1230. Estimating Effective Point-of-Use Biocide Levels for Legionella Control in Building Water Systems Using a Large, Real-World Dataset
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Background. Legionnaires’ disease is a potentially life-threatening illness often associated with Legionella growth in water sources. Oxidizing biocides, such as chlorine (CL), monochloramine (MC) and chlorine dioxide (CD), can reduce Legionella contamination. However, limited guidance exists regarding optimal target biocide levels in building water systems to prevent Legionella growth. We examined Legionella and biocide data collected by Department of Veterans Affairs medical facilities nationally to estimate effective biocide levels.

Methods. Water samples collected at point of use for routine surveillance purposes between 2015 and 2017 were used for this analysis. Samples were limited to those with reported biocide being CL, MC or CD. Samples with biocide levels above safe drinking water maximums and from nonpotable water sources were excluded. Samples were stratified by hot and cold water and univariate logistic generalized additive models were used to assess nonlinear associations of probability of Legionella positivity and biocide level.

Results. The dataset included 144,458 samples (cold: 72,674; hot: 71,784) from 789 buildings at 168 hospitals, with 99,419 samples with reported biocide as CL, 40,922 as MC, and 4,117 as CD. For CL, cold water analysis showed a minimum probability of positivity at approximately 0.5 parts per million (ppm), but with a second minimum at 2 ppm. Hot water showed an inflection point around 0.6 ppm, but the likelihood of positivity continued to decrease until plateauing beyond 2 ppm (Figure 1). Cold water with MC showed a minimum probability of positivity at 0.3 ppm followed by a second minimum at 1.7 ppm with plateau beyond that concentration. Hot water showed a similar graph with initial minimum at 0.25 ppm and a second minimum at 1.6 ppm (Figure 2). CD graphs for both hot and cold showed a decrease at 0.2 ppm (Figure 3).

Conclusion. The variability in the dynamics of Legionella inhibition by different biocides as seen in our analysis indicates minimum biocide targets for the different agents. For CL and MC, biocide levels >2 ppm at point of use in building water systems may not provide added benefit for suppression of Legionella.

Figure 1: Probability of Legionella Positivity by Chlorine Level

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The hierarchical location group levels consisted of room nested within floor, within model. A multi-level Bayesian logistic regression model was run in R version 3.5.1. through 2017 and for which complete information was reported were used for the Legionella VHA nationwide. Our goal was to understand when, where and why variations in the United States. We modeled the variability in potable water samples, for its 170 medical facilities (“stations”) distributed across VHA Medical Facilities.

Methods. We retrospectively analyzed 30 SSI outbreaks occurring over a period of 8 years in a network of 50 community hospitals from the Southeastern United States. We applied 24 control chart variations, including 2 optimized for SSI surveillance, 6 with expert-defined pre-outbreak baselines (used in our pilot study), 4 with lagged rolling baseline and (idem), and 12 common practice ones (using rolling baselines with no lag or fixed baseline). The charts used procedure-specific data from either the outbreak hospital or the entire network to compute baseline SSI rates. We calculated the average SSI rates during, before and after the outbreaks, and the months elapsed between SPC and traditional detection. We then used these values to estimate the number of SSI that could have been prevented by SPC, and corresponding deaths avoided and cost savings (Figure 1).

Results. Optimized charts detected 96% of the outbreaks earlier than traditional surveillance methods. While pilot study and common practice charts did so only 65% (58%) of the time (Figure 2). Optimized charts could potentially prevent 15.2 SSS, 0.64 deaths, and save $226,000 in excess care costs per outbreak. Overall, charts using network baselines performed better than those relying on local hospital data. Commonly used variations were the least effective, but were still able to improve on traditional surveillance (Figure 3).

Conclusion. SPC methods provide a great opportunity to prevent infections and deaths and generate cost savings, ultimately improving patient safety and care quality. While common practice SPC charts can also speed up outbreak detection, optimized SPC methods have a significantly higher potential to prevent SSI and reduce healthcare costs.

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Figure 1. Example calculation of prevented SSI and related estimates for one hospital. Left graph shows the SSI rate over time (days). Overall horizontal lines represent the average SSI rate before (orange), during (green), and after (yellow) the outbreak. SPC and traditional surveillance detection rates are depicted as and dashed lines while white boxes indicate different months represented by (black arrow). Right graph shows the equations used to calculate prevented SSI cases (using average pre- and post-outbreak SSI rates, months during average SSI mortality rate of 7.6%, and cost savings (averaging average cost per SSI of $12,725).

Figure 2. Outbreak-specific SPC and traditional detection relative to network outbreak (months). For each outbreak, each graph shows the actual difference between outbreak detection by optimized (dashed), pilot study (crosses), and common practice (dotted) charts relative to the estimated actual outbreak outbreak date. Negative values indicate detection prior to the outbreak onset, and positive values represent the overestimation. Also shown are the number of months between outbreak onset and traditional detection time (crosses).