

Influence of Available Network Model Detail on the Performance of Designs for Drinking Water Contamination Warning Systems

Michael J. Davis¹ and Robert Janke²

ABSTRACT

The effect of limitations in network model detail on contamination warning system (CWS) design was examined using the original and skeletonized network models for two water distribution systems (WDSs). The skeletonized models were used as proxies for incomplete network models. CWS designs were developed by optimizing sensor placements for worst-case and mean-case contamination events. Designs developed using the skeletonized network models were transplanted into the original network model for evaluation. CWS performance was defined as the number of people who ingest more than some quantity of a contaminant in tap water before the CWS detects the presence of contamination. Lack of detail in the network model can result in CWS designs that provide considerably less protection against worst-case contamination events than that obtained when a more complete network model is available. However, no consistent relationship was found between the degree of skeletonization and CWS performance. Mean-case designs can yield worst-case performances similar to those for worst-case designs when there is uncertainty in the network model. Improving network models for WDSs has the potential to result in significant improvements in CWS performance.

KEYWORDS: WATER DISTRIBUTION SYSTEMS; OPTIMIZATION; SIMULATION; WATER QUALITY; DRINKING WATER; PUBLIC HEALTH.

INTRODUCTION

Lack of detail in the network models developed for water distribution systems (WDSs) is

¹Argonne Associate of Seville, Argonne National Laboratory, Environmental Science Division, 9700 South Cass Avenue, Argonne, IL 60439. E-mail: mike_davis@anl.gov

²National Homeland Security Research Center, U.S. Environmental Protection Agency, 26 West Martin Luther King Drive (MS NG-16), Cincinnati, OH 45268. E-mail: janke.robert@epa.gov

known to reduce the accuracy of estimated adverse health effects associated with potential contamination events in these systems (e.g., Grayman et al. 1991; Grayman and Rhee 2000; Bahadur et al. 2008; Janke et al. 2007, 2009; Davis and Janke 2014). Lack of network model detail is also known to affect sensor placement in the design of contamination warning systems (CWSs) (Klise et al. 2013). All network models involve some degree of simplification relative to the actual WDS. The primary goal of this paper is to provide additional insight into how and to what extent limitations in the model detail available when designing a CWS might affect its performance when it is used in the actual distribution system.

When the nature of potential contamination events is uncertain and the objective is to minimize worst-case adverse consequences associated with the events, CWSs designed to minimize mean-case consequences are more robust than those designed to minimize worst-case consequences (Davis et al. 2013b). These designs are called mean-case and worst-case designs, respectively. Mean-case designs are more effective at reducing consequences over a range of conditions. The relative lack of robustness of worst-case designs is a consequence of the narrow focus of these designs, which handicaps their performance when conditions differ from those assumed as the basis for the design. An additional goal of this paper is to obtain some insight into the robustness of worst- and mean-case designs for a CWS when there are uncertainties in the network model used to represent a WDS.

Contamination in a distribution system has the potential to cause a variety of adverse effects. This paper considers adverse health effects associated with the ingestion of contaminated tap water; quantities of ingested contaminant, ingestion doses, are determined for those individuals who are potentially exposed to contaminated water. The term *dose level* is used to indicate the quantity of ingested contaminant for which adverse consequences are quantified. For a particular contaminant, dose level can be related to a health-effect level. For example, a dose level could correspond to the median lethal dose or the no-observed-adverse-effect level. Lower dose levels can be related to a particular health-effect level for more toxic contaminants and higher dose levels can be related to the same health-effect level for less toxic contaminants. The measure of adverse consequences

associated with a contamination event that is used in this paper, called *impact*, is the number of people who receive a dose of a contaminant above some dose level due to the ingestion of contaminated tap water.

The best available network models for two WDSs were used to represent the actual distribution systems, and skeletonized versions of these network models were used as proxies for incomplete network models that might be developed for these systems. Network models will always be incomplete to some, generally unknown, degree; using skeletonized network models together with best available network models allows the potential significance of uncertainties in network models to be studied. CWSs designed to minimize the adverse consequences of ingesting contaminated tap water were developed using the skeletonized models. These CWSs then were utilized in (transplanted into) the complete network models, where their performance was evaluated and compared to the performance of designs developed using the complete network models. This approach allows the influence of uncertainties in network model detail on CWS performance to be evaluated. Developing and transplanting both worst- and mean-case designs allows the relative robustness of these designs to be studied.

METHODS

Implementing the approach described above for actual distribution systems requires the following: the availability of reasonably complete (“all-pipes”) models for the WDSs, an approach to skeletonizing these models, a method for designing CWSs, and a method for evaluating the performance of the designs. Except for the evaluation of the performance of transplanted CWS designs developed using skeletonized network models, the methods used here have been documented in previous publications. The approach used here will be outlined with references provided to previous work.

Designs for CWSs were developed using the original and skeletonized versions of the network models for two WDSs. The characteristics of the network models used are summarized in Table 1. The network models were skeletonized using commercially available software to produce models

77 with three levels of skeletonization (20-, 30-, and 40-cm). All pipes having the specified or smaller
78 diameter were trimmed or merged. The methodology used for skeletonization is discussed in Davis
79 and Janke (2014). Table 2 summarizes the characteristics of the skeletonized network models. Note
80 that the ratio of the number of pipes to the number of nodes increases as the level of skeletonization
81 increases, illustrating the effect of the skeletonization process. The networks examined here (N1
82 and N3) are two of the three networks used in Davis and Janke (2014).

83 Developing the design for a CWS requires the definition of a design-basis threat and the quan-
84 tification of the potential adverse effects associated with that threat. A CWS is designed to provide
85 protection against these adverse effects. The threat considered here is the potential injection of
86 a fixed quantity of contaminant at any one of the nodes in a network or at any of the nonzero
87 demand (NZD) nodes in the network. The adverse effects examined are the impacts (as defined
88 above) associated with an injection at a network node. Contaminant injection, transport, and inges-
89 tion were simulated using TEVA-SPOT (U.S. EPA 2016). TEVA-SPOT uses Version 2.00.12 of
90 EPANET (Rossman 2000) for calculations involving contaminant transport. Quantities of ingested
91 contaminant were determined using probabilistic models for ingestion timing and volume. Nodal
92 population in a network was assumed to be proportional to nodal water demand. The methodology
93 used in carrying out these simulations is discussed in detail in Davis et al. (2013a). The analy-
94 sis here assumes 0.5-kg injections of a conservative contaminant over a 1-h period beginning at
95 0:00 hours local time. All simulations were 168-h in duration, which includes the 1-h injection.
96 The simulations used a 1-s water-quality time step and a 1-h hydraulic time step.

97 Using TEVA-SPOT, CWSs were designed to minimize worst- and mean-case impacts asso-
98 ciated with the design-basis threat. Development of CWS designs is discussed in Davis et al.
99 (2013b). TEVA-SPOT optimizes sensor placement using a heuristic approach (Berry et al. 2006).
100 Designs were developed for the original and the three skeletonized network models for each WDS
101 for three sensor set sizes (5, 10, and 25 sensors) and for five different dose levels ranging from 10^{-4}
102 to 1 mg. A total of 120 designs were developed for each network (two objectives, four network
103 models, three sensor set sizes, and five dose levels).

104 Sensors in CWSs were assumed to perform perfectly: they detect all contaminants and make
105 no errors. A zero response time was assumed; all water use stops immediately when a contaminant
106 is detected. CWS sensors are arrayed at locations within a network according to designs developed
107 as described above and in the following paragraphs. CWSs alert when any sensor detects contami-
108 nation during an event. Impact is determined by summing the number of receptors at all nodes who
109 have received doses above some dose level when the system alerts. The worst-case and mean-case
110 performances of a CWS are determined by the largest impact and the mean impact, respectively,
111 associated with a threat before contamination is detected by a sensor

112 The performance of the CWS designs developed for the original and skeletonized network
113 models for each WDS was evaluated using the original network model for the system. Performance
114 is the impact obtained using a particular design. Worst-case impacts were determined using both
115 worst-case and mean-case designs. To evaluate the performance of a design developed using a
116 skeletonized network model but applied to the original network model, the locations of the sensors
117 determined for the skeletonized network were used to define a sensor network for the original
118 model, and impacts were determined using this transplanted CWS. TEVA-SPOT has a built-in
119 capability, the *Regret Analysis* mode, that allows various designs to be easily evaluated and that
120 facilitates the selection of the best sensor design among those being considered (U.S. EPA 2016).

121 The approach described yields impacts for CWSs designed using the original network mod-
122 els as well as impacts for CWS designs developed using the skeletonized network models that
123 have been transplanted into the original models. Impacts determined using the transplanted de-
124 signs were compared with those determined using the original designs to obtain insights into the
125 extent to which CWS performance is adversely affected when designs are developed using incom-
126 plete information on a WDS. Comparing the relative worst-case performances of the transplanted
127 worst- and mean-case designs provides insight into the robustness of these designs when there is
128 uncertainty in the network model.

129 The heuristic method used for sensor placement generally produces optimal designs, but in
130 some cases can produce designs that are suboptimal (Davis et al. 2013b). For the original model

for Network N1 there were two instances of obvious suboptimality for worst-case designs out of the 15 cases (three sensor set sizes and five dose levels) examined; for Network N3 there was one. A design is suboptimal if larger impacts are obtained when the conditions used in the design and its evaluation are the same than when such conditions differ. Results were corrected to help minimize the effect of such obvious suboptimalities for a particular sensor set size and dose level by using the smallest impact from the five designs developed for different dose levels for that number of sensors. The corrections resulted in reductions in impacts of 6 and 18% for the two instances of suboptimality for Network N1 and a 9% reduction for the single instance for Network N3. The correction does not identify the optimal design; it only helps improve the estimate of impacts that would be obtained with the optimal design.

RESULTS AND DISCUSSION

This section considers several topics: (1) CWS performance given uncertainty in the network model, (2) contaminant mass imbalances that can occur in simulations due to the water-quality routing algorithm used in EPANET, and (3) the robustness of mean- and worst-case CWS designs when there is uncertainty in the network model. CWS performance is discussed in terms of the performance of the overall system and in terms of the performance of the individual sensors in a system.

CWS Performance: Overall System

CWSs developed using the skeletonized network models generally perform more poorly than do those developed using the original network model. The following paragraphs discuss the behavior of these different CWSs.

The plots in Fig. 1 compare estimated impacts for worst-case CWS designs developed for three sensor set sizes using the original and skeletonized network models for Network N1 and applied using those same models. In this figure, the designs developed using the skeletonized network models are non-transplanted designs: they are applied using the network model for which they were designed. Note the logarithmic scale on the vertical and horizontal axes. Results are given for four different CWS designs as a function of the dose level used for the design and evaluation.

158 Impacts decrease as dose level increases, but are relatively constant at smaller dose levels. Impacts
159 decrease as the number of sensors used in the CWS design increases. The four CWS designs being
160 evaluated for each system are the design developed using the original network model and the three
161 non-transplanted designs developed using the skeletonized networks. In the figure, a trim of 0 cm
162 corresponds to the original model and the 20-, 30-, and 40-cm trims correspond to the three levels
163 of skeletonization used. The estimated impacts obtained using the skeletonized network models
164 are similar to those obtained using the original network model. However, if CWSs are designed
165 using a skeletonized (i.e., an incomplete) network model and then implemented, they will be used
166 in actual system, which is better approximated by the original network model.

167 The results presented in this paper were obtained using an injection mass of 0.5 kg. The plots in
168 Fig. 1 and in other figures that present results as a function of dose level will have the same shape
169 if different injection masses are used. Although the results presented here were obtained using
170 a specific injection mass, figures can be re-scaled to accommodate different injection masses, if
171 desired. If the injected mass is increased by some factor, the values on the horizontal axis also need
172 to be increased by the same factor. For example, if the injection mass is 5 kg instead of 0.5 kg, the
173 values on the horizontal axis in Fig. 1 need to be multiplied by 10. However, the absolute value of
174 injection mass used is not an important factor in interpreting the results presented.

175 Again using Network N1, the plots in Fig. 2 compare (1) estimated impacts obtained when the
176 CWS designs developed using the skeletonized models are transplanted into the original network
177 model with (2) impacts estimated for the CWS designed using the original network model. The
178 plots also show estimated worst-case impacts when no CWS is used. Note the logarithmic scale
179 on the vertical and horizontal axes. The differences between the impacts estimated for the designs
180 developed for the original and the skeletonized network models for Network N1 generally become
181 larger when the designs for the skeletonized network model are transplanted into the original net-
182 work model.

183 The plots in Fig. 3 provide a comparison for Network N1 of the impacts obtained using de-
184 signs developed for the skeletonized network models when they are used in the skeletonized net-

185 work models (non-transplanted designs) and when they are transplanted into the original network
186 model. The same design is being used, but applied to different network models. Depending on the
187 dose level and number of sensors, the impacts estimated for Network N1 can be two to three times
188 larger when the designs are used in the original network rather than in the skeletonized network
189 where they were developed. In other words, an evaluation of a CWS designed and applied using
190 a skeletonized network model can yield results that considerably underestimate the actual conse-
191 quences that could occur if the design were used in the actual WDS. There is no consistent pattern
192 in impacts or relative impacts related to the level of skeletonization used. Note that the somewhat
193 jagged nature of some of the lines in the plots in Fig. 3 is the result of using only five points to
194 construct the lines in the plots in this (and other similar) figures.

195 The estimated percentage reductions in impacts obtained using the CWSs designed for Network
196 N1 relative to the worst-case impacts estimated for the network when no CWS is used are shown in
197 the plots in Fig. 4. (When no CWS is used, the relative reduction in impacts is 0%.) The reduction
198 in impacts for low dose levels (contaminants with relatively high toxicity) can be similar for the
199 original and transplanted designs. However, at higher dose levels (contaminants with relatively low
200 toxicity), the reduction in impacts obtained with transplanted designs can be considerably smaller
201 than that obtained with the original design. The reduction in impacts does not show a consistent
202 relationship with the level of skeletonization. Percentage reduction in impacts decreases as dose
203 level increases. Consequences associated with less toxic contaminants generally are more localized
204 than those associated with more toxic contaminants because of the larger quantity of contaminant
205 required to produce a similar health effect. CWSs are less effective in providing protection against
206 localized effects than effects that are more widespread.

207 Impacts estimated for CWSs in Network N3 are shown in the plots in Fig. 5, which provides
208 results similar to those in Fig. 2 for Network N1. The results for Network N3 are more consistent
209 than those for Network N1, with impacts generally increasing with increasing level of skeletoniza-
210 tion. As is the case for Network N1, the percentage reductions in impacts at larger dose levels
211 achieved using the transplanted CWS designs are generally considerably less than those obtained

212 using designs developed using the original network model, as shown in Fig. 6.

213 The relative performance of the transplanted worst- and mean-case CWS designs for Networks
214 N1 and N3 are summarized in Table 3. Performance is relative to the performance of a CWS
215 designed to minimize worst-case impacts using the original network model. For several dose
216 levels, the table gives the range (maximum and minimum values) in the ratios of worst-case impacts
217 obtained with the transplanted design to the worst-case impacts obtained with the original worst-
218 case design, as well as the median value of the ratio. The results shown for each network and
219 dose level are based on the nine ratios determined using three sensor set sizes and three levels of
220 skeletonization. For example, for the 1.0-mg dose level for Network N1 and the transplanted worst-
221 case design, the minimum value of the ratio of worst-case impacts obtained with the transplanted
222 worst-case design to the impact obtained with the original worst case design is 1.3. The largest
223 value of the ratio is 1.5 and the median for the nine ratios is 1.4.

224 The results in Table 3 indicate that for Networks N1 and N3 the relative performance of the
225 transplanted worst-case designs generally becomes poorer when the dose level is smaller than
226 1.0 mg. In particular, the median and maximum values of the ratios for the two networks generally
227 increase when the dose level decreases below 1.0 mg. The maximum ratios are generally consid-
228 erably larger for Network N3 than for Network N1, indicating that the relative performance of the
229 transplanted designs is network dependent.

230 The results in Table 3 also show that the relative performance of the transplanted mean-case
231 designs deteriorates when the dose level decrease below 1.0 mg. The results in the table show that
232 the relative worst-case performance of the transplanted mean-case designs is generally similar to
233 the relative worst-case performance of the transplanted worst-case designs: the ratios for the trans-
234 planted mean-case designs are generally similar to the corresponding ratios for the transplanted
235 worst-case designs.

236 CWS performance is influenced by the network nodes considered as possible injection loca-
237 tions. Fig. 7 provides results for Network N1 similar to those shown in Fig. 2 except that only NZD
238 nodes are used as injection locations. Differences in the performances of the transplanted designs

obtained with all nodes (Fig. 2) or only NZD nodes (Fig. 7) are noticeable when 10 or 25 sensors are used.

CWS Performance: Individual Sensors

The preceding discussion has examined the performance of CWSs as systems. Examining the performance of individual sensors in those systems provides some additional insight into how the overall systems perform. CWS designs were developed considering their performance when challenged by the possible injection of contaminants at any node in the network or at any NZD node. A CWS can detect some of the events, but, in general, with a limited number of sensors will not detect all events. The worst-case performance of a CWS is determined by the largest impact associated with any event before it is detected by a sensor. For Network N1 with a five-sensor CWS, the sensors detect about 3500 events. (The number of events detected for the original network model does decrease somewhat as the level of skeletonization increases, from about 3600 for the original design, to about 3500 for the 20-cm transplanted design to about 3450 for the 40-cm transplanted design.) About 7000 events are not detected by any sensor before the end of the simulation. The maximum impact for undetected events is about 5000, 4800, and 5700 for the original, 20-cm, and 40-cm designs, respectively. Fig. 8 shows how the individual sensors in a five-sensor CWS perform for the designs developed using the original network and for the 20-cm and 40-cm transplanted designs. Note that the vertical scale on the plot for the 20-cm design is different from the vertical scale used in the other two plots. The figure shows results considering NZD nodes as injection locations. The general locations of the five widely spaced sensors in the three designs are similar and the sensors are arbitrarily labeled as Sensors 1 through 5, consistently for all the designs. For the detected events, the impacts at the time the events are detected were sorted in ascending order for each of the five sensors and plotted against event number, starting with the lowest impact event for Sensor 1 and continuing using a cumulative count of events through the highest impact event for Sensor 5. The numbering of events in the three plots in Fig. 8 is independent. The highest impact for any event detected by any sensor is the worst-case impact for the CWS unless a higher impact is associated with any of the undetected events. No undetected

266 events with such higher impacts occur for Network N1 and five sensors.

267 In Fig. 8, the results for each of the five sensors are presented from left to right, with the results
268 labeled with the sensor number in the upper plot. As an example of how to interpret the plots in
269 the figure, in the upper plot the results for Sensor 4 begin at about Event 800 and continue to about
270 2200; about 1400 events are detected by this sensor. The maximum impact for any impact detected
271 by the sensor is about 2500. The highest impact for any event detected by any sensor is over 5000
272 for Sensor 5. This is the worst-case impact for the CWS.

273 The performance of the sensors varies substantially between the original and transplanted de-
274 signs. The worst-case impact for the original design is over 5000, as already noted, over 16,000 for
275 the transplanted 20-cm design, and over 5000 for the transplanted 40-cm design, similar to that for
276 the original design, but for a different sensor. The three worst-case impacts in Fig. 8 correspond
277 to the worst-case impacts in the upper plot in Fig. 7 for a dose level of 0.0001 mg. Fig. 7 shows
278 that the worst-case impacts for the original and 40-cm designs for five sensors are similar at that
279 dose level. Fig. 8 shows that these impacts were the result of events observed by different sensors.
280 Although not shown in the figure, the events in the two cases are also different. Fig. 7 suggests
281 that the original and 40-cm, five-sensor designs perform similarly at the 0.0001 mg. In fact, the
282 similarity results from sensors in different parts of the network detecting different events with the
283 same impacts.

284 **Contaminant Mass Imbalances**

285 Contaminant mass imbalances can occur during water-quality simulations that use EPANET
286 (Davis and Janke 2014; Davis et al. 2016). Large imbalances can be associated with elevated
287 estimates for impacts. Mass imbalances generally can be minimized using short water-quality
288 time steps. To minimize the opportunities for any mass imbalances, a water-quality time step of
289 1 s was used in all water-quality simulations for this study. However, in some cases, the time step
290 required to eliminate mass imbalances can be shorter than the minimum 1-s time step allowed in
291 EPANET.

292 The quantities of contaminant removed from a network (R), stored in pipes (P), and stored in

tanks (T) were determined at the end of simulations. Using the quantity of contaminant injected (I), mass-balance ratios, which are defined as $(R + P + T)/I$, were calculated. The mass imbalance at the end of the simulation is $|(mass\text{-}balance\ ratio - 1)|$. When the mass of contaminant stored in the network at the end of the simulation plus the contaminant mass removed during the simulation equals the mass of contaminant injected, the mass-balance ratio equals 1 and the imbalance is 0.

For Network N1 (about 13,000 nodes), there were three nodes with a mass imbalance greater than 10%. The three nodes with imbalances greater than 10% had imbalances of 15, 17, and 108%. Injections at these nodes produce no impacts. There were 13 nodes with an imbalance greater than 1%. For the skeletonized network models, there were no nodes with an imbalance greater than about 0.1%. When a water-quality time step of 1 min is used, the largest imbalance for the unskeletonized model is 90% and there are four nodes with an imbalance greater than 10%.

For Network N3 (about 12,000 nodes), there were seven nodes with a mass imbalance greater than 10% and 85 with an imbalance greater than 1%. The largest three imbalances were 22, 28, and 42%. Relative to injections at many other nodes, injections at these nodes do not produce large impacts. For the skeletonized network models, there were 9, 12, and 17 nodes with imbalances greater than 10% for the 20-, 30-, and 40-cm trimmed models, respectively. The largest imbalance was about 100% for all three skeletonized network models. There were 62, 81, and 50 injection nodes with imbalances greater than 1% for these three trim levels, respectively. When a water-quality time step of 1 min is used, the largest imbalance for the unskeletonized model is over 2000% and there are 48 nodes with imbalances greater than 10%. (A 1-min time step is considerably shorter than the default time step for EPANET, which is 5 min.) The injection node with the largest imbalance is associated with major impacts. Use of a 1-s water-quality time step in this study avoided this major mass imbalance.

The models for Networks N1 and N3 include some dead-end nodes for which no injected contaminant leaves the node, none is removed, and there is no storage, giving a calculated mass-balance ratio of zero. There are no impacts associated with injections at these nodes. For the original models for Networks N1 and N3 there are 402 and 110 such nodes, respectively. The skele-

tonized networks for Network N1 have considerably fewer such nodes than the original model. The skeletonized models for Network N3 have approximately the same number of such nodes as the original model. These dead-end nodes were not included when determining the statistics on contaminant imbalance in the preceding paragraphs.

Neglecting all zero-demand nodes as injection locations has only a minor influence on statistics for mass imbalance for Networks N1 and N3. Considering only nonzero demand nodes, there are no injection nodes with mass imbalances greater than 10% for the original or skeletonized models for Network N1. For Network N3, there are five NZD nodes with mass imbalances greater than 10% for the original network model and four, three, and five such nodes for the 20-, 30-, and 40-cm skeletonized models respectively. The largest imbalances for the original model are 15, 28, and 42%.

Robustness of Mean- and Worst-Case Designs

Figs. 9 and 10 provide a direct comparison of the worst-case impacts obtained with the transplanted mean- and worst-case designs for Networks N1 and N3. The figures are scatterplots of the impacts obtained with the two types of transplanted designs. Note the logarithmic scale on the vertical and horizontal axes. For each network, results are given for three sensors set sizes, three levels of skeletonization, and five dose levels, for a total of 45 comparisons in each figure. Note that some points in the figures overlap or are clustered closely together. For points that lie *above* the diagonal lines in the figures, the transplanted mean-case design yields smaller worst-case impacts than the transplanted worst-case design. For points *below* the lines, the worst-case design yields smaller impacts. For points on the line, both designs provide the same impacts.

For Network N1 there are 27 points in Fig. 9 that lie above the diagonal line, 9 points that lie on the line, and 9 points that lie below the line. For the comparisons used in Fig. 9, the transplanted mean-case designs yield worst-case impacts that are less than or equal to those yielded by the transplanted worst-case designs in 36 of the 45 cases for Network N1. The transplanted worst-case designs yield worst-case impacts that are less than or equal to those obtained for the transplanted mean-case designs in 18 of the 45 cases. For the 27 instances in which impacts for the worst-case

347 designs exceed those for the mean-case designs, the impacts are about 34% larger on average.
348 For the 9 instances in which the impacts for the mean-case designs are larger, they are about
349 59% larger on average. Considering only NZD nodes (not plotted), the transplanted mean-case
350 designs perform as well as or better than the transplanted worst-case designs in 32 of the 45 cases;
351 transplanted worst-case designs perform as well as or better than transplanted mean-case designs
352 in 28 of the 45 cases.

353 For Network N3 there are 6 points in Fig. 10 that lie above the diagonal, 27 points that lie
354 on the line, and 12 points that lie below the line. The transplanted mean-case designs yield im-
355 pacts less than or equal to those for the worst-case designs in 33 of the 45 cases for Network N3.
356 The transplanted worst-case designs yield worst-case impacts that are less than or equal to those
357 obtained with the transplanted mean-case designs in 39 of the 45 cases. For the 6 instances in
358 which impacts for the worst-case designs exceed those for the mean-case designs, the impacts are
359 about 96% larger on average. For the 12 instances in which the impacts for the mean-case designs
360 are larger, they are about 120% larger on average. Considering only NZD nodes (not plotted),
361 the transplanted mean-case designs perform as well as or better than the transplanted worst-case
362 designs in 28 of the 45 cases; transplanted worst-case designs perform as well as or better than
363 transplanted mean-case designs in 38 of the 45 cases.

364 For the two network studied, the mean-case designs developed using the skeletonized network
365 models yield results that are comparable to those obtained with the worst-case designs developed
366 using the skeletonized network models when the designs are transplanted into the original network
367 models. Mean-case designs perform somewhat better for Network N1 and somewhat poorer for
368 Network N3. As discussed above, mean-case designs are more robust than worst-case designs
369 when the objective is to minimize worst-case impacts and there is uncertainty concerning the con-
370 ditions of a contamination event. The results presented here for Networks N1 and N3 indicate
371 that transplanted mean-case and worst-case designs can be similarly robust when used to estimate
372 worst-case impacts in the original network models. The small sample size limits the ability to make
373 any more general conclusions about the overall robustness of mean-case designs under conditions

374 of uncertainty in the network model. Evaluations using additional networks would be helpful.

375 **CONCLUSIONS**

376 On the basis of the two networks examined, lack of network model detail results in worst-case
377 CWS designs that perform more poorly than worst-case designs developed using the original “all-
378 pipes” network model. Relative performance, as measured by the reduction in worst-case impacts,
379 generally improves as the dose level decreases. However, at smaller dose levels a lack of network
380 model detail can yield CWS designs that have worst-case impacts three to five times larger than
381 those obtained using a complete network model.

382 Although lack of model detail generally has an adverse effect on CWS performance, no con-
383 sistent relationship was found between the degree of skeletonization and loss of performance.

384 In spite of the negative effect of loss of network model detail on CWS performance, CWSs
385 designed using incomplete network models can provide substantial reductions in adverse conse-
386 quences compared to results obtained when no CWS is used, except at high dose levels, for which
387 consequences tend to be localized near the injection location.

388 Proper understanding of the basis for CWS performance requires an understanding of the per-
389 formance of the individual sensors used in the CWS.

390 Mean-case designs developed using incomplete network models can provide worst-case results
391 that are generally comparable to those obtained with worst-case designs developed using the same
392 incomplete models, consistent with a conclusion that mean-case designs can provide robust results
393 under conditions of uncertainty. However, results for more networks are needed before any broader
394 conclusions can be made.

395 Improvement in network models, by reducing the uncertainty in the network model, has the
396 potential to yield significantly better performing CWSs.

397 **ACKNOWLEDGMENTS AND DISCLAIMER**

398 The U.S. Environmental Protection Agency’s (EPA) Office of Research and Development
399 funded, managed, and participated in the research described here under an interagency agreement.

400 This paper has been subjected to EPA’s review and has been approved for publication. The views
401 expressed in this paper are those of the authors and approval does not signify that the contents
402 necessarily reflect the views of the Agency. Mention of trade names, products, or services does
403 not convey official EPA approval, endorsement, or recommendation. Work at Argonne National
404 Laboratory was sponsored by the EPA under an interagency agreement through U.S. Department
405 of Energy Contract DE-AC02-06CH11357.

406 Because of the confidentiality of the information, the identities of the WDSs used in this paper
407 and any information that could be used to identify the systems cannot be disclosed.

408 REFERENCES

409 Bahadur, R., Johnson, J., Janke, R., and Samuels, W. B. (2008). “Impact of model skeletoniza-
410 tion on water distribution model parameters as related to water quality and contaminant con-
411 sequence assessment.” *Water Distribution System Analysis Symp. 2006*, ASCE, Reston, VA.
412 10.1061/40941(247)64

413 Berry, J., Hart, W. E., Phillips, C. A., Uber, J. G., and Watson, J.-P. (2006). “Sensor placement in
414 municipal water networks with temporal integer programming models.” *J. Water Resour. Plann.*
415 *Manage.*, 10.1061/(ASCE)0733-9496(2006)132:4(218), 218-224.

416 Davis, M. J., and Janke, R. (2014). “Influence of network model detail on estimated
417 health effects of drinking water contamination events.” *J. Water Resour. Plann. Manage.*,
418 10.1061/(ASCE)WR.1943-5452.0000436, 04014044.

419 Davis, M. J., Janke, R., and Magnuson, M. L. (2013a). “A framework for estimating the adverse
420 health effects of contamination events in water distribution systems and its application.” *Risk*
421 *Anal.*, 10.1111/risa.12107

422 Davis, M. J., Janke, R., and Phillips, C. A. (2013b). “Robustness of designs for drinking
423 water contamination warning systems under uncertainty.” *J. Water Resour. Plann. Manage.*,
424 10.1061/(ASCE)WR.1943-5452.0000408, 04014028.

425 Davis, M. J., Janke, R., and Taxon, T. N. (2016). "Assessing inhalation exposures associ-
 426 ated with contamination events in water distribution systems." *PLoS ONE*, 11(12):e0168051,
 427 10.1371/journal.pone.0168051

428 Grayman, W. M., Males, R. M., and Clark, R. M. (1991). "The effects of skeletonization on dis-
 429 tribution system modeling." *Proc. AWWA Conf. on Computers in the Water Industry*, American
 430 Water Works Association, Denver, CO, 661-684.

431 Grayman, W. M., and Rhee, H. (2000). "Assessment of skeletonization in network models." *Proc.*
 432 *2000 Joint Conf. Water Resource Engineering and Water Resources Planning and Management*,
 433 ASCE, Reston, VA. 10.1061/40517(2000)196

434 Janke, R., et al. (2009). "Sensor network design and performance in water systems dominated
 435 by multi-story buildings." *Proc. World Environ. and Water Resources Congress 2009*, ASCE,
 436 Reston, VA. 10.1061/41036(342)46

437 Janke, R., Murray, R., Uber, J., Bahadur, R., Taxon, T., and Samuels, W. (2007). "Using TEVA
 438 to assess impact of model skeletonization on contaminant consequence assessment and sensor
 439 placement design." *Proc. World Environ. and Water Resources Congress 2007*, ASCE, Reston,
 440 VA. 10.1061/40927(243)527

441 Klise, K. A., Phillips, C. A., and Janke, R. J. (2013). "Two-Tiered Sensor Placement for Large Wa-
 442 ter Distribution Network Models." *J. Infrastruct. Syst.*, 10.1061/(ASCE)IS.1943-555X.0000156,
 443 465-473.

444 Rossman, L. A. (2000). "EPANET 2 users manual," *EPA/600/R-00/057*, National Risk Manage-
 445 ment Research Laboratory, Office of Research and Development, U.S. Environmental Protection
 446 Agency, Cincinnati, OH.

447 U. S. EPA. (2016). "Models, tools and applications for homeland security research."
 448 ([https://www.epa.gov/homeland-security-research/models-tools-and-applications-homeland-](https://www.epa.gov/homeland-security-research/models-tools-and-applications-homeland-security-research)
 449 [security-research](https://www.epa.gov/homeland-security-research/models-tools-and-applications-homeland-security-research)) (Dec. 14, 2016).

450 **List of Tables**

451	1	Network Descriptions	19
452	2	Network Skeletonization	20
453	3	Ratios of Worst-Case Impacts Obtained with Transplanted and Original CWS De-	
454		signs	21

TABLE 1. Network Descriptions

Quantity	Network	
	N1	N3
Population (10^3)	250	350
Area (km^2)	490	800
Nodes (10^3)	13	12
NZD nodes (10^3)	11	11
Pipes (10^3)	15	14
Tanks	2	21
Reservoirs	2	3
Pumps	4	43
Valves	5	32
Mean NZD nodal pop.	24	31
Median NZD nodal pop.	16	15

Note: All numbers are rounded independently to two significant figures. NZD, non-zero demand.

TABLE 2. Network Skeletonization

Model	Number of			$\frac{\text{Pipes}}{\text{Nodes}}$
	Nodes	NZDNs	Pipes	
N1	13,000	11,000	15,000	1.2
N1 20 cm	4,300	3,400	5,600	1.3
N1 30 cm	3,100	2,600	4,300	1.4
N1 40 cm	2,800	2,400	4,000	1.5
N3	12,000	11,000	14,000	1.2
N3 20 cm	4,500	4,300	6,000	1.3
N3 30 cm	3,500	3,300	5,000	1.4
N3 40 cm	3,200	3,000	4,700	1.5

Note: All numbers are rounded independently to two significant figures. NZDN, non-zero demand node.

TABLE 3. Ratios of Worst-Case Impacts Obtained with Transplanted and Original CWS Designs

Dose Level (mg)	Ratio of Worst-Case Impacts					
	Network N1			Network N3		
	Min.	Median	Max.	Min.	Median	Max.
<i>Transplanted Worst-Case Design</i>						
10^{-4}	1.1	2.2	4.0	1.0	1.4	6.3
10^{-2}	1.0	2.1	4.1	1.0	2.3	6.6
1.0	1.3	1.4	1.5	1.1	1.6	2.2
<i>Transplanted Mean-Case Design</i>						
10^{-4}	1.0	1.7	4.3	1.3	5.6	6.3
10^{-2}	1.0	1.8	4.2	1.1	2.8	6.6
1.0	1.2	1.3	1.5	1.3	1.6	2.2

Note: Ratio is the ratio of the worst-case impact obtained with the transplanted design divided by the worst-case impact obtained with the worst-case design developed using the original network model. Minimum (Min.), median, and maximum (Max.) values for the ratio are given for the nine ratios determined for the three sensor set sizes and the three skeletonizations.

455 **List of Figures**

456	1	Worst-case impact versus dose level for original and non-transplanted, worst-case	
457		CWS designs for Network N1	23
458	2	Worst-case impact versus dose level for original and transplanted, worst-case CWS	
459		designs for Network N1	24
460	3	Relative worst-case impacts for transplanted and non-transplanted worst-case CWS	
461		designs for Network N1	25
462	4	Reduction in worst-case impacts obtained with original and transplanted worst-	
463		case CWS designs for Network N1 relative to impacts obtained when no CWS is	
464		used	26
465	5	Worst-case impact versus dose level for original and transplanted, worst-case CWS	
466		designs for Network N3	27
467	6	Reduction in worst-case impacts obtained with original and transplanted worst-	
468		case CWS designs for Network N3 relative to impacts obtained when no CWS is	
469		used	28
470	7	Worst-case impact versus dose level for original and transplanted, worst-case CWS	
471		designs for Network N1, non-zero demand nodes only	29
472	8	Performance of individual sensors for five-sensor, worst-case CWS designs for	
473		Network N1 and a dose level of 10^{-4} mg using nonzero demand nodes as possible	
474		injection locations	30
475	9	Comparison of worst-case impacts for transplanted mean- and worst-case CWS	
476		designs, Network N1 (numbers and arrows indicate overlapping or clustered points)	31
477	10	Comparison of worst-case impacts for transplanted mean- and worst-case CWS	
478		designs, Network N3 (numbers and arrows indicate overlapping or clustered points)	32

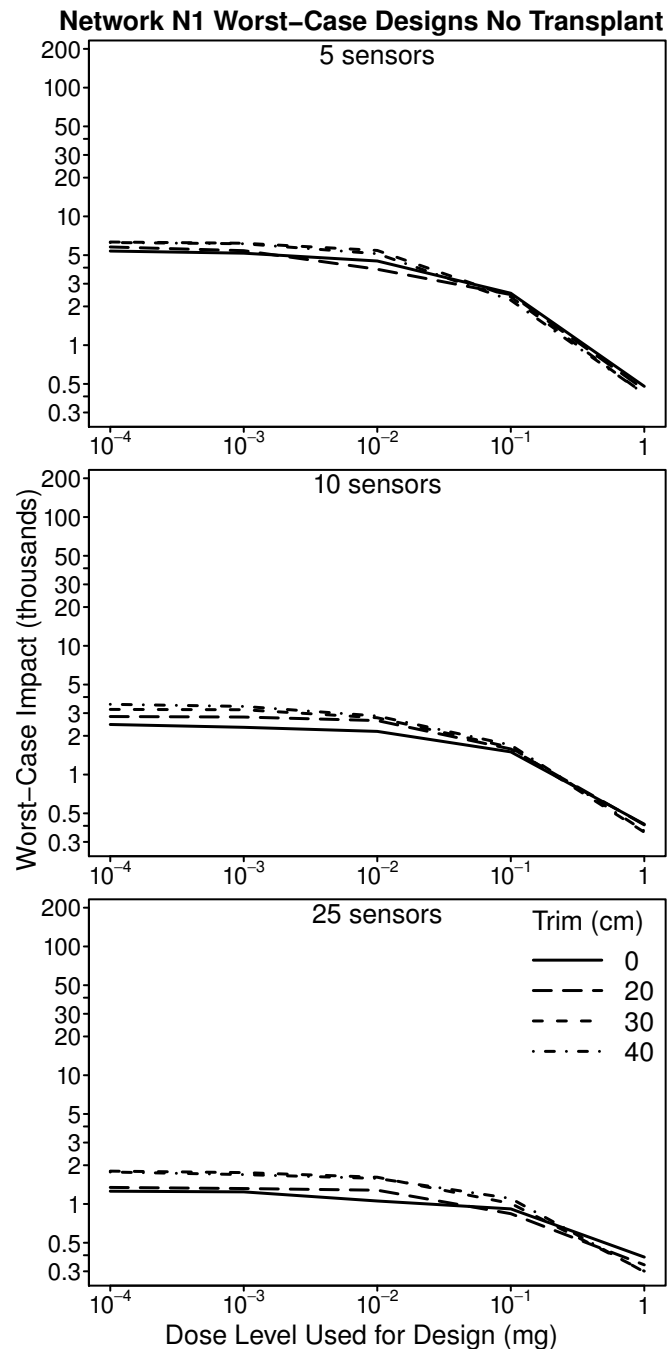


FIG. 1. Worst-case impact versus dose level for original and non-transplanted, worst-case CWS designs for Network N1

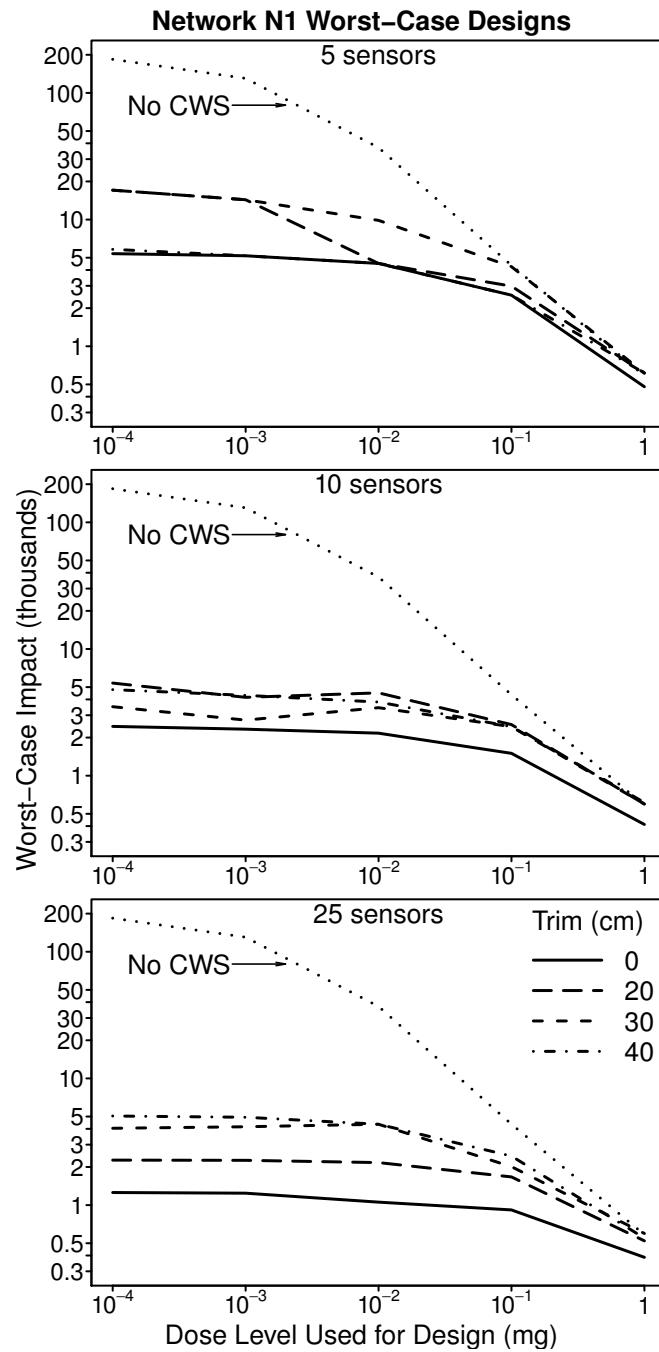


FIG. 2. Worst-case impact versus dose level for original and transplanted, worst-case CWS designs for Network N1

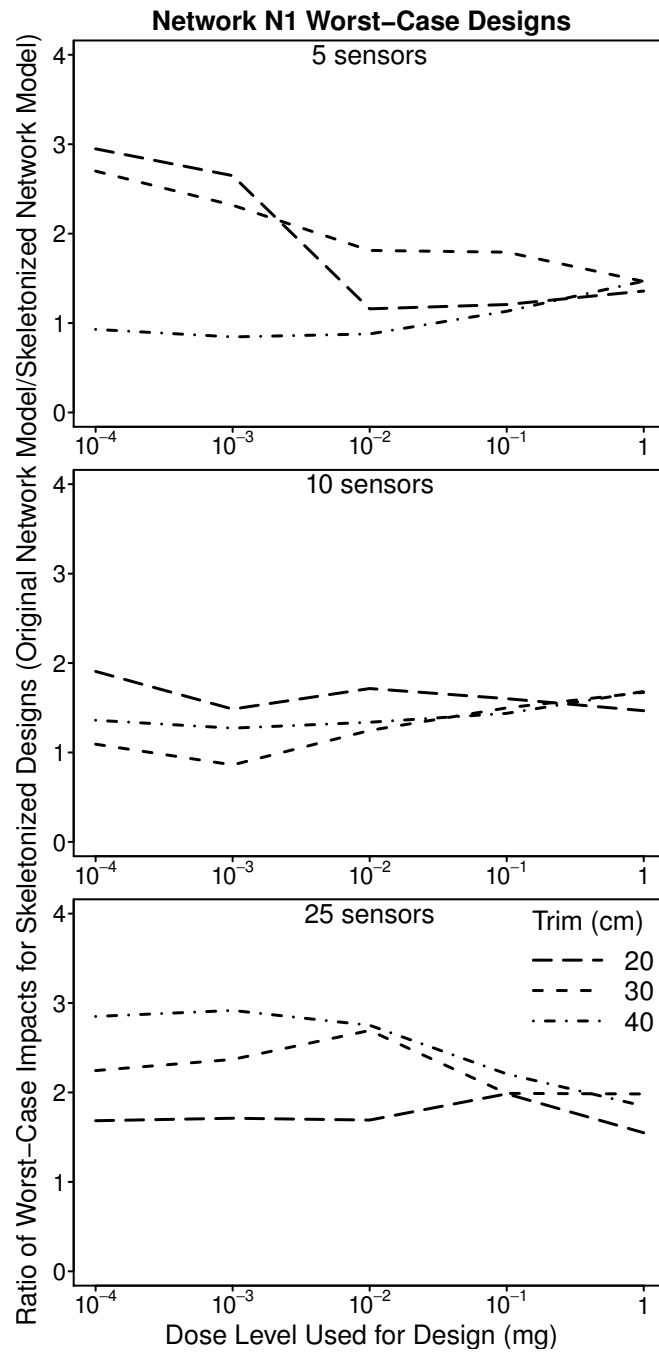


FIG. 3. Relative worst-case impacts for transplanted and non-transplanted worst-case CWS designs for Network N1

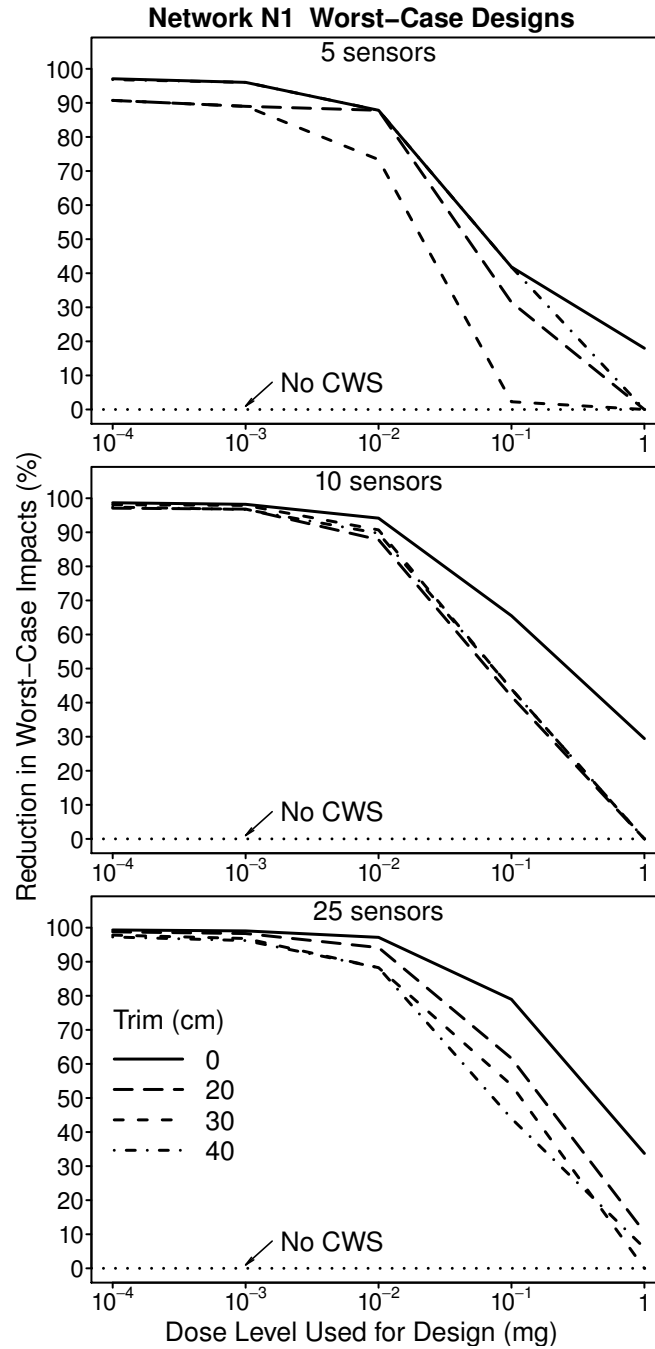


FIG. 4. Reduction in worst-case impacts obtained with original and transplanted worst-case CWS designs for Network N1 relative to impacts obtained when no CWS is used

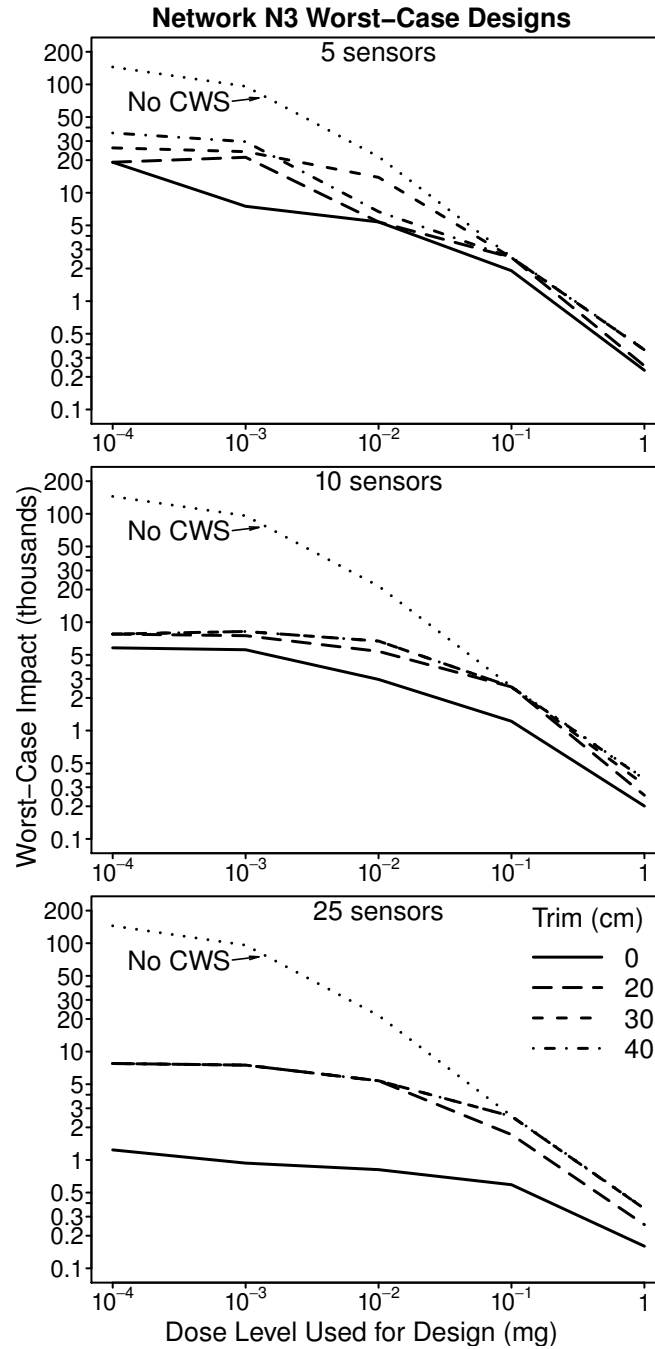


FIG. 5. Worst-case impact versus dose level for original and transplanted, worst-case CWS designs for Network N3

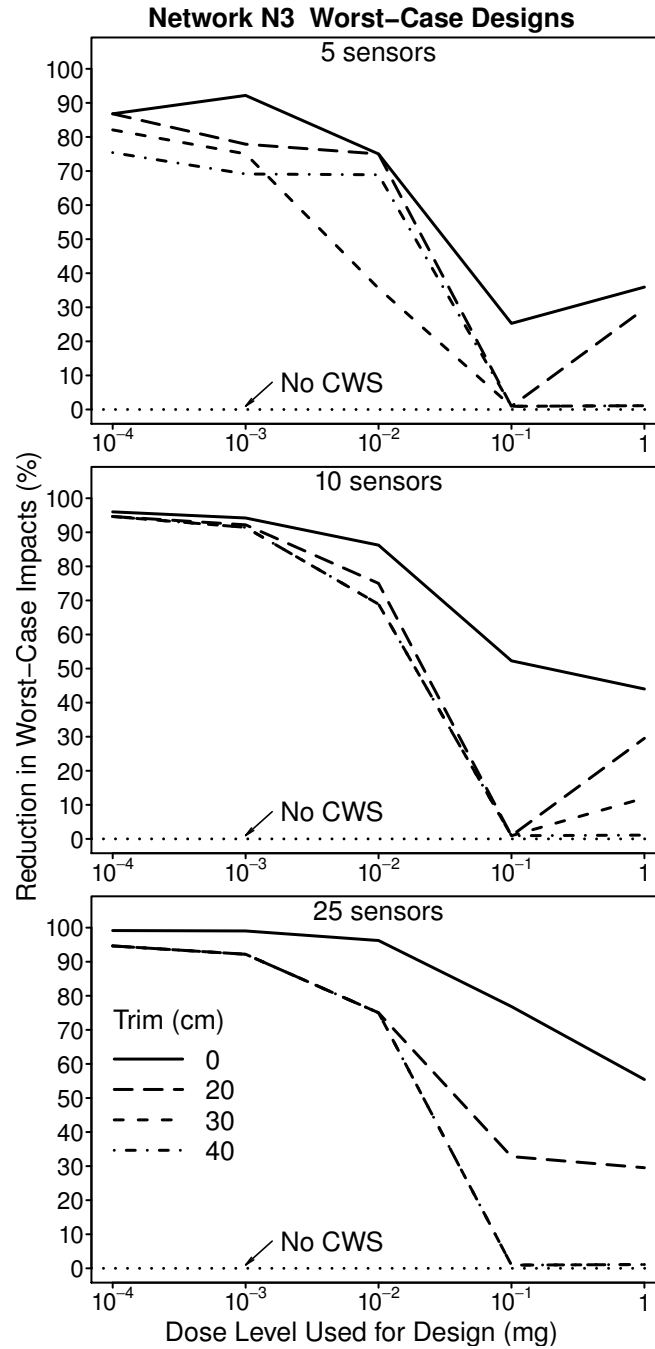


FIG. 6. Reduction in worst-case impacts obtained with original and transplanted worst-case CWS designs for Network N3 relative to impacts obtained when no CWS is used

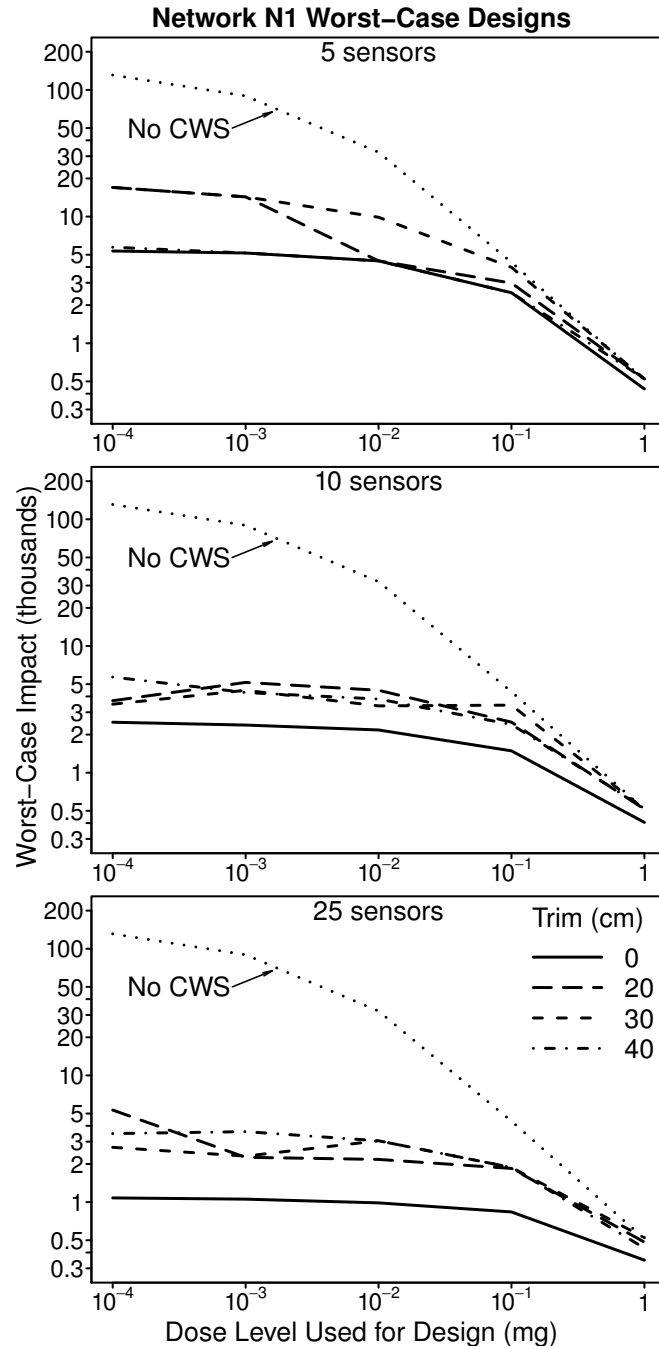


FIG. 7. Worst-case impact versus dose level for original and transplanted, worst-case CWS designs for Network N1, non-zero demand nodes only

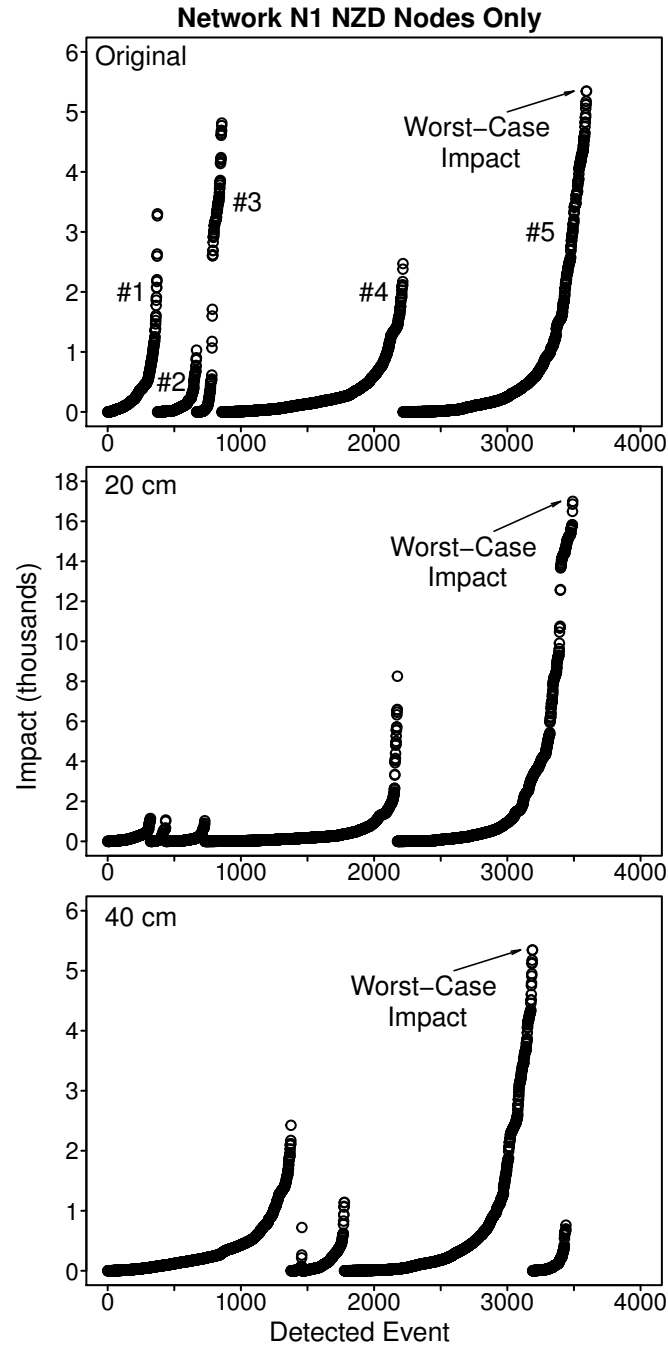


FIG. 8. Performance of individual sensors for five-sensor, worst-case CWS designs for Network N1 and a dose level of 10^{-4} mg using nonzero demand nodes as possible injection locations

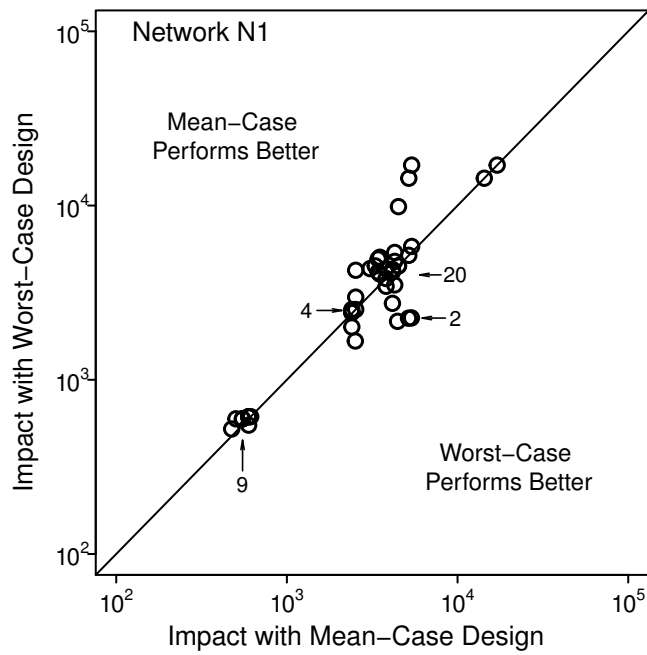


FIG. 9. Comparison of worst-case impacts for transplanted mean- and worst-case CWS designs, Network N1 (numbers and arrows indicate overlapping or clustered points)

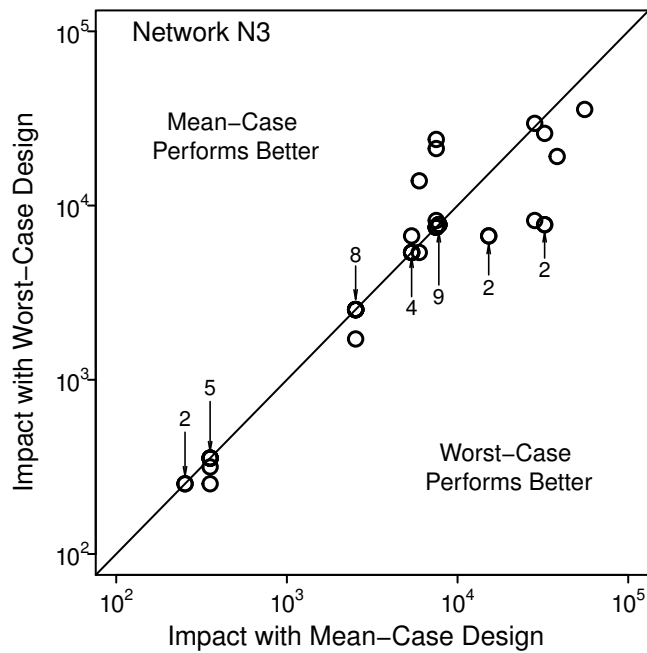


FIG. 10. Comparison of worst-case impacts for transplanted mean- and worst-case CWS designs, Network N3 (numbers and arrows indicate overlapping or clustered points)