Models for predicting heavy metal concentrations in residential plumbing pipes and hot water tanks

Shakhawat Chowdhury, Fayzul Kabir, Mohammad Abu Jafar Mazumder, Khalid Alhooshani, Amir Al-Ahmed and M. S. Al-Suwaiyan

Abstract

Supply water is an important source of human exposure to heavy metals through the oral pathway. Due to stagnation of water in plumbing systems, exposure concentrations of heavy metals from tap water can be higher than water distribution systems (WDS), which is often ignored by the regulatory agencies. In this study, concentrations of a few heavy metals (arsenic (As), chromium (Cr), copper (Cu), mercury (Hg), manganese (Mn), magnesium (Mg), zinc (Zn) and iron (Fe)) and water quality parameters were monitored in WDS, plumbing pipe (PP) and hot water tanks (HWT). Multiple models were trained for predicting metal concentrations in PP and HWT, which were validated. Heavy metal concentrations in HWT were 1.2–8.1 and 1.4–6.7 times the concentrations in WDS and PP respectively. Concentrations of As, Cr, Cu, Hg and Zn were in the increasing order of WDS, PP and HWT. Concentrations of Cr and Fe were higher during summer while Cu and Zn were higher in winter. The models showed variable performances for PP and HWT (R²: PP = 0.61–0.99; HWT = 0.71–0.99). The validation data demonstrated variable correlation coefficients (r: PP = 0.45–0.99; HWT = 0.83–0.99). Few models were useful to predict heavy metals in tap water to reduce the cost of expensive sampling and analysis.

Key words: heavy metals, hot water tank, model validation, modeling heavy metal concentrations, plumbing premise, water stagnation

Highlights

- Heavy metal (HM) concentrations were in the increasing order of WDS, PP and HWT.
- Few HM were higher in summer than winter while others were higher in winter.
- Multiple models were trained and validated to predict HM in PP and HWT.
- Models showed varying performances (R² for PP: 0.61–0.99; HWT: 0.71–0.99).
- Few models were useful to predict HM in PP and HWT with very good accuracy.
INTRODUCTION

Few heavy metals are necessary for humans while an excess amount can pose elevated risks (ATSDR 2015; USEPA 2017, 2019). Drinking water is an important source of human exposure to heavy metals. In contrast, safe drinking water must not impose an elevated risk (WHO 2017). Natural and industrial processes generate wastes with heavy metals, which are mostly discharged into the environmental systems (Szefer et al. 1999; Chowdhury et al. 2016). The sources of industrial pollution include electroplating, metal smelting, chemical and mining industries and manufacturing processes (He et al. 2008; Liu et al. 2011, 2012). Improperly treated industrial, domestic and agricultural wastewater often contains higher levels of metals, which are typically released into the environment (Gupta 2008). In 50 districts of Bangladesh, levels of arsenic (As) in groundwater exceeded 50 μg/L, the limit established for Bangladesh (Uddin & Huda 2011; Jiang et al. 2013), which was due to arsenic contamination through natural processes (Karim 2000; Chakraborti et al. 2010). Several other sources were reported to pollute the environment and water sources (Wu et al. 2014; Wang et al. 2015; Chowdhury et al. 2016).

Despite water treatment plants (WTPs) applying various treatments to remove different pollutants, drinking water contains some heavy metals in trace concentrations. In addition, leaching of metals from water distribution system (WDS) can increase the concentrations of these metals (Alam & Sadiq 1989; Tamasi & Cini 2004; Chowdhury et al. 2018; Kabir et al. 2018). Kabir et al. (2018) summarized the effects of source water quality, treatment, diurnal and seasonal variability in water use, temperature and water chemistry on the concentrations of heavy metals in WDS, plumbing pipes (PP) and hot water tanks (HWT). However, no predictive model was presented in this study. From WDS, water enters the plumbing premise...
while it can stay in PP and HWT for a significant amount of time, leading to increased leaching of metals into water. Concentrations of Cu were found to increase up to 67% during stagnation of water from the first floor (600 μg/L) to the sixth floor (1,000 μg/L) of a six-storey building in Dhahran (Alam & Sadiq 1989). A study in Riyadh reported maximum concentrations of Fe (411.7 μg/L), Pb (59.8 μg/L) and Ni (228.7 μg/L) in cooler water, which were much lower in WDS (20.4, 2.9 and 1.7 μg/L respectively) feeding these coolers (Kutty et al. 1995). In the Flint Water System, an increase in Cu and Pb was reported in tap water, which was due to increased corrosion from the application of ferric chloride to reduce disinfectant byproducts (DBPs) formation (Flint Water Study Updates 2017). In addition, water quality parameters (WQP), type of pipe materials and faucets can also affect the leaching of metals into water (Kabir et al. 2018).

Populations consume tap water inside the house containing higher concentrations of these metals, which can pose elevated risks to humans (e.g. cancer, kidney function, gastrointestinal disorders, cardiovascular defects, embryotoxicity and anaemia) (ATSDR 2015; IARC 2016; USEPA 2017, 2019). The International Agency for Research on Cancer (IARC) characterized Cd and inorganic arsenic as human carcinogens (IARC 2016). Other effects including anemia from Pb, heart disease and cholesterol from Sb, liver and kidney damage from Hg, and gastrointestinal disorders from Cu were also reported (Flora et al. 2012; ATSDR 2015; Assi et al. 2016; USEPA 2017). Further details on possible effects can be found in the literature (ATSDR 2015; Chowdhury et al. 2016; USEPA 2019). A number of regulatory agencies have set guideline values of different heavy metals for consumption (AUS 2011; UK 2015; Health Canada 2017; USEPA 2017; WHO 2017). The recommended concentrations of heavy metals are summarized in Table 1.

Monitoring programs typically analyze the samples from WDS or WTP to ensure easy access, which do not include the implications of plumbing systems. Changes of heavy metal concentrations in plumbing systems (e.g. WDS to PP and HWT) have not been given much attention. To date, limited studies have proposed models to predict heavy metals in plumbing systems. Recently, models were proposed to predict the concentrations of lead ions (Pb²⁺) in PP and HWT (Chowdhury et al. 2018). In the current research, changes of concentrations of some heavy metals (As, Cr, Cu, Hg, Mn, Mg, Zn and Fe) from WDS to PP and HWT, and the related WQP, were investigated. A number of linear, nonlinear and neural network models were trained for predicting As, Cr, Cu, Hg, Mn, Mg, Zn and Fe in PP and HWT. These models were validated

| Table 1 | Guideline concentrations of some heavy metals in drinking water (μg/L) |
|---------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Metal   | USEPA (2017) | Health Canada (2017) | WHO (2017) | NZ (2005) | AUS (2011) | UK (2015) | Possible health effects (USEPA 2017) |
| As      | 10          | 10                        | 10            | 10            | 10            | 10            | Skin damage; increased risk of getting cancer |
| Be      | 4           | –                         | –             | 60            | –             | –             | Intestinal lesions |
| Ba      | 2,000       | 1,000                      | 1,300         | 700           | 700           | –             | Increase blood pressure |
| Cd      | 5           | 5                         | 3             | 4             | 2             | 5             | Kidney damage |
| Cr      | 100         | 50                        | 50            | 50            | 50            | 50            | Allergic dermatitis |
| Cu      | 1,300       | ≤1,000                     | 2,000         | 2,000         | 2,000         | 2,000         | Gastrointestinal distress; Liver or kidney damage |
| Fe      | 300         | ≤300                      | 100           | 200           | 300           | 200           | – |
| Hg      | 2           | 1                         | 6 (Inorganic) | 7 (Inorganic) | 1             | 1             | Kidney damage |
| Mn      | 50          | ≤50                       | 0             | 40            | 500           | 50,000        | – |
| Mo      | –           | –                         | –             | 70            | 50            | –             | – |
| Na      | –           | ≤200,000                  | 50,000        | 200,000       | 180,000       | 20,000        | – |
| Ni      | –           | –                         | 70            | 80            | 20            | 20            | – |
| Pb      | 15          | 10                        | 10            | 10            | 10            | –             | Delays in physical/mental development; Kidney problems; high blood pressure |
| Zn      | 5,000       | ≤5,000                     | 5,000         | 1,500         | 3,000         | –             | – |

USEPA, US Environmental Protection Agency; UK, United Kingdom; AUS, Australia; NZ, New Zealand; HC, Health Canada; WHO, World Health Organization. Arsenic (As), beryllium (Be), barium (Ba), cadmium (Cd), lead (Pb), chromium (Cr), copper (Cu), mercury (Hg), manganese (Mn), magnesium (Mg), zinc (Zn) and iron (Fe), molybdenum (Mo), sodium (Na).
using a different dataset from a completely different plumbing premise that was excluded from model training. The performances of the models was analyzed and the best predictive models were identified.

**MATERIALS AND METHODS**

**Data collection**

The bi-weekly water samples obtained from a residential area at King Fahd University of Petroleum & Minerals (KFUPM) from 01/11/2016 to 29/05/2017 were brought to the laboratory immediately following collection. A constant time gap was ensured throughout the sampling period. The samples were analyzed in duplicate seven different times in a day resulting in 42, 28 and 28 samples from WDS, PP and HWT respectively. Figure 1 explains the sampling details to better understand the diurnal variability. S1 represents the samples from WDS in the late evening following 10 minutes free flow through a tap. S2 shows the water in the early next morning collected from this tap in the first flush. The S3 and S4 samples were obtained from this tap in the morning representing HWT and WDS respectively. S5, S6 and S7 were the samples collected in the afternoon representing PP, HWT and WDS respectively. The WDS samples were obtained following 10 minutes free flow of water. The samples were collected in two types of bottles: a 100 mL glass bottle for metal analysis and a 125 mL plastic bottle for WQP analysis. The samples were stored at 4 °C in a temperature-controlled refrigerator in the laboratory and analyzed within 7 days of collection.

**Laboratory analysis**

Standard methods were followed in analyzing the samples (USEPA 2016). Dissolved organic carbon (DOC), free chlorine (FCl), turbidity, total chlorine (TCl) and absorbance of UV at 254 nm (UV254) were analyzed at room temperature. pH and temperature were quantified on site. The FCl and TCl were quantified using a HACH instrument (Model: DR 3900) following 8167 and 8021 methods respectively. DOC was analyzed by a TOC analyzer (Model: Shimadzu TOC-L-CSN) according to method 5310B (AWWA 2012). UV254 was analyzed by a spectrophotometer through a quartz cell with a 10-mm optical path (Genesys 10 UV-VIS model). Analysis for metals was performed using the ICP-MS (ICP-MS XSERIES-II model Inductively Coupled Plasma – Mass Spectrometer from Thermo) using method 200.8 (USEPA 1994). PlasmaLab Windows platform software was used to process the data.

**Model development and validation**

In developing models, the WQP (DOC, UV254, TCl, FCl, pH and T) and the heavy metal data (As, Cr, Cu, Co, Fe, Hg, Mn, Mg, Mo, Ni, Pb, Sr, V and Zn) in the WDS, PP and HWT were combined in a single dataset (Kabir et al. 2018), and plotted through the matrix plot to identify the possible linear and nonlinear relationships among the input factors and the outputs.

![Sampling program](attachment://sampling_program.png)

**Figure 1** | Data collection approach; (S1 = 1st water sample in the evening after 10 min. free flow; S2: water from 1st flush of the same tap in next day morning; S3: water samples of hot water tap in morning; S4: water sample in morning after 10 min. free flow; S5: water sample from tap following normal uses in afternoon; S6: sample from hot water tap following normal uses in afternoon; S7: samples after 10 min free flow in the afternoon.)
The correlated parameters with the target outputs (e.g. heavy metals in PP and HWT) were separated and the models were trained using JMP™ software for each output independently. Using the significant factors, the models were developed (SAS Inc. 2019). The linear, nonlinear (NL) and neural network (NN) models were applied to predict metal concentrations in PP and HWT. In linear models, linear main factors (LMF), linear main factors with interactions (LMFI) and linear logarithmic (LL) models were investigated (Montgomery & Runger 2018; SAS Inc. 2019). Equations (1)–(3) show the LMF, LMFI and LL models respectively. For NL models, the models from the ‘Nonlinear models’ library in JMP™ were plotted with the experimental data (SAS Inc. 2019), which were then converged for parameter optimization using standard methods (e.g. Newton–Raphson method). Statistical adequacy was tested through root mean squared errors (RMSE), coefficient of determination ($R^2$) and model plots. The logistic three parameters (LM-3P) and Weibull four parameters (WM-4P) models are shown in Equations (4) and (5):

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \ldots + \varepsilon$$

(1)

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{j=1}^{n} \beta_{i,j} x_i x_j + \sum_{i=1}^{n} \beta_i x_i^2 + \ldots + \varepsilon$$

(2)

$$\ln (y) = \beta_0 + \sum_{i=1}^{n} \beta_i [\ln (x_i)] + \ldots + \varepsilon$$

(3)

$$y = \frac{\theta_1}{(1 + \theta_2 \exp(\theta_3 x))}$$

(4)

$$y = \theta_1 - \theta_2 \exp(-\exp[\theta_5 + \theta_4 \ln(x)])$$

(5)

where $\beta_0 = \text{intercept}; y = \text{output}; \beta_i = \text{model parameters}; \theta_1-\theta_4 = \text{nonlinear model parameters}; x = \text{predictor variables}; \varepsilon = \text{residuals}; \text{and } i, j = 1, 2, 3, \ldots \ldots n$.

The NN models have input and output layers, and several hidden layers (Kasabov 1997; SAS Inc. 2019). The input data define the number of nodes in these layers. Equations (6) and (7) show an NN model with three-hidden-nodes ($H_γ$). $H_γ$ is the hyperbolic tangent function of linear combinations of the input factors:

$$y = \lambda_0 + \sum_{\gamma=1}^{3} \lambda_\gamma H_\gamma$$

(6)

$$H_\gamma = \tan H[0.5*(a_0 + a_1x_i)]$$

(7)

where $\lambda = \text{coefficients}; H_\gamma = \gamma \text{th hidden node}; a_0 = \text{intercept of input factors}; a_1 = \text{coefficients of input factors}$. The model validation was performed using another set of experimental data from a completely different plumbing premise. The correlation coefficients ($r$) were determined for the validation data. The software packages (JMP™ and Minitab™) were used for this study.

**RESULTS**

**Statistics**

The DOC in the WDS, PP and HWT were in the ranges of 0.11–10.24, 0.24–3.98 and 0.30–4.49 mg/L, respectively (Kabir et al. 2018). The ranges of pH were 6.4–8.2, 6.2–7.4 and 6.3–8.0 with averages of 6.93, 6.83 and 6.77 respectively. The averages of pH were slightly acidic. The aggressivity index (AI) of water is a function of pH, alkalinity and calcium hardness, which is calculated as: $AI = pH + CH + DA$; where $CH = \text{Logarithm (base 10) of calcium hardness (mg/L)}$; and $DA = \text{Logarithm (base 10) of alkalinity (mg/L)}$. The AI values <10, 10–12 and >12 indicate highly aggressive, moderately aggressive and non-aggressive water respectively (Kim et al. 2011). Lower values of pH could lower AI, leading to increased corrosivity. Temperatures in WDS, PP and HWT were 23.0–33.0, 22.5–32.0 and 58.0–62.0 °C respectively. Concentrations of Cr and Mg showed higher variability in HWT than WDS and PP. Averages of Cr in WDS, PP and HWT were 0.60–0.63, 0.56–0.57 and 0.68–0.79 μg/L respectively. Higher Cr in HWT can be partially attributed to increased reaction with the wall.
and deposits in the HWT (Wigginton et al. 2007). The averages of As, Fe and Zn were higher in HWT than WDS (p-value = 0.002). In WDS, the averages of Fe and As were 60 and 0.5 μg/L respectively, which increased to 72 and 1.0 μg/L, in HWT respectively (Kabir et al. 2018). The average of Mn in PP (1.91 μg/L) was almost 1.8 times the average in WDS (1.05 μg/L). The average of Hg was 0.9 μg/L in WDS, which increased to 1.1 μg/L in PP. The higher averages of the metals in PP indicated the effects of water stagnation in PP (Table 2). In PP, the averages of Cu, Hg and Zn were 3.2, 2.6 and 204.6 μg/L respectively, while in WDS, these were 0.8, 1.5 and 43.5 μg/L respectively. In general, precipitates, sediments and corroded metals are deposited in HWT, which could have increased the metals in HWT (Wigginton et al. 2007). In addition, water demand variability could have implications on metal concentrations (Del Toral et al. 2013). The elevated levels of As, Cr, Cu, Hg and Pb could have higher risks to humans (ATSDR 2015; USEPA 2017). Further details on the variability of the metals and WQP can be found in Kabir et al. (2018).

### Table 2 | The models developed to predict heavy metals in plumbing pipes (PP)

| Output | Model | Expression | R² | RMSE | Corr. (r) |
|--------|-------|------------|----|------|-----------|
| As_pp  | LMF   | As_pp = β₀ + β₁⁎Na_p + β₂⁎Fe_p + β₃⁎Mn_p; β₀ = 0.09; β₁ = 5.71×10⁻⁵; β₂ = 0.02; β₃ = -0.12 | 0.89 | 0.13 | 0.89 |
|        | NN    | As_pp = 1.99 + (3.56 × H1) + (1.24 × H2) + (-5.42 × H3) | 0.99 | 0.12 | 0.94 |
| Cu_pp  | LMFI  | Cu_pp = β₀ + β₁⁎V_p + β₂⁎Fe_p + β₃⁎Hg_p + β₄⁎H₂O_p + (4.2×I_p) + β₅⁎TCl_p; β₀ = -6.22; β₁ = 0.82; β₂ = 0.065; β₃ = 0.014; β₄ = 0.014; β₅ = 0.014 | 0.89 | 0.17 | 0.48 |
| Cr_pp  | NL    | Cr_pp = 1.58 + (1.76 × H1) + (3.73 × H2) + (1.11 × H3) | 0.98 | 0.02 | 0.97 |
| Hg_pp  | LMF   | Hg_pp = β₀ + β₁⁎Hg_p + β₂⁎Fe_p + β₃⁎V_p + β₄⁎TCl_p; β₀ = 2.53; β₁ = 0.59; β₂ = -0.03; β₃ = 1.8; β₄ = 0.001 | 0.61 | 1.06 | 0.50 |
| Zn_pp  | NN    | Zn_pp = 6.33 + (16.29 × H1) + (10.65 × H2) + (13.53 × H3) | 0.93 | 0.37 | 0.71 |
| Fe_pp  | LMF   | Fe_pp = β₀ + β₁⁎Cr_p + β₂⁎Fe_p + β₃⁎V_p + β₄⁎TCl_p; β₀ = 15.98; β₁ = 80.15; β₂ = 1.09; β₃ = -2.34 | 0.95 | 0.61 | 0.91 |
|        | NN    | Fe_pp = 54.33 + (65.17 × H1) + (-17.01 × H2) + (-21.04 × H3) | 0.94 | 0.47 | 0.99 |

LMF, Linear model with main factors; LM-3P, Logistic models with 3 Parameters; NN, Neural network model; WDS, Water distribution system; PP, Plumbing pipe; HWT, Hot water tank; DOC, Dissolved organic carbon (mg/L); T, Temperature (°C); TC, total chlorine (mg/L); FC, Free chlorine (mg/L); UV, UV absorbance at 254 nm wavelength; θ — non-linear model parameters; β — linear model parameters; H1, H2 and H3, hidden layer functions; PP, Plumbing pipe.
Models
Models for heavy metals in PP
The models for predicting heavy metals in PP are summarized in Table 2. In Table 2, the best performing models are shown while no acceptable model could be developed for predicting Mg and Mn in PP (Table 2). In LMF models, the main factors having a p-value of <0.05 were selected as significant while in the LMFI models, significant higher order and interaction terms were also included. In LL models, significant log-transformed main factors were selected. The time difference for sampling from WDS, PP and HWT were constant throughout the entire sampling program. As such, reaction time was excluded from modeling. Further, lack of fits (e.g. \( p = 0.1 \)) were tested to ensure model adequacy. For NL models, the ‘Non-linear models’ library from JMP™ were tested, plotted and the best fit models were selected for parameter optimization (SAS Inc. 2019). The model parameters were optimized using Newton–Raphson techniques (SAS Inc. 2019). For the NN model, the ‘Neural Network Modeling’ module from JMP™ was used for parameter optimization, and model training and validation. The model validation data were taken from a completely different plumbing premise, which were excluded from model training (SAS Inc. 2019). The adequacy of the models was tested following numerical and graphical techniques (Montgomery & Runger 2018).

For predicting AsPP, LMF and NN models were selected. Both LMF and NN models had excellent predictive capabilities while the other models were not included due to their poor performances. In LMF and NN models, NaPP, ZnWDS and MnWDS were the significant main factors (Table 2). In the LMF model, NaPP and ZnWDS showed positive effects while MnWDS had a negative effect on the model. AsWDS was not a significant factor indicating that the contribution of AsWDS to AsPP was negligible. As accumulated in PP along with calcite in the iron pipe, which was transported to the consumer tap through the PP (Bardelli et al. 2011). The relatively acidic water increased As through corrosive action, and enhanced reactions with plumbing materials and coatings (Bardelli et al. 2011).

The LMFI and NN models (Table 2) were selected for predicting CuPP. Both models fit very well with the model training data. However, low values of \( r \) with validation data needs further attention. In LMF model, \( V_{WDS}, TP, TCiPP \) and the interaction effects of \( V_{WDS}TP \) and \( V_{WDS}TCiPP \) were significant. In the NN model, \( FePP, CuPP, ZnPP \) and \( ZnPP \) were the significant factors (Table 2). The iron pipe corrosion byproducts contained Cu, V, Fe and Zn. Due to physical and chemical disturbances (i.e. changing temperature), Cu was released into PP along with other metals (Gerke et al. 2010). Cu may also have been originated from copper pipes and fixtures due to dissolution in the household plumbing system, which was affected by the stagnation period (MDH 2005; Alabdula’ay & Khan 2009). Increase in alkalinity was found to reduce the release of some metals, including Fe, Cu and Pb from pipe materials. In contrast, a decrease in alkalinity increased the dissolution of these metals (Sarin et al. 2003). The brass faucets in plumbing systems consist of Cu and Zn, which could have been corroded continuously at acidic pH, and served as a source of Cu and Zn in PP (Boyd et al. 2008; Scardina & Edwards 2010).

The LMFI, NL (LM-3P) and NN models (Table 2) were selected for predicting CrPP. The models showed very good to excellent capabilities. In the LMFI and NN models, \( V_{WDS}, FePP, MnPP \) were the significant factors (Table 2). In the NL model, \( FePP \) was the significant factor. \( Cr_{WDS} \) was not a significant factor indicating that the contribution of \( Cr_{WDS} \) to \( CrPP \) was negligible. The NL model showed a low p-value for being a single factor model. The iron pipe corrosion byproducts contained high levels of V, Cr, Fe and Mn leading to increased CrPP. Cr could have also been originated from leaching of WDS materials and reactions in PP (Mcneill et al. 2012). The overnight stagnation of water in the cooler was reported to increase Cr, Al, Cu, Fe, Zn, Ni, Mn and Pb in tap water (Alabdula’ay & Khan 2009). The LMFI and NN models (Table 2) were selected for predicting HgPP. The NN model showed an excellent fit with the model training data while the value of \( r \) was relatively low (\( r = 0.71 \)). The LMFI model showed poor fit with model data and had a lower value of \( r \) (\( r = 0.50 \)). The HgPP was significantly influenced by the \( Hg_{WDS} \) indicating the effect of the plumbing system. The oxidized form of mercuric chloride (HgCl\(_2\)) may have resulted from source water and remained soluble till reaching the consumer’s tap (USEPA 2014). The corrosion byproducts of iron pipes contained Hg, Sr and Fe. The physical and chemical disturbances of the pipe inner surface may have caused Hg to release into PP (Deshommes et al. 2010).

The NN model (Table 2) was selected for predicting ZnPP. TCiWDS, TP and CuPP were the significant factors. ZnPP had a negligible effect from \( Zn_{WDS} \). The relatively acidic water increased Zn through corrosive action and increased the reaction period with plumbing materials and inner coatings. Changes of concentrations of disinfectant or water temperature could cause the release of Zn from corrosion scale deposits. Application of zinc orthophosphate inhibitor for corrosion control may have also served as a potential source of ZnPP (USEPA 2004). To predict FePP, LMF, LMFI, NL (LM-3P) and NN
models were selected. Three models (LMF, LMFI and NN) showed excellent predictive capacities ($R^2 = 0.95–0.97$) with comparable RMSE (4.2–6.1). The NL model showed relatively weaker performance (Table 2). In the NN model, $Fe_{WDS}$, $Hg_{WDS}$, $V_{WDS}$ and $C_{PP}$ were significant. The relatively acidic water could have increased $Fe$ through corrosive action and increased the reaction with pipe coatings and plumbing materials (Alabdula’aly & Khan 2009). In addition, mechanical disturbances could have also released $Fe$ in PP (Deshommes et al. 2010). Flushing of the consumer tap after long stagnation may have caused the release of $Fe$ along with other metals.

Models for heavy metals in HWT
The LMF, NL (LM-3P) and NN models (Table 3) were selected for predicting $As_{HWT}$. All models showed excellent performances. In the LMF and NN models, $Na_{HWT}$, $Ba_{HWT}$ and $Cr_{HWT}$ were the significant factors (Table 3). In the NL model,

| Output | Model | Model expression | $R^2$ | RMSE | Corr. ($r$) |
|--------|-------|------------------|-------|------|-------------|
| $As_{HWT}$ | LMF | $A_{S_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Fe_{HWT} + \beta_3 Cr_{HWT}$ | 0.98 | 0.26 | 0.99 |
| | NL (LM-3P) | $A_{S_{HWT}} = \beta_1 (1 + \theta_1exp(\theta_2 Na_{HWT}))$ | 0.87 | 0.63 | 0.91 |
| | NN | $A_{S_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Fe_{HWT} + \beta_3 Cr_{HWT}$ | 0.92 | 0.325 | 0.89 |
| $Cu_{HWT}$ | LMF | $C_{u_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cu_{HWT} + \beta_3 Mn_{HWT}$ | 0.92 | 0.107 | 0.98 |
| | NL (LM-3P) | $C_{u_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cu_{HWT} + \beta_3 Mn_{HWT}$ | 0.93 | 0.31 | 0.99 |
| | NN | $C_{u_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cu_{HWT} + \beta_3 Mn_{HWT}$ | 0.90 | 0.07 | 0.98 |
| $Cr_{HWT}$ | LMF | $C_{r_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.91 | 0.107 | 0.98 |
| | NL (LM-3P) | $C_{r_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.90 | 0.07 | 0.98 |
| $Hg_{HWT}$ | LMF | $H_{g_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.92 | 0.14 | 0.92 |
| | NN | $H_{g_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.71 | 1.43 | 0.92 |
| $Mn_{HWT}$ | LMF | $M_{n_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Fe_{HWT} + \beta_3 Cr_{HWT}$ | 0.86 | 0.08 | 0.84 |
| | NN | $M_{n_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Fe_{HWT} + \beta_3 Cr_{HWT}$ | 0.99 | 0.14 | 0.98 |
| $Mg_{HWT}$ | LMF | $M_{g_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.85 | 0.051 | 0.96 |
| | NN (LM-4P) | $M_{g_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.85 | 0.19 | 0.88 |
| $Fe_{HWT}$ | LMF | $F_{e_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.85 | 0.11 | 0.83 |
| | NN | $F_{e_{HWT}} = \beta_0 + \beta_1 Na_{HWT} + \beta_2 Cr_{HWT}$ | 0.95 | 0.06 | 0.98 |

LMF, Linear model with main factors; LM-3P, Logistic models with 3 Parameters; NN, Neural network model; WDS, Water distribution system; PP, plumbing pipe; HWT, Hot water tank; DOC, Dissolved organic carbon (mg/L); T, Temperature (°C); TCl, total chlorine (mg/L); FCl, Free chlorine (mg/L); UV, UV absorbance at 254 nm wavelength; $a$ – non-linear model parameters; $A$ – linear model parameters; H1 - H3, functions for hidden layers; HWT, Hot water tank.
Na\textsubscript{HWT} was the significant factor. As\textsubscript{WDS} was not a significant factor in any model indicating that the contribution of As\textsubscript{WDS} to As\textsubscript{HWT} was negligible. The hard scale deposits on the heater wall (Ca and Mg ions) and corroded metals (i.e., Mn, Cu, Fe, As and Hg) were potential sources for As\textsubscript{HWT} (Mcneill \textit{et al.} 2012). To predict Cu\textsubscript{HWT}, the LMF and NN models were selected. Both models showed excellent predictive capabilities. In the LMF model, Na\textsubscript{HWT}, DOC\textsubscript{HWT}, UV\textsubscript{HWT} and Mn\textsubscript{HWT} were the significant factors (Table 3) while in the NN model, DOC\textsubscript{HWT}, UV\textsubscript{HWT} and Mn\textsubscript{HWT} were significant (Table 3). Cu\textsubscript{HWT} was not significantly influenced by the Cu\textsubscript{WDS}. Past studies indicated that corrosion of brass fittings and other plumbing fixtures were some of the potential sources of Cu\textsubscript{HWT} (Boyd \textit{et al.} 2008; Scardina \& Edwards 2010). The deposits of scales and corroded metals (i.e. Mn and Fe) on the heater wall were also the sources of Cu\textsubscript{HWT} (Mcneill \textit{et al.} 2012).

The LMFI and NN models were selected (Table 3) for predicting Cr\textsubscript{HWT}. Both models showed excellent predictive capabilities. In the LMFI model, Fe\textsubscript{HWT}, Sr\textsubscript{HWT}, Pb\textsubscript{WDS}, Mn\textsubscript{HWT} and interaction of Fe\textsubscript{HWT} and Mn\textsubscript{HWT} were significant (Table 3). In the NN model, Fe\textsubscript{HWT}, Pb\textsubscript{WDS}, Mn\textsubscript{HWT} and Cr\textsubscript{WDS} were significant (Table 3). Corrosion of nichrome coil (alloys of nickel, chromium, and iron) and stainless steel were the sources of Cr\textsubscript{HWT}. The dissolution of hard scale deposits and other corroded metals (i.e. Cr, Sr) may have caused the release of Cr in HWT along with Sr (Mcneill \textit{et al.} 2012). The NL (WM-4P) model was selected (Table 3) for predicting Hg\textsubscript{HWT}. In this model, Zn\textsubscript{WDS} was the best fit with Hg\textsubscript{HWT}. The deposits of scales and other corroded metals on the heater wall were the sources of Hg\textsubscript{HWT}. Dissolution of scales due to sudden excessive usage, physical disturbance or abrupt chemical changes of water property may have caused the release of Hg\textsubscript{HWT} (Deshommes \textit{et al.} 2010). The LMF and NN models were selected (Table 3) for predicting Mn\textsubscript{HWT}. The models showed very good to excellent predictive capabilities. In the LMFI model, V\textsubscript{HWT}, Cr\textsubscript{HWT} and Fe\textsubscript{HWT} were significant (Table 3). In the NN model, Mn\textsubscript{WDS} was also found to be a significant factor. The hard scale and other corroded metals (i.e. Fe, V and Mn) deposited on the heater wall were the sources of Mn\textsubscript{HWT} (Mcneill \textit{et al.} 2012).

The LMF, NL (LM-4P) and NN models (Table 3) were selected for predicting Mg\textsubscript{HWT}. The models showed very good to excellent performance. In the LMF and NN models, Sr\textsubscript{HWT}, Ca\textsubscript{HWT}, H\textsubscript{HWT} and Ba\textsubscript{HWT} were significant (Table 3). In the NL model, Ca\textsubscript{HWT} was a significant factor. The hard scale deposits (Ca and Mg ions) and other corroded metals (i.e. Sr, Hg) on the heater wall could be some of the sources for Mg\textsubscript{HWT}. The sacrificial anodes (a rod screwed into the top of HWT and made of Mg or Al that is formed around a steel core wire) used for rust protection of HWT could also be a potential source of Mg (Water Heater Rescue 2017). To predict Fe\textsubscript{HWT}, the LMF and NN models were selected (Table 3). Both models showed excellent predictive capacities while the NN model showed better performance. In both models, Cu\textsubscript{HWT}, Pb\textsubscript{HWT} and V\textsubscript{HWT} were significant (Table 3). The scale deposits (Ca and Mg ions) and other corroded metals (i.e. Fe, Cu, Pb and V) on the heater wall could be the potential sources for Fe\textsubscript{HWT}.

**DISCUSSION**

Most of the heavy metals had higher concentrations in PP and HWT than that of WDS. The heavy metal concentrations in HWT were 1.2–8.1 and 1.4–6.7 times the concentrations in WDS and PP respectively. Overall, concentrations of As, Cr, Cu, Hg and Zn were in the increasing order of WDS, PP and HWT. Seasonal variability indicated that the concentrations of Cr and Fe were higher during summer while Cu and Zn were higher in winter. The findings were in agreement with earlier studies. Past studies demonstrated an increase of metal release during 20–24 h of stagnation (Lytle \& Schock 2005). The overnight stagnation of water in a cooler increased Cr, Al, Cu, Fe, Zn, Ni, Mn and Pb in tap water (Alabdula’aly \& Khan 2009). An approximately 100% increase in Fe release was reported for an increase in stagnation from 2 to 20 weeks (Lasheen \textit{et al.} 2008).

In recent years, polymeric (e.g. polypropylene (POPR), polyvinyl chloride (PVC) and polyethylene (PE)) pipes have been mainly used in WDS and PP. Several stabilizers, composed of metallic salt (i.e. Ca-Zn, Ba-Zn) are often used as an additive to PVC polymer, which may serve as potential sources of metals (Kim 2001). The GI pipe consists of a zinc coating, which can be a source of Zn and Pb release (AWWA 1996; Kimbrough 2007; Sarver \textit{et al.} 2010). Lasheen \textit{et al.} (2008) reported the variability of Pb and Fe release depending on pipe material following a 72 h water stagnation experiment. Fe release was similar in POPR (0.067 mg/L) and PVC pipe (0.068 mg/L) networks while around 20 times higher values were observed in the GI pipe (1.379 mg/L) network. Use of brass faucets in plumbing systems can be a potential source of metal release (Boyd \textit{et al.} 2008; Scardina \& Edwards 2010). The main factors for dezincification were higher chloride (>200 mg/L), lower alkalinity, pH of approximately 8, higher ammonia (>15 mg/L) and higher natural organic matter (NOM) (>1 mg/L) (Brandl \textit{et al.} 2009; Zhang \& Edwards 2011). Leaching of Ni from nickel/chromium-plated taps and corrosion of stainless-steel pipes and fittings may also induce metal release into tap water. An increase in pH to optimal
level may provide a partial solution to Cu and Ni corrosion (Cartier et al. 2012a, 2012b). Increase of pipe age was reported to increase corrosion deposits, which could serve as a source of metal (Lasheen et al. 2008). Mechanical disturbances could also release the metals, including Pb, Fe and Al (O’Reilly & Hochella 2003; Mohapatra et al. 2009; Deshommess et al. 2010; Kim et al. 2011; Kabir et al. 2018).

Temperature affects water properties, corrosion scale, reaction rates and thermodynamics of scales leading to the discharge of heavy metals (Johnson et al. 1993). Concentrations of few heavy metals (e.g. Pb, Cr and Fe) in summer were higher than in winter (Kabir et al. 2018). Volk (2000) reported lower Fe concentrations and corrosion rates in winter while more red water incidents (i.e. higher iron) were reported during summer. Temperature dependent variation was also observed in corrosion of Cu and Pb (Johnson et al. 1993; Boulay & Edwards 2001). Through changing flow acceleration, on and off flow regimes and/or varying water demand at different time, release of heavy metals could be controlled (Zidouh 2009; Del Toral et al. 2013). Concentrations of Cu and Fe increased with lowering pH to acidic range (Boffardi 1990) while a decrease in Fe release was observed when pH was increased from 7.5 to 9.5 (Sarin et al. 2003; Gerke et al. 2010). The rate of ferric hydroxide formation increased with an increase of pH above the neutral range where ferric hydroxides were less likely to dissolve than ferrous solid (Sarin et al. 2004). Increase of alkalinity reduced the release of Cu, Fe and Pb in water (Sarin et al. 2003) and in anoxic conditions it reduced the solubility of ferrous carbonate phase, resulting in decreased Fe release. On the contrary, dissolution of carbonate-containing Fe (i.e. FeCO3) increased Fe concentration at lower alkalinity (Sarin et al. 2005). Higher alkalinity offered higher buffer capacity and the denser scale structure could decrease Fe release (Sarin et al. 2004).

Among the models for PP (Figure 2), the NN model for AsPP showed very good agreement with the line of equal concentration (LOEC) in model development and validation studies (Figure 2(a) and 2(b)). For CuPP, the NN model showed very good agreement with LOEC in model development while the LMF model predictions were distributed sparsely (Figure 2(c)). However, none of these models showed good agreement with LOEC in the validation study (Figure 2(d)). In predicting CrPP, the LMF and NN models showed very good agreement with LOEC in model training data (Figure 2(e)). In the validation study, LMF model showed weaker performance while the NN model showed better performance. Overall, the NN models were the best, followed by the LMF models (Figure 2(a)-2(f)). Among the models for HWT (Figure 3), the LMF model for AsHWT showed very good agreement with LOEC for model development and validation studies (Figure 3(a) and 3(b)). The LM-3P model showed good agreement with LOEC in both modeling and validation studies (Figure 3(a) and 3(b)). For CuHWT, the LMF and NN models showed very good agreement with LOEC in model development and validation studies (Figure 2(c) and 2(d)). In predicting CrHWT, the LMFI and NN models showed similar agreement with LOEC for model training and validation data (Figure 3(e)-3(f)). The models for predicting metal concentrations in HWT had better performance than the models in PP. To date, no study is available to compare the models for PP and HWT. The performances of the models can be improved through validating the models by collecting data from multiple sources under variable environmental conditions. The models can be applied to predict heavy metal concentrations in PP and HWT. Using the predicted values, human exposure and risk can be estimated. Based on the acceptance levels of risk, the maximum allowable limits of the metals in tap water can be suggested. The scopes of applications of these models are:

\[
\text{Predicted Risk} = \int (\text{Exposure factors, Metal concentrations predicted by the models})
\]

The predicted risk should be less than the acceptable risk level. If the predicted risk is higher, intakes of the metals should be lowered through altering the drinking water sources and/or applying improved treatment. In this study, several WQP and heavy metals were monitored in WDS, PP and HWT. Few other WQP, such as hardness, alkalinity, nitrate, total dissolved solids and turbidity, were not included in this monitoring program. The study focused on tap water with the objective of modeling the changes of heavy metal concentrations from WDS to PP and HWT. The models for the PP and HWT showed very good to excellent performances in both model development and validation studies, indicating that the exclusion of these WQP did not have significant effects on the models. The heavy metals were selected based on their possible effects to humans (USEPA 2017, 2019). In future, the lists of WQP and heavy metals can be enhanced, and more comprehensive investigation can be performed.
CONCLUSIONS

In this research, WQP and occurrences of several heavy metals in WDS, PP and HWT were quantified and compared. The effects of the WQP were analyzed. Several models were trained to predict metal concentrations in PP and HWT. Few models showed very good to excellent performances, which also demonstrated very good to excellent validation performances. In general, the NN models showed the best performances. The LMF models also showed very good to excellent performances. The NL models used the single most important factors resulting in weaker performances. The models were found to be favorable in comparison to the costly experiments. These models were developed and validated using the monitoring data from multiple houses in KFUPM. As such, generalization of these models for other areas need validation studies. In future, these models can be validated through collecting data from multiple areas with different environmental settings. Further, the model parameters often have uncertainty, which can be incorporated through considering multiple study locations in

![Figure 2](http://iwaponline.com/aqua/article-pdf/70/7/1038/953216/jws0701038.pdf)  
**Figure 2** | Comparison of the modeled and measured concentrations for some heavy metals in plumbing pipes.
future. Despite these limitations, this study sheds light on the robust predictions of heavy metals in tap water to better protect humans.

ACKNOWLEDGEMENTS

The author would like to acknowledge the support provided by the Deanship of Research at King Fahd University of Petroleum & Minerals (KFUPM) for funding this work through project No. RG 1409-1 and 2.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.
REFERENCES

Alabudla’aly, A. I. & Khan, M. A. 2009 Heavy metals in cooler waters in Riyadh, Saudi Arabia. *Environmental Monitoring and Assessment* **157** (1), 23–28.

Alam, I. A. & Sadiq, M. 1989 Metal concentration of drinking water from corrosion of distribution pipes. *Environmental Pollution* **57**, 167–178.

Assi, M. A., Hezmee, M. N. M., Haron, A. W., Sabri, M. Y. M. & Rajion, M. A. 2016 The detrimental effects of lead on human and animal health. *Veterinary World* **9** (6), 660–671.

ATSDR (Agency for Toxic Substances and Disease Registry) 2015 *Toxicological Profiles, Toxic Substances Portal*. Available from: http://www.atSDR.cdc.gov/toxprofiles/index.asp (accessed October 2017).

AUS (Australian Drinking Water Guidelines) 2011 *National Health and Medical Research Council*, (2011). Updated October 2017. Available from: https://www.nhmr.gov.au/guidelines-publications/eh52 (accessed 10 December 2017).

AWWA (American Water Works Association) 2012 *Standard Methods for the Examination of Water and Wastewater*, 22nd edn. Water Environment Federation. Available from: https://www.awwa.org/store/productdetail.aspx?productid = 28493774 (accessed December 2017).

Bardelli, F., Benvenuti, M., Costagliola, P., Di Benedetto, F., Lattanzi, P., Meneghini, C., Romanelli, M. & Valenzano, L. 2011 Arsenic uptake by natural calcite: an XAS study. *Geochimica et Cosmochimica Acta* **75**, 3011–3023.

Boffardi, B. P. 1990 Minimization of lead corrosion in drinking water. *Materials Performance* **29** (8), 45–49.

Boulay, N. & Edwards, M. 2001 Role of temperature, chlorine, and organic matter in copper corrosion by-product release in soft water. *Water Research* **35**, 685–690.

Boyd, G. R., Pierson, G. L., Kirmeyer, G. J., Britton, M. D. & English, R. J. 2008 Lead release from new end-use plumbing components in Seattle public schools. *Journal of the American Water Works Association* **100**, 105–114.

Brandl, E., Malke, R., Beck, T., Wanner, A. & Hack, T. 2009 Stress corrosion cracking and selective corrosion of copper-zinc alloys for the drinking water installation. *Materials and Corrosion* **60**, 251–258.

Cartier, C., Arnold, R. B., Triantafyllidou, S., Prévost, M. & Edwards, M. 2012a Effect of flow rate and lead/copper pipe sequence on lead release from service lines. *Water Research* **46**, 5120–5126.

Cartier, C., Nour, S., Richer, B., Deshommes, E. & Prévost, M. 2012b Impact of water treatment on the contribution of faucets to dissolved and particulate lead release at the tap. *Water Research* **46**, 5205–5216.

Chakraborti, D., Rahman, M. M., Das, B., Murrill, M., Dey, S., Mukherjee, S. C., Dhar, R. K., Biswas, B. K., Chowdhury, U. K., Ro, S., Sorif, S., Selim, M., Rahman, M. & Quazi, Q. 2010 Status of groundwater arsenic contamination in Bangladesh: a 14-year study report. *Water Research* **44**, 5789–5802.

Chowdhury, S., Mazumder, M. J., Al-Attas, O. & Husain, T. 2016 Heavy metals in drinking water: occurrences, implications, and future needs in developing countries. *Science of The Total Environment* **476**, 468–488.

Chowdhury, S., Kabir, F., Mazumder, M. A. J. & Zahir, M. H. 2018 Modeling lead concentration in drinking water of residential plumbing pipes and hot water tanks. *Science of The Total Environment* **635**, 35–44.

Del Toral, M. A., Porter, A. & Schock, M. R. 2015 Detection and evaluation of elevated lead release from service lines: a field study. *Environmental Science & Technology* **47** (16), 9300–9307.

Deshommes, E., Laroche, L., Nour, S., Cartier, C. & Prévost, M. 2010 Source and occurrence of particulate lead in tap water. *Water Research* **44** (12), 3734–3744.

Flint Water Study Updates 2017 *Up-to-date Information on our Collaborative Research and Citizen Science Work with the Residents of Flint, MI in Light of Reported Water Quality Issues*. Available from: http://flintwaterstudy.org/ (accessed December 2017).

Flora, G., Gupta, D. & Tiwari, A. 2012 Toxicity of lead: a review with recent updates. *Interdisciplinary Toxicology* **5** (2), 47–58.

Gerke, T. L., Scheckel, K. G. & Maynard, J. B. 2010 Speciation and distribution of vanadium in drinking water iron pipe corrosion by-products. *Science of the Total Environment* **408**, 5845–5853.

Gupta, D. A. 2008 Implication of environmental flows in river basin management. *Physics and Chemistry of the Earth* **33** (5), 298–303.

He, T. R., Feng, X. B., Guo, Y. N. & Qiu, G. L. 2008 The impact of eutrophication on the biogeochemical cycling of mercury species in a reservoir: a case study from Hongfeng Reservoir, Guizhou, China. *Environmental Pollution* **154**, 56–67.

Health Canada 2017 *Guidelines for Canadian Drinking Water Quality Summary Table*. Available from: https://www.canada.ca/content/dam/hc-sc/migration/hc-sc/ewh-semt/alt_formats/pdf/pubs/water-eau/sum_guide-res_recom/sum_guide-res_recom-eng.pdf (accessed 30 October 2017).

IARC (International Agency for Research on Cancer) 2016 *IARC Monographs on the Evaluation of Carcinogenic Risks to Humans*. Vol. 1–115. Available from: http://monographs.iarc.fr/ENG/Classification/latest_classif.php (accessed 12 April 2016).

Jiang, J.-Q., Ashekuzzaman, S. M., Jiang, A., Sharifuzzaman, S. M. & Chowdhury, S. R. 2013 Arsenic contaminated groundwater and its treatment options in Bangladesh. *International Journal of Environmental Research and Public Health* **10**, 18–46.

Johnson, B., Yorton, R., Tran, T. & Kim, J. 1993 Evaluation of corrosion control alternatives to meet the lead and copper rule for Eastern Massachusetts. *Journal of the New England Water Works Association* **3**, 24–45.
Kabir, F., Chowdhury, S., Mazumber, M. A. J., Zahir, M. H. & Alhooshani, K. 2018 Effects of plumbing premise on the occurrences and variability of heavy metals in desalinated and blended tap water. *Desalination and Water Treatment* 107, 257–271.

Karim, M. M. 2000 Arsenic in ground water and health problems in Bangladesh. *Water Research* 34 (1), 304–310.

Kasabov, N. K. 1997 Foundations of neural networks, fuzzy systems, and knowledge engineering. *Computers & Mathematics with Applications* 33, 122–136.

Kim, S. 2001 Pyrolysis kinetics of waste PVC pipe. *Waste Management* 21, 609–616.

Kim, E. J., Herrera, J. E., Huggins, D., Braam, J. & Koshowski, S. 2011 Effect of pH on the concentrations of lead and trace contaminants in drinking water: a combined batch, pipe loop and sentinel home study. *Water Research* 45 (9), 2763–2774.

Kimbrough, D. E. 2007 Brass corrosion as a source of lead and copper in traditional and all-plastic distribution systems. *American Water Works Association* 99 (8), 70–76.

Kutty, P. C. M., Noman, A. A., Al-Sulami, A. & Al-Rabeh, A. 1995 Monitoring of trace metals in desalinated drinking water and their permissible levels. In: *Proceedings of IDA Conference*, Abu Dhabi, pp. 18–24.

Lashen, M. R., Sharaby, C. M., El-Kholy, N. G., Elsherif, I. Y. & El-Wakeel, S. T. 2008 Factors influencing lead and iron release from some Egyptian drinking water pipes. *Journal of Hazardous Materials* 160 (2), 675–680.

Liu, J., Zhang, X. H., Tran, H., Wang, D. Q. & Zhu, Y. N. 2011 Heavy metal contamination and risk assessment in water, paddy soil, and rice around an electroplating plant. *Environmental Science and Pollution Research* 18 (9), 1623–1632.

Liu, Q. Y., Liu, Y. J. & Zhang, M. G. 2012 Mercury and cadmium contamination in traffic soil of Beijing, China. *Bulletin of Environmental Contamination and Toxicology* 88, 154–157.

Lytle, D. A. & Schock, M. R. 2005 Formation of Pb (IV) oxides in chlorinated water. *American Water Works Association* 97 (11), 102–114.

McNeill, L., Mclean, J., Edwards, M. & Parks, J. 2012 State of the Science of Hexavalent Chromium in Drinking Water. *Water Research Foundation*, Denver, Colorado. Available from: http://www.waterrf.org/ProjectsReports/ProjectPapers/Lists/PublicProjectPapers/Attachments/2/4404_ProjectPaper.pdf

MDH (Minnesota Department of Health) 2005 *Copper in Drinking Water: Health Effects and How to Reduce Exposure Fact Sheet*. Available from: http://www.health.state.mn.us/divs/eh/water/factsheet/com/copper.html?SM_AU_¼iV63ZTW6Hl4k540 (accessed 30 October 2017).

Mohapatra, M., Rout, K., Mohapatra, B. K. & Anand, S. 2009 Sorption behavior of Pb (II) and Cd (II) on iron ore slime and characterization of metal ion loaded sorbent. *Journal of Hazardous Materials* 166 (2), 1506–1513.

Montgomery, D. C. & Runger, G. C. 2018 *Applied Statistics and Probability for Engineers*, 4th edn. John Wiley and Sons, Phoenix, AZ, USA.

NRC (National Research Council) 1982 *Monitoring of Trace Metals in Desalinated Drinking Water*. *National Research Council Safe Drinking Water Committee*. National Academies Press, Washington, DC. Available from: https://www.ncbi.nlm.nih.gov/books/NBK216607 (accessed December 2017).

NZ (New Zealand) 2005 *Drinking-water Standards for New Zealand*. Available from: http://www.health.govt.nz/publication/drinking-water-standards-new-zealand-2005-revised-2008.

O’Reilly, S. E. & Hochella, M. F. 2003 Lead sorption efficiencies of natural and synthetic Mn and Fe-oxides. *Geochimica et Cosmochimica Acta* 67 (23), 4471–4487.

Sarin, P., Clement, J. A., Snoeyink, V. L. & Kriven, W. M. 2003 Iron release from corroded, unlined cast-iron pipe. *American Water Works Association* 95 (11), 85–96.

Sarin, P., Snoeyink, V. L., Lytle, D. A. & Kriven, W. M. 2004 Iron corrosion scales: model for scale growth, iron release, and colored water formation. *Journal of Environmental Engineering* 130, 364–373.

Sarver, E., Zhang, Y. & Edwards, M. 2010 Review of brass dezincification corrosion in potable water systems. *Corrosion Reviews* 28 (3–4), 155–196.

SAS Inc 2019 *Statistical Software JMP From SAS*. Available from: https://www.jmp.com/en_us/home.html (accessed January 2020).

Scardina, P. & Edwards, M. 2010 Lead-contaminated water from brass plumbing devices in new buildings. *American Water Works Association* 102 (11), 66–76.

Szteker, P., Glasyb, G. P., Stuben, D., Kusak, A., Geldon, J., Berner, Z., Neumann, T. & Warzocha, J. 1999 Distribution of selected trace heavy metals and rare earth elements in surficial sediments from the polish sector of the Vistula Lagoon. *Chemosphere* 39, 2785–2798.

Tamasi, G. & Cini, R. 2004 Heavy metals in drinking waters from Mount Amiata (Tuscany, Italy). Possible risks for arsenic for public health in the Province of Siena. *Science of the Total Environment* 327 (1), 41–51.

Uddin, R. & Huda, N. H. 2011 Arsenic poisoning in Bangladesh. *Oman Medical Journal* 26 (3), 207.

UK (United Kingdom) 2015 *Drinking Water Guidelines*. Available from: http://www.dwi.gov.uk (accessed 10 December 2017).

USEPA (United States Environmental Protection Agency) 1994 *ICP MS, Method 200.8, Revision 5.4: Determination of Trace Elements in Waters and Wastes by Inductively Coupled Plasma Mass Spectrometry*. Available from: https://www.epa.gov/sites/produ-ction/files/2015-08/documents/method_200-8_rev_5-4_1994.pdf (accessed October 2017).

USEPA (United States Environmental Protection Agency) 2004 *Investigation of Potential Environmental Impacts due to the use of Phosphate-Based Corrosion Inhibitors in the District of Columbia*. Available from: http://taskmediator.com/op/op.Download.php?documentId = 2153&version = 1.

USEPA (United States Environmental Protection Agency) 2014 *Decontamination of Drinking Water Infrastructure: A Literature Review and Summary*, 2014. Available from: https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId = 274760 (accessed 30 October 2017).
USEPA (United States Environmental Protection Agency) 2016 Quick Guide to Drinking Water Sample Collection. Available from: https://www.epa.gov/sites/production/files/201511-/documents/drinking_water_sample_collection.pdf (accessed October 2017).

USEPA (United States Environmental Protection Agency) 2017 National Primary Drinking Water Regulations. Available from: https://www.epa.gov/ground-water-and-drinking-water/national-primary-drinking-water-regulations#Inorganic (accessed October 2017).

USEPA (United States Environmental Protection Agency) 2019 Integrated Risk Information System. Available from: https://www.epa.gov/iris (accessed January 2020).

Volk, C. 2000 Practical evaluation of iron corrosion control in a drinking water distribution system. Water Research 34, 1967–1974.

Wang, G., Yinglan, A., Jiang, H., Fu, Q. & Zheng, B. 2015 Modeling the source contribution of heavy metals in surficial sediment and analysis of their historical changes in the vertical sediments of a drinking water reservoir. Hydrology 520, 37–51.

Water Heater Rescue 2017 Hot Water Heater Anodes and Rust Protection. Available from: http://www.waterheaterrescue.com/Longevity/water-heater-anodes.html (accessed 30 October 2017).

WHO (World Health Organization) 2017 Guidelines for Drinking-Water Quality, 4th edn. World Health Organization, Geneva.

Wigginton, A., McSpirit, S. & Sims, C. D. 2007 Heavy metal accumulation in hot water tanks in a region experiencing coal waste pollution and comparison between regional water systems. Bulletin of Environmental Contamination and Toxicology 79 (4), 405–409.

Wu, B., Wang, G., Wu, J., Fu, Q. & Liu, C. 2014 Sources of heavy metals in surface sediments and an ecological risk assessment from two adjacent plateau reservoirs. PLoS ONE 9 (7), e102101.

Zhang, Y. & Edwards, M. 2011 Zinc content in brass and its influence on lead leaching. American Water Works Association 103 (7), 76–81.

Zidouh, H. 2009 Velocity profiles and wall shear stress in turbulent transient pipe flow. International Journal of Dynamics of Fluids 5, 61–83.

First received 14 April 2021; accepted in revised form 4 August 2021. Available online 9 September 2021.