety at specific*
 277 *locations*

278 Based on the above-mentioned risk thresholds and frequency of their occurrence on specific
 279 locations, high-risk sites may be identified. For some example studies, see Table 4.

280 **Table 4. Validation approaches in selected FCD-based studies (sorted by study date)**

Reference	Location; indicator type	Validation
Mousavi, Parr, Pande, & Wolshon (2015)	Louisiana highways; jerks	21 jerk value thresholds evaluated in the sensitivity analysis; segment jerk-rates compared to crash rates
Reinau et al. (2016)	Aalborg city (Denmark); speed and jerks	visual comparison of crash location map vs. risk location map
Ambros et al. (2017)	Czech rural roads; speed	speed consistency (i.e. differences between speeds in tangents and following curves) related to a long-term crash frequency
Pande et al. (2017)	California freeways; jerks	relating 10 jerk thresholds (varying from 0.50 to 2.75 ft/s ³ , with an increment of 0.25) to crash frequency

281 Obviously two approaches to validation exist: “theory-based” (confirmatory, testing hypotheses) or
 282 “data-based” (exploratory, data mining).

283 In addition, collecting network-wide FCD also enables studying relationships between speed and
 284 driving/environmental characteristics. For example in Denmark, using FCD data from ITS Platform
 285 enabled quantifying the influence of road and shoulder width, curve radii, the extent of road

286 markings and the section lengths on speed (Andersen et al., 2016; Rimme et al., 2016). A model,
287 based on Czech FCD data on rural roads, confirmed that increasing road width and enabling
288 overtaking and climbing are associated with an increase of speed (Ambros et al., 2017). An Israeli
289 FCD study (Gitelman et al., 2016) found that changing shoulder width, recovery-zone width (clear
290 zone) or intersection has a potential to affect travel speeds.

291 Unfortunately, in several studies explanatory power (R^2) of the mentioned FCD-speed models was
292 found relatively low (approx. 30 – 40%; Ambros et al., 2017; Andersen, Reinau, & Agerholm,
293 2016; Gaca & Kieć, 2016). This finding may be explained by the characteristics of FCD:
294 conventional spot-speed data are based on samples collected in more or less controlled conditions
295 (daytime, season, weather, etc.) and may thus yield homogeneous results with high R^2 values; on
296 the other hand, FCD studies use an “anonymous” sample collected in various days, seasons and
297 weather conditions, leading to heterogeneous results with lower R^2 values. The low explanatory
298 power may lead to insufficient reliability in cases when models are applied in different time and
299 space from the original conditions. Therefore, the models could benefit from the improvement: e.g.
300 adding potential additional explanatory variables, and/or considering vehicle and driver
301 characteristics using random effect models (Bassani, Cirillo, Molinari, & Tremblay, 2016).

302 **Summary, discussion and conclusions**

303 The goal of this review was to identify challenges and opportunities regarding using FCD speeds to
304 develop potential surrogate safety measures.

305 The review has some limitations. Exploratory nature of the review permitted only cursory critique
306 of the studies. In addition, the reviewed studies were of varied quality and objectives, which limited
307 comparability of beyond the high level findings. Robust studies were given more prominence. In
308 addition, as the reviewed field is quickly evolving, new studies are being published and may change
309 the validity of the reported findings.

310 Regarding conclusions, firstly it is important to consider benefits and limitations of FCD:

- 311 • Compared to traditional spot-speed measurements, FCD has benefits of unlimited spatial
312 coverage, as well as availability of historical data. However, FCD may not be sufficient in
313 case of low traffic volumes.
- 314 • Anonymity of FCD may limit distinguishing different vehicle types or driver characteristics.
315 It also complicates determination of free-flow speed.
- 316 • In a long run, continuity and quality of FCD measurements is beyond the direct sphere of
317 influence of end users.

318 Secondly it is important to remember that FCD was originally serving navigation and then traffic
319 monitoring purposes. In order to make sure that FCD may be confidently used in road safety
320 research, the differences from the original purposes need to be considered in context of surrogate
321 safety measures:

- 322 1. Sampling rate needs to be planned, based on requirements and type of data collected.
- 323 2. Study size also needs to be planned, especially in conditions of low traffic volume.
- 324 3. There is not any universal approach to free-flow speed determination, most are estimations
325 only.
- 326 4. Reliability and validity: FCD speed reliability and relation to the ground truth is uncertain
327 and is strongly dependent on the compared sources. There are no guidelines for detecting
328 risk thresholds (e.g. rapid braking), nor uniform approach to validating FCD speeds against
329 safety.

330 Some issues may be inherent to the method: for example, FCD is usually collected out of urban
331 areas, with not-fully-representative vehicle fleet and drivers sample. Both pros and cons of FCD
332 need to be carefully weighed, based on the requirements of specific research tasks. For example,

333 using FCD for network-wide speeding trends may not be as data-hungry as using FCD to assess
334 specific driving styles.

335 Nevertheless, FCD quality and coverage is continuously increasing. FCD found its way into
336 commercial services, such as PTV Visum (with TomTom FCD) or VIA Traffic Solutions Software
337 and ARRB Aperture tool (with HERE Traffic Analytics). With continuing data collection and
338 investigations, focusing on the mentioned issues, added knowledge will enable developing FCD-
339 speed-based surrogate safety measures.

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344 **References**

345 Aarts, L. T., Bijleveld, F. D., & Stipdonk, H. L. (2015). Usefulness of 'floating car speed data' for
346 proactive road safety analyses: Analysis of TomTom speed data and comparison with loop
347 detector speed data of the provincial road network in the Netherlands. Report R-2015-3.
348 Leidschendam, the Netherlands: SWOV. Retrieved from
349 <https://www.swov.nl/sites/default/files/publicaties/rapport/r-2015-03.pdf>

350 Aichinger, C., Nitsche, P., Stütz, R., & Harnisch, M. (2016). Using low-cost smartphone sensor
351 data for locating crash risk spots in a road network. *Transportation Research Procedia*, 14,
352 2015–2024.

353 Ambros, J., & Kysely, M. (2016). Free-flow vs car-following speeds: Does the difference matter?
354 *Advances in Transportation Studies*, 40, 17–26.

355 Ambros, J., Valentová, V., Gogolín, O., Andrášik, R., Kubeček, J., & Bíl, M. (2017). Improving the
356 self-explaining performance of Czech national roads. *Transportation Research Record*, 2635,
357 62–70.

358 Andersen, C. S., Reinau, K. H., & Agerholm, N. (2016). The relationship between road
359 characteristics and speed collected from floating car data. *Journal of Traffic and*
360 *Transportation Engineering*, 4, 291–298.

361 Backer-Grøndahl, A., Phillips, R., Sagberg, F., Toulou, K., & Gatscha, M. (2009). Topics and
362 applications of previous and current naturalistic driving studies. PROLOGUE project
363 deliverable 1.1. Retrieved from <https://prologue.kfv.at/prologue/deliverables/>

364 Bagdadi, O., & Várhelyi, A. (2011). Jerky driving – An indicator of accident proneness? *Accident*
365 *Analysis & Prevention*, 43, 1359–1363.

366 Bar-Gera, H. (2007). Evaluation of a cellular phone-based system for measurements of traffic
367 speeds and travel times: A case study from Israel. *Transportation Research Part C*, 15, 380–
368 391.

369 Bärgrman, J. (2015). On the Analysis of Naturalistic Driving Data: Development and Evaluation of
370 Methods for Analysis of Naturalistic Driving Data from a Variety of Data Sources.
371 Gothenburg, Sweden: Chalmers University of Technology. Retrieved from
372 <http://publications.lib.chalmers.se/records/fulltext/210436/210436.pdf>

373 Barnard, Y. (Ed.) (2017). Updated Version of the FESTA Handbook. FOT-Net Data project
374 deliverable 5.4. Retrieved from <http://fot-net.eu/Documents/festa-handbook-version-7/>

- 375 Bassani, M., Cirillo, C., Molinari, S., & Tremblay, J. (2016). Random effect models to predict
376 operating speed distribution on rural two-lane highways. *Journal of Transportation*
377 *Engineering ASCE*, 142, 04016019.
- 378 Bekhor, S., Lotan, T., Gitelman, V., & Morik, S. (2013). Free-flow travel speed analysis and
379 monitoring at the national level using global positioning system measurements. *Journal of*
380 *Transportation Engineering ASCE*, 139, 1235–1243.
- 381 Berntsen, M., Molnár, P., & Zděnek, M. (2016). Driving behavior and risk of accident: evidence
382 from Norway. Trondheim, Norway: NTNU.
- 383 Bessler, S., & Paulin, T. (2013). Literature study on the state of the art of probe data systems in
384 Europe. Vienna, Austria: FTW Telecommunications Research Center. Retrieved from
385 http://www.fot-net.eu/download/fcd-report_final.pdf
- 386 Brockfeld, E., Lorkowski, S., Mieth, P., & Wagner, P. (2007). Benefits and limits of recent floating
387 car data technology – an evaluation study. Presented at 11th WCTR Conference, Berkeley,
388 CA.
- 389 Carsten, O., Kircher, K., & Jamson, S. (2013). Vehicle-based studies of driving in the real world:
390 The hard truth? *Accident Analysis & Prevention*, 58, 162–174.
- 391 Clergue, L., & Buttignol, V. (2014). Using GPS data in favour of traffic knowledge. Presented at
392 Transport Research Arena 2014, Paris, France.
- 393 de Boer, G., & Krootjes, P. (2012). The Quality of Floating Car Data Benchmarked: An alternative
394 to roadside equipment? Presented at 19th ITS World Congress, Vienna, Austria.
- 395 Diependaele, K., Riguelle, F., & Temmerman, P. (2016). Speed behavior indicators based on
396 floating car data: Results of a pilot study in Belgium. *Transportation Research Procedia*, 14,
397 2074–2082.
- 398 Ellison, A. B., Greaves, S. P., & Bliemer, M. C. J. (2015). Driver behaviour profiles for road safety
399 analysis. *Accident Analysis & Prevention*, 76, 118–132.
- 400 Elvik, R. (2009). The Power Model of the relationship between speed and road safety: Update and
401 new analyses. Report 1034/2009. Oslo, Norway: Institute of Transport Economics. Retrieved
402 from <https://www.toi.no/getfile.php?mmfileid=13206>
- 403 Elvik, R. (2013). A re-parameterisation of the Power Model of the relationship between the speed of
404 traffic and the number of accidents and accident victims. *Accident Analysis & Prevention*, 50,
405 854–860.
- 406 Espada, I., & Bennett, P. (2015). Probe data and its application in traffic studies. Presented at 2015
407 IPWEA/IFME Conference, Rotorua, NZ.
- 408 Feng, F., Bao, S., Sayer, J. R., Flannagan, C., Manser, M., & Wunderlich, R. (2017). Can vehicle
409 longitudinal jerk be used to identify aggressive drivers? An examination using naturalistic
410 driving data. *Accident Analysis & Prevention*, 104, 125–136.
- 411 Gaca, S., & Kieć, M. (2016). Speed management for local and regional rural roads. *Transportation*
412 *Research Procedia*, 14, 4170–4179.
- 413 Gitelman, V., Pesahov, F., Carmel, R., & Bekhor, S. (2016). The identification of infrastructure
414 characteristics influencing travel speeds on single-carriageway roads to promote self-
415 explaining roads. *Transportation Research Procedia*, 14, 4160–4169.
- 416 Hakkert, A. S., & Gitelman, V. (Eds.) (2007). Road Safety Performance Indicators: Manual.
417 SafetyNet project deliverable 3.8. Retrieved from [http://erso.swov.nl/safetynet/fixe/WP3/](http://erso.swov.nl/safetynet/fixe/WP3/sn_wp3_d3p8_spi_manual.pdf)
418 [sn_wp3_d3p8_spi_manual.pdf](http://erso.swov.nl/safetynet/fixe/WP3/sn_wp3_d3p8_spi_manual.pdf)

- 419 Händel, P., Skog, I., Wahlström, J., Bonawiede, F., Welch, R., Ohlsson, J., & Ohlsson, M. (2014).
420 Insurance telematics: Opportunities and challenges with the smartphone solution. *IEEE*
421 *Intelligent Transportation Systems Magazine*, Winter 2014, 57–70.
- 422 Hrubeš, P., & Blümelová, J. (2015). Comparative Analysis for Floating Car and Loop Detectors
423 Data. Presented at 22nd ITS World Congress, Bordeaux, France.
- 424 INRIX (2016). INRIX I-95 VPP Data Summary Validation. Retrieved from [http://inrix.com/case-](http://inrix.com/case-studies/inrix-i-95-vpp-data-summary-validation-case-study/)
425 [studies/inrix-i-95-vpp-data-summary-validation-case-study/](http://inrix.com/case-studies/inrix-i-95-vpp-data-summary-validation-case-study/)
- 426 Johnson, D. A., & Trivedi, M. M. (2011). Driving Style Recognition Using a Smartphone as a
427 Sensor Platform. Presented at 14th International IEEE Conference on Intelligent
428 Transportation Systems, Washington, DC.
- 429 Johnston, I. (2004). Reducing injury from speed related road crashes: Towards the achievement of a
430 population based preventive strategy. *Injury Prevention*, 10, 257–259.
- 431 Joubert, J. W., de Beer, D., & de Koker, N. (2016). Combining accelerometer data and contextual
432 variables to evaluate the risk of driver behaviour. *Transportation Research Part F*, 41, 80–96.
- 433 Jurewicz, C., Tofler, S., & Makwasha, T. (2015). Improving the performance of safe system
434 infrastructure: final report. Publication AP-R498-15. Sydney, NSW: Austroads.
- 435 Jurewicz, C., Espada, I., Makwasha, T., Han, C., Alawi, H., & Ambros, J. (2017). Validation and
436 applicability of floating car speed data for road safety. Presented at 2017 Australasian Road
437 Safety Conference, Perth, WA.
- 438 Jurewicz, C., Han, C., & Espada, I. (2018). Use of big data for speed management in road safety.
439 Submitted to the 28th ARRB International Conference, Brisbane, Qld.
- 440 Kraft, W. H., Homburger, W. S., & Pline, J. L. (Eds.) (2009). Traffic Engineering Handbook, 6th
441 Edition. Washington, DC: ITE.
- 442 Laporte, S. (Ed.) (2010). Design of a naturalistic riding study – Implementation plan. 2BESAFE
443 project deliverable 5. Retrieved from [http://www.transport-research.info/project/2-wheeler-](http://www.transport-research.info/project/2-wheeler-behaviour-and-safety)
444 [behaviour-and-safety](http://www.transport-research.info/project/2-wheeler-behaviour-and-safety)
- 445 Lattimer, C. R., & Glotzbach, G. (2012). Evaluation of Third-Party Travel Time Data in
446 Tallahassee, FL. Presented at ITS America 2012, National Harbor, MD.
- 447 Leduc, G. (2008). Road Traffic Data: Collection Methods and Applications. JRC Technical Notes
448 47967. Luxembourg: European Communities. Retrieved from
449 <http://ftp.jrc.es/EURdoc/JRC47967.TN.pdf>
- 450 Mousavi, S.-M., Parr, S. A., Pande, A., & Wolshon, B. (2015). Identifying High-Risk Roadways
451 Through Jerk-Cluster Analysis. Presented at 2015 Road Safety & Simulation International
452 Conference, Orlando, FL.
- 453 Narasimha Murthy, A. S., & Mohle, H. R. (2001). Transportation Engineering Basics, 2nd Edition.
454 Reston, VA: ASCE.
- 455 Naude, C., Serre, T., Dubois-Lounis, M., Fournier, J.-Y., Lechner, D., Guilbot, M., & Ledoux, V.
456 (2017). Acquisition and analysis of road incidents based on vehicle dynamics. *Accident*
457 *Analysis & Prevention*, in press.
- 458 Nilsson, G. (2004). Traffic Safety Dimensions and the Power Model to Describe the Effect of Speed
459 on Safety. Bulletin 221. Lund, Sweden: Lund University. Retrieved from
460 <https://lup.lub.lu.se/search/ws/files/4394446/1693353.pdf>

- 461 Paefgen, J., Kehr, F., Zhai, Y., & Michahelles, F. (2012). Driving behavior analysis with
462 smartphones: insights from a controlled field study. Presented at 11th International Conference
463 on Mobile and Ubiquitous Multimedia, Ulm, Germany.
- 464 Pande, A., Chand, S., Saxena, N., Dixit, V., Loy, J., Wolshon, B., & Kentda, J. D. (2017). A
465 preliminary investigation of the relationships between historical crash and naturalistic driving.
466 *Accident Analysis & Prevention*, 101, 107–116.
- 467 Pascale, A., Deflorio, F., Nicoli, M., Dalla Chiara, B., & Pedroli, M. (2015). Motorway speed
468 pattern identification from floating vehicle data for freight applications. *Transportation
469 Research Part C*, 51, 104–119.
- 470 PIARC (2003). Road Safety Manual: recommendations from the World Road Association (PIARC).
471 Harrogate, UK: Route2market.
- 472 Pline, J. L. (Ed.) (1992). Traffic Engineering Handbook, 4th Edition. Washington, DC: ITE.
- 473 Punzo, V., Borzacchiello, M. T., & Ciuffo, B. (2011). On the assessment of vehicle trajectory data
474 accuracy and application to the Next Generation SIMulation (NGSIM) program data.
475 *Transportation Research Part C*, 19, 1243–1262.
- 476 Rapolu, S., & Kumar, A. (2015). Comparing Arterial Speeds from “Big-Data” Sources in Southeast
477 Florida (Bluetooth, HERE and INRIX). Presented at 15th TRB National Transportation
478 Planning Applications Conference, Atlantic City, NJ.
- 479 Reinau, K. H., Andersen, C. S., & Agerholm, N. (2016). A New Method for Identifying Hazardous
480 Road Locations using GPS and Accelerometer. Presented at 23rd ITS World Congress,
481 Melbourne, Vic.
- 482 Rimme, N., Nielsen, L., Kjems, E., Tønning, C., Lahrman, H. S., & Agerholm, N. (2016). Speed
483 Choice and Curve Radius on Rural Roads. Presented at 29th ICTCT Workshop, Lund,
484 Sweden.
- 485 Rose, G. (2006). Mobile phones as traffic probes: Practices, prospects and issues. *Transport
486 Reviews*, 26, 275–291.
- 487 Ryder, B., Gahr, B., Egolf, P., Dahlinger, A., & Wortmann, F. (2017). Preventing traffic accidents
488 with in-vehicle decision support systems – The impact of accident hotspot warnings on driver
489 behaviour. *Decision Support Systems*, 99, 64–74.
- 490 Sagberg, F., Selpi, S., Piccinini, G. F. B., & Engström, J. (2015). A review of research on driving
491 styles and road safety. *Human Factors*, 57, 1248–1275.
- 492 Smith, B. L., Zhang, H., Fontaine, M. & Green, M. (2003). Cell-phone probes as an ATMS tool.
493 Report STL-2003-01. Charlottesville, VA: Smart Travel Laboratory. Retrieved from
494 <https://ntl.bts.gov/lib/23000/23400/23431/CellPhoneProbes-final.pdf>
- 495 Spasovic, L. N., Dimitrijevic, B., & Kim, K. (2013). Probe Vehicle Data Comparative Validation
496 Study – New Jersey and New York – Final Report. Newark, NJ: New Jersey Institute of
497 Technology. Retrieved from
498 [http://www.utrc2.org/sites/default/files/TRANSCOM_ProbeVehicle_Final_06-025-
499 2013%20.pdf](http://www.utrc2.org/sites/default/files/TRANSCOM_ProbeVehicle_Final_06-025-2013%20.pdf)
- 500 Srinivasan, K. K., & Jovanis, P. P. (1996). Determination of number of probe vehicles required for
501 reliable travel time measurement in urban network. *Transportation Research Record*, 1537,
502 15–22.
- 503 Tarko, A., Davis, G., Saunier, N., Sayed, T., & Washington, S. (2009). White Paper Surrogate
504 Measures of Safety. Washington, DC: TRB.

- 505 Toledo, T., Musicant, O., & Lotan, T. (2008). In-vehicle data recorders for monitoring and feedback
506 on drivers' behavior. *Transportation Research Part C*, 16, 320–331.
- 507 TomTom (2016). TomTom Traffic Index: Measuring Congestion Worldwide. Retrieved from
508 https://www.tomtom.com/en_gb/trafficindex/about
- 509 TRB (2011). Modeling Operating Speed: Synthesis Report. TR Circular E-C151. Washington, DC:
510 TRB. Retrieved from <http://onlinepubs.trb.org/onlinepubs/circulars/ec151.pdf>
- 511 Tselentis, D. I., Yannis, G., & Vlahogianni, E. I. (2017). Innovative motor insurance schemes: A
512 review of current practices and emerging challenges. *Accident Analysis & Prevention*, 98,
513 139–148.
- 514 Valero-Mora, P. M., Tontsch, A., Welsh, R., Morris, A., Reed, S., Toulou, K., & Margaritis, D.
515 (2013). Is naturalistic driving research possible with highly instrumented cars? Lessons learnt
516 in three research centres. *Accident Analysis and Prevention*, 58, 187–194.
- 517 Vandenberghe, W., Vanhauwaert, E., Verbrugge, S., Moerman, I., & Demeester, P. (2012).
518 Feasibility of expanding traffic monitoring systems. *IET Intelligent Transport Systems*, 6,
519 347–354.
- 520 Wang, J., Dixon, K., Li, H., & Hunter, M. (2006). Operating-speed model for low-speed urban
521 tangent streets based on in-vehicle global positioning system data. *Transportation Research*
522 *Record*, 1961, 24–33.
- 523 Wang, X., Fan, T., Chen, M., Deng, B., Wu, B., & Tremont, P. (2015). Safety modeling of urban
524 arterials in Shanghai, China. *Accident Analysis & Prevention*, 83, 57–66.
- 525 Wang, X., Fan, T., Li, W., Yu, R., Bullock, D., Wu, B., & Tremont, P. (2016). Speed variation
526 during peak and off-peak hours on urban arterials in Shanghai. *Transportation Research Part*
527 *C*, 67, 84–94.
- 528 Welsh, R., Reed, S., Talbot, R., & Morris, A. (2010). Data collection, analysis methods and
529 equipment for naturalistic studies and requirements for the different application areas.
530 PROLOGUE project deliverable 2.1. Retrieved from
531 <https://prologue.kfv.at/prologue/deliverables/>
- 532 Yim, Y. (2003). The State of Cellular Probes. California PATH Research Report UCB-ITS-PRR-
533 2003-25. Berkeley, CA: University of California. Retrieved from
534 <http://escholarship.org/uc/item/8g90p0vw>