






Proceeding Paper

Detection of Deteriorated Areas in Water Distribution Networks Exploiting Chlorine Measurements in a Bayesian Framework [†]

Benedetta Sansone ^{1,*}, Alfonso Cozzolino ^{1,2}, Roberta Padulano ¹, Cristiana Di Cristo ¹
and Giuseppe Del Giudice ¹

¹ Department of Civil, Architectural and Environmental Engineering, University of Naples Federico II, Via Claudio 21, 80125 Naples, Italy; alfonso.cozzolino@unina.it (A.C.); roberta.padulano@unina.it (R.P.); cristiana.dicristo@unina.it (C.D.C.); giuseppe.delgiudice@unina.it (G.D.G.)

² University School for Advanced Studies IUSS Pavia, Piazza della Vittoria, 15, 27100 Pavia, Italy

* Correspondence: benedetta.sansone@unina.it

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Abstract

This study proposes a methodology to identify deteriorated pipes in water distribution networks using prior system information and routine chlorine residual data. While bulk chlorine decay k_{bulk} can be measured in laboratories, wall decay k_{wall} depends on pipe material, diameter, and ageing, particularly in unlined metallic pipes. Empirical data were used to estimate k_{wall} , which was integrated into a Bayesian inference framework solved with Markov Chain Monte Carlo. Applied to an Italian network with synthetic chlorine data, this method demonstrated effectiveness across three test scenarios, exploiting the contrast between k_{wall} and k_{bulk} to detect deteriorated pipes within a computationally efficient environment.

Keywords: Bayesian inference; Metropolis–Hastings; deteriorated pipes; chlorine decay; wall decay

1. Introduction

Chlorine is the typical disinfectant used in water distribution systems for its efficiency and cost-effective use in ensuring safe drinking water. Chlorine decay occurs due to reactions in the bulk water and at the pipe wall. First-order (FO) kinetics are commonly used to model both bulk decay and wall decay, by means of two decay coefficients (k_{bulk} and k_{wall} , respectively). Under simplified assumptions of uniform pipe characteristics, the total decay constant k_{tot} can be considered as the sum of k_{bulk} and k_{wall} [1].

Residual chlorine concentrations are a function of decay constants and residence times in the network. Chlorine decreases with increasing residence time, while decay rates vary with flow conditions accelerating at higher Reynolds numbers and slowing down under hydraulic transients [2].

Total chlorine decay k_{tot} is commonly quantified by calibrating hydraulic models, such as EPANET, against measured chlorine concentrations [3]. The bulk decay rate k_{bulk} is typically obtained through laboratory bottle tests on inlet water, where wall effects are absent [4], and the wall decay rate k_{wall} is typically derived as the difference between the two [4]. In this paper, derived k_{wall} values were used to predict the “state of ageing” of network pipes, reflecting their degradation conditions. This approach is based on a



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functional formula relating k_{wall} to pipe diameter, age, and materials, which was calibrated with empirical observations collected by previous authors [5].

Water utilities routinely monitor residual chlorine to ensure compliance with minimum quality standards. In the proposed work, these residual chlorine data were incorporated into a Bayesian Markov Chain Monte Carlo (MCMC) framework, which allowed for the prediction of the state of ageing of network pipes by looking for the best match between observed and simulated chlorine concentrations. Bayesian approaches have never been applied to detect deteriorated pipe clusters in distribution networks. The MCMC framework was operationally solved with the Metropolis–Hastings (M–H) algorithm [6], which allows robust estimation from limited monitoring data and provides probabilistically credible solutions.

This paper is organised as the following: the Section 2 introduces chlorine decay processes and the assumed relationship between k_{wall} and pipe characteristics, followed by a short description of the methodological framework and the case study (Section 3). The last section present and discuss the main results and future research directions.

2. Materials and Methods

In the proposed methodology, chlorine decay is expressed as referring to first-order kinetics, as a function of the initial chlorine concentration and k_{tot} , which is the overall chlorine decay constant [1/day], defined as the sum of the bulk and wall decay coefficients.

The k_{wall} data, estimated from more than 300 pipes, were collected and related to the pipe's age, diameter, and material by Al-Jasser [5]. The present study focuses on unlined cast iron, unlined steel, and polyethylene, still widespread in water distribution systems. Data for unlined cast iron and steel pipes (up to 50 years) and polyethylene pipes (up to 25 years) [5] were used to derive material-specific equations for estimating the wall decay coefficient k_{wall} as a function of the pipe diameter (D) and age (A). The proposed model is

$$k_{wall} = \delta \cdot D^{\beta} \cdot A^{\gamma} \quad (1)$$

where parameters δ , β , and γ are estimated by Ordinary Least Squares for each of the three materials separately.

This methodology consisted of three phases. First, with prior knowledge about the network's physical features, k_{wall} was assigned to each pipe according to Equation (1), while k_{bulk} was set to a realistic value [7], and k_{tot} could be computed as their sum. The calibrated network was simulated through EPANET and chlorine data were extracted at different locations, acting as measurement points. These data were considered as chlorine observations for the algorithm. The second phase initialised the Bayesian inference, coupling EPANET with MATLAB 2024, enabling automatic model runs with tentative assumptions about the pipes' age. The third phase explored the MCMC framework using the M–H algorithm. In this step, candidate solutions were rejected or accepted according to their closeness to the target solution (i.e., the one that provided simulated chlorine values equal to the observed ones at the measurement sections), until they reached the stop criterion, based on the stabilization of the acceptance.

3. Case Study

The proposed methodology was applied to the distribution network of Casalnuovo, a municipality in the metropolitan area of Naples with about 50,000 inhabitants. The network extends over 75 km with roughly 2000 pipes and junctions, supplied by six reservoirs, and is divided into 13 districts, each with a specific demand pattern. Hydraulic simulations were performed with EPANET using Hazen–Williams headloss coefficients calibrated for steel, cast iron, and polyethylene pipes, while water quality was modelled with first-order

kinetics, assuming $k_{bulk} = 0.72 \text{ day}^{-1}$ and initial pipe ages of one year for the estimate of k_{wall} (Equation (1)).

Three test cases were examined as the following: the first test considered one deteriorated pipe aged to 10 years; the second, with a cluster of 30 hydraulically connected deteriorated pipes, aged to 10 years; and the third, where the same cluster was considered, but the number of deteriorated pipes was unknown. For the MCMC framework, pipe age could range between 1 and 50 years, and for the last test, the cluster size was bound between 1 and the total number of pipes ($S = 1831$). Synthetic chlorine data were generated through a 48 h simulation, extracting results from the last 24 h, ensuring a steady state, for $M = 12$ nodes acting as chlorine monitoring sections, yielding $n = M \times 24$ measurements.

4. Results and Conclusions

Experimental data from Al-Jasser [5] were used to calibrate Equation (1) for the cast iron, steel, and polyethylene pipes through Ordinary Least Squares. The regressions show that diameter (β) negatively affected k_{wall} for all materials, while age (γ) increased k_{wall} for cast iron and steel but decreased it for polyethylene. The scaling factor δ reflects corrosion and biofilm effects, which were stronger in metallic pipes. The model explains a large share of variance, as testified by the high values of the coefficient of determination R^2 , ranging between about 77% and 92.4%.

A comparison of different tests showed that, while the identification of a single deteriorated pipe was challenging due to its limited influence on chlorine concentrations, the methodology performed more effectively when a larger cluster was involved, as the deterioration had a stronger impact on residual chlorine levels. Figure 1 shows the results for the third test in terms of comparison between the “known” deteriorated cluster and the one identified by the algorithm. A comprehensive accuracy assessment was not performed due to the limited number of test cases; the proposed framework lays the groundwork for future validation through systematic testing under varying boundary conditions.

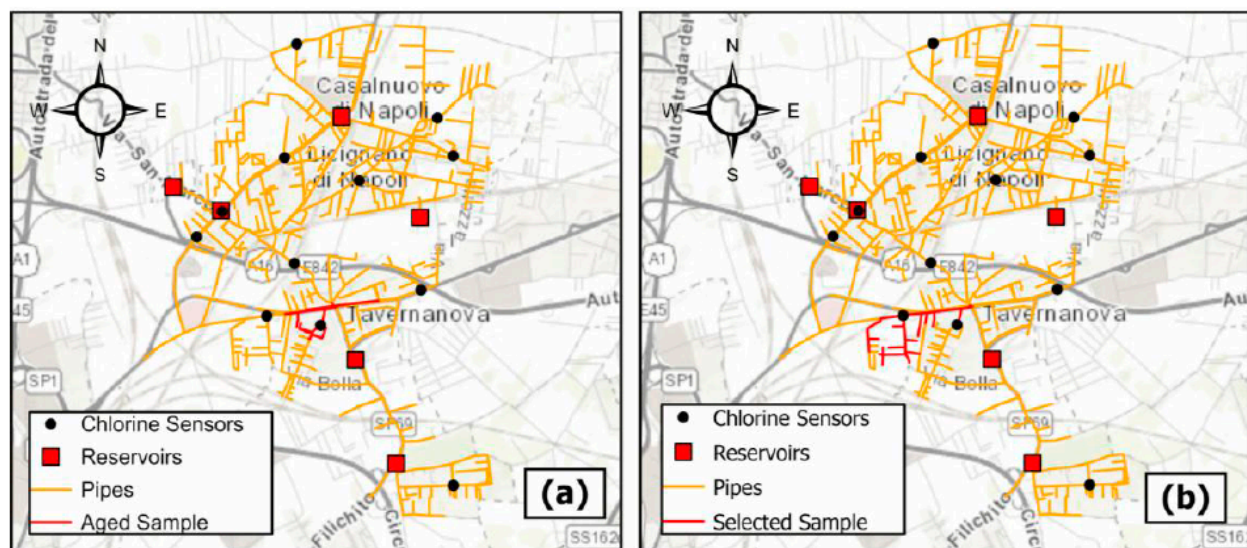


Figure 1. True deteriorated cluster (a) and deteriorated cluster identified by MCMC (b) for the third test.

The effectiveness of the overall method relied on the marked contrast between k_{wall} and k_{bulk} in unlined metallic pipes, which made ageing effects distinguishable from the uncertainty in bulk decay. This method is therefore most suitable for older networks with cast iron and steel pipes, while its applicability to plastic or coated systems is limited. Its performance also depends on operational factors, particularly the number and distribution

of monitoring points, which could be optimised in future applications. Despite these constraints, this case study demonstrates that this methodology is generalizable to other systems, with performance influenced by pipe characteristics, network configuration, and measurement infrastructure.

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Abbreviations

The following abbreviations were used in this manuscript:

| | |
|----------------|------------------------------|
| FO | First order (kinetics) |
| MCMC | Markov Chain Monte Carlo |
| M–H | Metropolis–Hastings |
| R ² | Coefficient of determination |
| RMSE | Root Mean Square Error |
| TA | First level of tests |
| TB | Second level of tests |

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