

Research vs. practice: An international review of challenges and opportunities in development and use of crash prediction models

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Abstract

Over the past ten years, crash prediction models (CPMs) have become the fundamental scientific tools of road safety management. However, there is a gap between state-of-the-art and state-of-the-practice, with the practical applications lagging behind scientific progress. This motivated the review of international experience with CPMs from the practitioner perspective: how and why should they consider using CPMs? Findings indicate that developing and using CPMs has its challenges. However, these may be minimised by increased communication between researchers (who develop CPMs) and agencies (who use CPMs), resulting in easy-to-use and transparent tools, which will also enable calibrating the CPMs to local conditions.

Introduction

Crash prediction models (CPMs) are mathematical equations, which link safety performance and risk factors. Over the past ten years, CPMs have become the fundamental scientific tools of quantitative road safety management, forming the foundation of the USA Highway Safety Manual (HSM) and the Australian National Risk Assessment Model (ANRAM). CPMs may be used for various key tasks, including network safety screening, economic analysis and road safety impact assessments. However, there are gaps between state-of-the-art (what is published by academics/researchers) and state-of-the-practice (what is needed/used by practitioners), which limits the practical use of CPMs. On this background, the presented review aims to investigate how are CPMs developed and applied. The answers should be of help to a user (e.g. an agency engineer/manager) asking about how and why they should consider using CPMs.

Methods

The goal of the review was to critically summarize international experience in the development and application of CPMs, with a focus on practical use by road agencies. In this regard, both scientific and practice-oriented literature was retrieved based on the following criteria:

- Sources:
 - academic: Web of Science and Scopus, including selected references (snowballing)
 - practical: reports of agencies (e.g. FHWA, Austroads, NZTA)
 - both: ARRB Knowledge Base, TRID database, reports of European institutes, EU project deliverables
- Keywords: accident prediction model, crash prediction model, safety performance function
- Language: English
- Time frame restriction: none

To focus on the typical road settings (the main road network, i.e. motorways/freeways/expressways and national roads), the following specific issues were not considered:

- Macro/planning-level applications (analysis based on land-use zones in assignment models)
- Specific CPMs for vulnerable road users, such as pedestrians or bicyclists
- CPMs for specific site elements (e.g. railway level crossings, bridges, tunnels, etc.)

43 The retrieved materials were mainly from Europe, Australia, New Zealand and North America. In
 44 order to stress the practical focus, the aim was to select the works related to the most frequent
 45 applications of CPMs.

46 The final literature selection thus focused on developing and using CPMs of typical elements (rural
 47 road segments or intersections), from the perspective of non-US practitioner, aiming to conduct
 48 typical tasks, such as road safety impact assessment or network screening. The review is structured
 49 along the following sections, given by the hierarchical steps of developing and applying CPMs:

- 50 1. Data collection, sample size and time period
- 51 2. Road network segmentation
- 52 3. Selection of explanatory variables
- 53 4. Model function forms and other statistical considerations
- 54 5. Model validation
- 55 6. Using CPMs in network screening
- 56 7. Using CPMs in developing crash modification factors (CMFs)
- 57 8. Using CPM tools

58 Previous reviews related to CPMs (e.g. OECD, 1997; Lord & Mannering, 2010; Yannis et al., 2015;
 59 Basu & Saha, 2017) usually considered some of these steps only, mainly 3 and 4. The presented
 60 review fills the gap by compiling information on all six steps, followed by summarised challenges
 61 and opportunities, with available solutions.

62 **Review**

63 CPMs express the expected crash frequency and/or severity of a site (e.g. road segment or
 64 intersection) as a function of explanatory variables. These variables (risk factors) describe exposure
 65 and other characteristics, related to cross section, road design and other attributes. The typical
 66 model form is:

$$67 \quad \text{crash frequency/year} = \exp(\beta_0) \cdot (\text{exposure})^{\beta_i} \cdot \exp(\sum_{i=2}^n (\beta_i \cdot x_i)) \quad (1)$$

68 where x_i are explanatory variables, β_0 is intercept and β_i ($i = 1, 2, \dots$) are regression coefficients.
 69 The coefficients cannot be estimated by the traditional ordinary least squares. In order to correctly
 70 consider discrete and non-negative character of crash frequencies, and their negative binomial
 71 probability distribution, generalized linear modelling (GLM) methods are typically used.

72 For crash data, the variance (dispersion) typically exceeds the mean: they are overdispersed. The
 73 degree of overdispersion in a negative binomial model is represented by overdispersion parameter
 74 that is estimated during modelling along with the regression coefficients of the regression equation.
 75 The overdispersion parameter is used to determine the value of a weight factor for use in the
 76 empirical Bayes (EB) method. This method combines expected (modelled) and recorded (observed)
 77 crash frequencies, in order to improve reliability of a specific site safety level estimation (Hauer,
 78 1997). Applications of EB methods are described in later sections of the review.

79 CPMs may be used for various tasks:

- 80 1. to explore and compare combinations of individual risk factors
- 81 2. for network safety screening (also known as safety ranking or identification of black spots)
- 82 3. for impact assessments, i.e. assessing safety of contemplated (re)constructions
- 83 4. for economic analysis

84 It is to be noted that Task 1 is rather research-oriented; Tasks 2, 3 and 4 represent typical practical
 85 tasks.

86 Given the range of potential applications, CPMs have been acknowledged worldwide as
87 recommended tools, on which rational road safety management should be based. However, at the
88 same time, it has been known that prediction modelling is not a simple task (Turner, Durdin, Bone,
89 & Jackett, 2003; Eenink, Reurings, Elvik, Cardoso, Wichert, & Stefan, 2008; Elvik, 2010) and
90 involve various analytical choices, which are often done without explicit justification. This may
91 explain why there are gaps between state-of-the-art and state-of-the-practice; and this may in turn
92 limit the practical use of CPMs. For example, a survey among European road agencies found that
93 70% of them rarely or never systematically use CPMs in their decision-making (Yannis et al.,
94 2014).

95 According to a review of North American practices (Persaud, 2001), network screening is the most
96 common application of CPMs. In Europe, cost-benefit analysis was identified as a common use of
97 CPM application (Yannis et al., 2014).

98 Regarding the selection of research for inclusion in the review, another distinction needs to be
99 made. In 2010, American Association of State Highway and Transportation Officials (AASHTO)
100 published the first edition of Highway Safety Manual (AASHTO, 2010), which introduces a set of
101 CPMs (referred to as safety performance functions, SPFs, in the HSM) and crash modification
102 factors (CMFs). Crash prediction in the HSM has two main two steps: (1) prediction of a baseline
103 crash rates using SPFs/CPMs for nominal route and intersection conditions, and (2) multiplying the
104 ‘baseline’ models by crash modification factors (CMFs) to capture changes in geometric design and
105 operational characteristics (deviations from nominal conditions). This approach has gained
106 popularity, being incorporated into Interactive Highway Safety Design Model (IHSDM), recently
107 adopted in the European CPM (Yannis et al., 2015), and used in the New Zealand Crash Estimation
108 Compendium (NZTA, 2016).

109 The CPMs/SPFs in the HSM and ISHDM, developed from data in several US states, are not directly
110 transferable to other jurisdictions (inside or outside US). Some studies confirmed good
111 transferability, mainly between US states (Sun, Li, Magri, & Shirazi, 2006; Xie, Gladhill, Dixon, &
112 Monsere, 2011; Bornheimer, Schrock, Wang, & Lubliner, 2012), but some were less successful
113 when applied abroad, for example in Canada, Italy or Korea (Persaud, Lord, & Palmisano, 2002;
114 Kim, Lee, Choi, Choi, & Choi, 2010; Persaud et al., 2012; Sacchi, Persaud, & Bassani, 2012;
115 Young & Park, 2013). Therefore, it is recommended that each country and jurisdiction (e.g. State)
116 develop their own specific CPMs. The present review, written by non-US authors, adopts this
117 perspective.

118 ***Data collection***

119 In a theory, to obtain sufficiently representative models, one should randomly sample from the
120 population of similar road types or intersections. In this regards, given the variance of crash
121 frequencies, several authors recommended minimal sample sizes, such as at least 50 sites (Turner et
122 al., 2003), 200 crashes (Jonsson, 2005) or 300 crashes (Srinivasan, Carter, & Bauer, 2013). The
123 HSM (AASHTO, 2010) advises using a sample of 30–50 locations with a total of at least 100
124 crashes per year. However, others were critical about the one-size-fits-all approach. For example
125 Lord (2006) provided guidance on necessary sample size based on sample mean, i.e. for example
126 200 segments in case of average of 5 crashes per segment, or 1000 segments in case of average of 1
127 crash per segment. (Note that these considerations do not apply in case of network screening, whose
128 goal is to screen the complete network.)

129 Data on crashes, traffic volumes and potentially other factors need to be assigned to all the sample
130 sections/sites. Crash data are known for various biases, such as underreporting, location errors,
131 severity misclassification or inaccurate identification of contributory factors. Also traffic volume

132 data may be prone to errors: typical measure of traffic volume AADT is an average, it is an
133 aggregate of various vehicle types (Elvik, 2010).

134 Choice of time period for crash and AADT data requires another decision. A 1- to 5-year period is
135 usually recommended for safety ranking, with 3-year period being the most frequent (Elvik, 2008).
136 Using longer time periods (beyond five years) may cause problems due to changes in conditions,
137 such as a substantial increases in traffic volumes or layout changes, over the time period. Probably
138 due to these issues there are no specific guidelines for time period choice. An exception was the
139 simulation study of Cheng & Washington (2005) which concluded there is little gain in the network
140 screening accuracy when using a period longer than 6 years. Also using several consistency tests, 4
141 years were found sufficient for developing a CPM in a study by Ambros, Valentová, & Sedoník
142 (2016). Usually a compromise between the need for early analysis of new treatments and the need
143 for accumulating sufficient crashes to permit analysis is accepted (Elvik, 2010).

144 Regarding data collection, differences between rural and urban settings are also worth mentioning.
145 Traditionally most focus has been given to rural roads (as also evident from CPM reviews by
146 Reurings, Janssen, Eenink, Elvik, Cardoso, & Stefan, 2005 or Yannis et al., 2014, 2015), as is also
147 the focus of the present paper. In contrast, modelling urban safety is more challenging, due to
148 higher presence of vulnerable road users and complex environments, including facilities for
149 different road users, mixed land use or higher density of various intersection types, such as those
150 signalised or with a roundabout layout.

151 Ideal data sources are road agency asset inventories. Unfortunately, they may not be complete, and
152 a modeller thus needs to combine various data sources into the geodatabase on their own.
153 Additional surveys are also conducted, either in the field (pedestrian exposure, visibility, speed,
154 etc.) or via online maps. Recent emergence of big data and open government policies (e.g. open
155 data initiatives such as data.vic.gov.au) have aided these efforts substantially; it is feasible to pull
156 together substantial amounts of road data from publicly available and road agencies' own sources.

157 ***Road network segmentation***

158 CPMs are typically developed either for road intersections or segments. In the latter case,
159 segmentation has to be conducted, in order to divide the network into homogeneous segments, i.e.
160 with constant values of explanatory variables. However, in case of multiple variables, this practice
161 can naturally lead to short segments, which may for example complicate assigning crashes. Some
162 authors set fixed segment lengths of several hundred meters (Cenek, 1997; Geyer et al., 2008; da
163 Costa, Jacques, Pereira, Freitas, & Soares, 2015), or used patterns based on tangents and curves
164 (Koorey, 2009; Turner, Singh, & Nates, 2012; Cafiso & D'Agostino, 2013). On the other hand, for
165 network screening, longer segments (1 – 5 km) are often used (Ragnøy, Christensen, & Elvik, 2002;
166 Pardillo Mayora, Bojórquez Manzo, & Camarero Orive, 2006; Gitelman & Doveh, 2016).

167 ***Explanatory variables***

169 Selection of explanatory variables should be guided by previously documented crash and injury risk
170 factor evidence available from research literature. However, in practice it is often dictated simply by
171 data availability. Explanatory variables generally include exposure, transport function, cross
172 section, traffic control; less often variables describing alignment or road user behaviour are used
173 (Reurings et al., 2005). When actual variables are not available, proxy variables may be used, e.g.
174 abutting land use as a proxy for pedestrian movement counts.

175 In order to identify the statistically significant variables, a stepwise regression approach is typically
176 used. It may be applied either in a forward selection or a backward elimination manner; in both
177 cases selected goodness-of-fit (GOF) measures are used to assess the statistical significance.

178 Common GOF measures include information criteria such as AIC or BIC, while others use for
179 example scaled deviance (Fridstrøm, Ifver, Ingebrigtsen, Kulmala, & Thomsen, 1995; Turner et al.,
180 2003) or proportion of explained systematic variance (Kulmala, 1995; Ambros et al., 2016).

181 Based on a number of explanatory variables (model complexity), CPMs may be simple (exposure-
182 only) or multivariate (fully-specified) (Persaud, 2001). Sawalha & Sayed (2006) warned against
183 temptations to build overfit models, i.e. containing too many insignificant variables. In fact, a
184 number of studies found that additional predictors are not as beneficial as expected (Peltola,
185 Kulmala, & Kallberg, 1994; Wood, Mountain, Connors, Maher, & Ropkins, 2013; Saha, Alluri, &
186 Gan, 2015). One should strive for parsimonious models, i.e. the ones containing as few explanatory
187 variables as possible (Reurings et al., 2005). Such models enable simple interpretation and
188 understanding, as well as easy updating (Ambros et al., 2016).

189 On the other hand, in case of leaving out an influential explanatory variable due to unavailable data,
190 so called “omitted variable bias” occurs. The bias results in biased parameter estimates that can
191 produce erroneous inferences and crash frequency predictions (Lord & Mannering, 2010; Mitra &
192 Washington, 2012; Mannering & Bhat, 2014).

193 *Model function forms and other statistical considerations*

194 Before modelling itself, exploratory data analysis should be conducted, in order to detect potential
195 outliers, check the extreme values, potential mistakes, etc.

196 Crash frequency (i.e. response variable) ideally should not involve mixed levels of crash severity
197 and crash types, as it may produce uninterpretable results (Elvik, 2010). It is thus recommended to
198 develop disaggregated CPMs (Reurings et al., 2005). Alternatively one may use the observed
199 proportion of a given crash type or severity and apply it to the CPM that has been estimated for total
200 crashes (Srinivasan & Bauer, 2013). However, this has been found a questionable practice, leading
201 to estimation errors (Jonsson, Lyon, Ivan, Washington, van Schalkwyk, & Lord, 2009). The current
202 recommendation is estimating separate CPMs by crash types. New Zealand practice is developing
203 models for key (or common) crash types and, if necessary, scaling their predictions to represent
204 total crash frequency (Turner et al., 2003), to allow for less common crash types. Some studies
205 (Garach, de Oña, López, & Baena, 2016; Gitelman & Doveh, 2016) used sub-samples (for example
206 stratification based on AADT under/over specific limits) in order to improve model quality. In any
207 case, developing disaggregated CPMs obviously requires larger sample sizes. In terms of severity
208 either models are developed by severity levels (usually with fatal and serious injury crashes
209 combined), as with the ANRAM models (Jurewicz, Steinmetz, & Turner, 2014), or severity factors
210 (proportions) are applied to models developed for all injury crashes (NZTA, 2016) or all crashes
211 (including non-injury).

212 To select the most suitable mathematical forms of explanatory variables, one may use graphical
213 relationships to crash frequency (Arndt & Troutbeck, 2006), or use more complex techniques, such
214 as empirical integral functions and cumulative residuals (CURE; Hauer & Bamfo, 1997). According
215 to Hauer (2004), the model equation may have both multiplicative components (to represent the
216 influence of continuous factors, such as lane width or shoulder type), and additive components (to
217 account for the influence of point hazards, such as driveways or narrow bridges). Despite these
218 recommendations, the typical modelling approach is often simple. The general model form of
219 equation (1) is widely adopted. Exposure is usually modelled in terms of traffic volume, i.e. single
220 AADT value for road segments, or product of major and minor AADTs for road intersections.

221 There is no universal guidance and various function forms are used in the literature. For example,
222 traffic volume is typically used in a power form, but some authors considered it jointly with an
223 exponential form (so called Ricker model; Roque & Cardoso, 2014). Another example is segment

224 length, usually applied as an offset, i.e. with regression coefficient = 1, but often also in a power
225 form (Hadi, Aruldas, Chow, & Wattleworth, 1995; Reurings & Janssen, 2007; Roque & Cardoso,
226 2014).

227 According to Hauer (2001), segment length should also be considered when estimating the over-
228 dispersion parameter to be used in the empirical Bayes approach. However, the exact form of the
229 relationship is not definite (Cafiso, Di Silvestro, Persaud, & Begum, 2010); in fact, not only length
230 but also other variables may play a role (Geedipally, Lord, & Park, 2009).

231 *Model validation*

232 The goal of validation is proving whether the developed model is acceptable from both scientific
233 and practical perspective. It is thus surprising that most of modelling guidelines seem to overlook
234 this step (Maher & Summersgill, 1996; Hauer, 2004, 2015; Sawalha & Sayed, 2006; Wood &
235 Turner, 2007; AASHTO, 2010; Srinivasan & Bauer, 2013; Fridstrøm, 2015).

236 According to Oh, Lyon, Washington, Persaud, & Bared (2003), one may distinguish between
237 internal validity (agreement with theoretical expectations and past research) and external validity
238 (goodness-of-fit). The latter may be evaluated by comparing either models from two independent
239 samples, or a model from a complete sample applied on selected sub-samples that have not been
240 used in the model building.

241 *Using CPMs in network screening*

242 Previous reviews (Elvik, 2008; Montella, 2010) indicated that current practices are “not close to the
243 state-of-the-art”. According to the EB method, CPMs should be used and their results (expected
244 crash frequencies) combined with crash history (observed crash frequencies) to obtain so called
245 “expected average crash frequency with empirical Bayes adjustment” (in short EB estimate). Apart
246 from EB estimates, other variants exist, for example:

- 247 • Potential for safety improvement (PSI), which represents the difference between EB
248 estimate and expected frequency, i.e. the potential safety savings (Persaud et al., 1999).
- 249 • Level of service of safety (LOSS), which labels the sites into four classes, based on
250 deviations between observed and expected crash frequencies (Kononov & Allery, 2003).
- 251 • Scaled difference, i.e. the difference between the observed and predicted crash frequencies,
252 divided by the predicted standard deviation of the crash frequency (Butsick, Wood, &
253 Jovanis, 2017).

254 In Australia and New Zealand, where low-volume rural roads generate very low numbers of crashes
255 per kilometre (or zero), CPMs can provide a continuous proxy measure of safety. In Australia the
256 ANRAM model uses EB estimates of severe casualty crashes to remove the random variation in
257 observed crash data: sites are prioritised simply on the EB estimate (Jurewicz et al., 2014).

258 Given the variety of available methods, the Highway Safety Manual (AASHTO, 2010) notes that
259 “using multiple performance measures to evaluate each site may improve the level of confidence in
260 the results.” Hence sites may be ranked for treatment based on several different methods (Montella,
261 2010; Yu, Liu, Chen, & Wang, 2014; Manepalli & Bham, 2016). Those that rank consistently high
262 using several methods are the sites where treatment should be focused.

263 *Using CPMs in developing crash modification factors*

264 Crash modification factor (CMF) is a multiplicative factor used to compute the expected number of
265 crashes after implementing a given countermeasure at a specific site. CMFs may be derived from
266 before-after or cross-sectional studies; however, each method has its own challenges, and obtained

267 CMFs can thus often highly inconsistent (Gross, Persaud, & Lyon, 2010). Before and after studies
268 are generally the preferred source of CMFs, particularly for the HSM. However they typically only
269 look at features in isolation and so when the combined effects of features on crash occurrence is not
270 the sum of the effects of each individual feature, then they may provide misleading results. Several
271 solutions to developing multiple treatment CMFs have been proposed, without reaching definite
272 conclusions (Elvik, 2009; Gross & Hamidi, 2011; Park, Abdel-Aty, & Lee, 2014).

273 Cross-sectional studies (i.e. the ones based on CPMs) have been criticised for being more prone to
274 non-causal safety effects, due to bias-by selection (Elvik, 2011; Carter, Srinivasan, Gross, &
275 Council, 2012; Hauer, 2015). Bias-by-selection can occur when a treatment (like a cycle lane or
276 crash barrier) is applied more often to sites that already have a crash problem than to those that do
277 not. They do however provide a much better crash prediction for the combination of road features.
278 In some cases CMFs are developed from CPMs where limited before and after studies are available.

279 *Using CPM tools*

280 The above-mentioned analytical steps (data preparation, exploratory analysis, modelling,
281 calculations) are typically conducted in statistical software or spreadsheets. Nevertheless, for an end
282 user it is beneficial to be able to visualize the results. These may take form of tables or map outputs,
283 for example the identified hotspots or the lists of ranked segments.

284 One option is using stand-alone software solutions, such as the following two from the USA:

- 285 • IHSDM Crash Prediction Module estimates the frequency and severity of crashes on a
286 highway using geometric design and traffic characteristics. This helps users evaluate an
287 existing highway, compare the relative safety performance of design alternatives, and assess
288 the safety cost-effectiveness of design decisions. (FHWA, 2003)
- 289 • SafetyAnalyst (commercial software) Network Screening Tool identifies sites with potential
290 for safety improvement. In addition, it is able to identify sites with high crash severities and
291 with high proportions of specific crash types. (FHWA, 2010)

292 Note that there are close links between IHSDM, SafetyAnalyst and Highway Safety Manual.
293 According to Harwood, Torbic, Richard, & Meyer (2010), SafetyAnalyst Module 1 (network
294 screening) is to be applied first, followed by Module 2 (diagnosis and countermeasure selection),
295 Module 3 (economic appraisal and priority ranking) and IHSDM to perform safety analyses as part
296 of the design process.

297 The Finnish evaluation tool TARVA also deserves mentioning. Its purpose is to provide a common
298 method and database for (1) predicting the expected number of crashes, and (2) estimating the
299 safety effects of road safety improvements (Peltola, Rajamäki, & Luoma, 2013). Based on simple
300 CPMs and pre-determined CMFs, it currently exists in Finnish and Lithuanian versions, with
301 planned applications in other countries.

302 Capabilities of network screening and road safety impact assessment are also built in commercial
303 software PTV Visum Safety (<http://vision-traffic.ptvgroup.com/en-us/products/ptv-visum-safety/>).

304 There are also applications in the form of Excel spreadsheets, for example British COBALT,
305 Swedish TS-EVA or Norwegian CPMs for national and country roads (Høye, 2014, 2016). In the
306 US, spreadsheets were developed for safety analysis of freeway segments and interchanges (ISAT:
307 Torbic, Harwood, Gilmore, & Richard, 2007; ISATe: Bonneson, Geedipally, Pratt, & Lord, 2012).

308 The Australian National Risk Assessment Model (ANRAM) tool, available to road agencies, is a
309 network screening and prioritisation tool which uses CPMs for different road stereotypes, together
310 with CMFs and observed crash data to estimate severe injury crashes across segmented road
311 network (Jurewicz et al., 2014). ANRAM allows users to develop and estimate benefits of road

312 network and corridor treatment programs. This tool has gained wide use among state road agencies
313 in Australia, particularly for the rural road networks where actual severe crashes are randomly
314 distributed. ANRAM is available in a spreadsheet form, with planned online adaptations.

315 New Zealand also has a history of various safety prediction tools. Turner, Tate, & Koorey (2007)
316 stressed the practical need of such tools and after review of overseas applications, considered
317 IHSDM as worth transferring into New Zealand conditions, for assessing new road designs. A later
318 work (Turner & Brown, 2013) reviewed New Zealand spreadsheet applications, as well as
319 experience with using and calibrating the ISAT tool from the USA.

320 **Challenges and opportunities**

321 The review indicated various challenges, as well as opportunities and solutions for the mentioned
322 issues. They are briefly summarized in the following paragraphs.

323 *Data collection*

324 Sample sizes are the limiting factor. Unlike in the case of large USA and Canadian samples, smaller
325 countries are limited in their samples of network and crash data. For example, Turner et al. (2003)
326 mentioned, that New Zealand road network size limits the development of models for some
327 segment and site types, e.g. interchanges. This factor also reduces chances of disaggregation CPMs
328 into all crash types and severity levels. In addition, there is no universal guidance either on
329 necessary sample size, or recommended time period for crash data.

330 *Road network segmentation*

331 Division of road network into segments is likely to be dictated by structure of national road
332 databanks. For example in the Czech Republic, national traffic census (as the main source of AADT
333 data) does not cover all minor roads; thus process of aggregating segments into longer segment
334 including minor intersections was found feasible (Ambros, Sedoník, & Křivánková, 2017a). As the
335 segments may be subject to further investigations, their length should be feasible for on-site visits or
336 crash analyses.

337 Use of long road segments, e.g. matching measured AADTs, can lead to loss of meaningful
338 responsiveness to variables of interest to practitioners. Long segments are more likely to contain
339 multiple design scenarios, e.g. pavements of different widths or multiple curves. Shorter segments
340 are more likely to identify such changes and measure their influence. This is offset by loss fidelity
341 of AADT and crash data location. This issue requires some optimisation based on experience with
342 available data.

343 *Explanatory variables*

344 Network-wide data availability is again the guiding principle. Additional data collection is usually
345 costly and limiting in perspective of future updating. For most practical applications, such as
346 network screening, simple models (exposure-only) have been found sufficient (Srinivasan & Bauer,
347 2013). A practice-driven approach was adopted in developing New Zealand rural road CPMs
348 (Turner et al., 2012); when it was found that the statistically significant variables did not include the
349 parameters that were of most interest to practitioners, two distinct models were developed:
350 statistical models (best performing models according to GOF measures at 95% confidence levels)
351 and practitioners' models (containing also additional variables of interest to safety professionals, at
352 confidence levels of 70% or more).

353

354 *Model and function forms*

355 Simple CPM form (Equation 1) is used the most often. Traffic volumes (flows) should be adapted
356 to the specific segment and intersection types. For example, New Zealand CPMs (NZTA, 2016)
357 apply either product of flows or conflicting flows, based on the type of intersection, urban/rural
358 settings and speed limits.

359 *Model validation*

360 The developed CPMs should be validated, either by comparing models from two independent
361 samples, or comparing a model from a complete sample to the models based on selected sub-
362 samples (not used in the modelling). However, this practice is probably seen as difficult, since most
363 guidelines do not mention this step.

364 *Using CPMs in network screening*

365 Network screening should be based on empirical Bayes (EB) method, which combines CPM
366 predictions with observed crash frequencies to assess and rank the sites. There are several different
367 methods; EB estimates and potential for safety improvement (PSI) are used the most often.

368 *Using CPMs in developing crash modification factors*

369 Although the practice of deriving crash modification factors (CMFs) from cross-sectional CPMs has
370 been criticised, it is relatively common. Again there are various approaches: for example Park et al.
371 (2014) tested six different methods of combining CMFs and concluded that one should not rely on
372 only one of them. Interim solution is applying ‘rule-of-thumbs’, such as using the product of no
373 more than three separate independent countermeasures (OECD, 2012) or reducing the product
374 through multiplying by a ratio 2/3 (Turner, 2011).

375 *Using CPM tools*

376 Several tools for modelling and visualization exist; probably the most easy-to-use are spreadsheet
377 applications. When implemented online (such as Finnish TARVA or planned version of Australian
378 ANRAM), they enable periodical updates, as well as joint use of other online data sources.

379 Increasingly, online business analytics software has been used to display CPM results in map
380 format, often with dynamic filtering and computational functions. Examples include open source
381 and free resources such as ArcGIS Online, QGIS, Tableau, or Microsoft Power BI. These solutions
382 make it easy for practitioners to access and understand the value of CPMs.

383 **Summary and conclusions**

384 A number of steps have been reviewed: from data collection and road network segmentation to
385 choosing variables and function forms, validating models and using them in practice, including
386 description of available tools. From the review it is obvious that developing CPMs is not a
387 straightforward task: there is a number of available choices and decision during the process (without
388 definite guidance), which explains the diversity of approaches and techniques, as well as resulting
389 models developed worldwide. While this may be interesting from a research perspective, it
390 definitely limits understanding and application by practitioners, and complicates international
391 comparability or transferability. There is a need to identify the solutions, which will be scientifically
392 sound and valid, while also feasible with regards to real-life conditions and needs.

393 The main point is that the end users of CPMs are the practitioners, i.e. road agencies, which “cannot
394 always afford the luxury of doing state-of-the-art crash modelling” (Elvik, 2010). The review aimed

395 to answer the original questions, how and why should they consider using CPMs? The answers may
396 be following:

- 397 • CPMs are valuable tools, which help link crashes with risk factors. This is especially
398 valuable in current conditions of scattered crash occurrence (less crash black-spots), where
399 traditional crash-based approaches do not work well.
- 400 • Developing and using CPMs has its challenges (as described above). However, these may be
401 minimised by increased communication between researchers (who develop CPMs) and users
402 (agencies), resulting in easy-to-use tools. However it is important that these tools do not
403 become black-boxes, and that users do have a basic understanding of CPMs and CMFs, and
404 that local CPMs and CMFs can be used in the tools (or that there is a method to calibrate the
405 CPMs and CMFs to local conditions).
- 406 • Applying network-wide CPMs enables performing effective road safety impact assessment
407 and network screening.

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