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Pipe Deterioration Modelling in Heterogeneous Water Distribution Networks

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Abstract. This study examines the robustness and transferability of data-driven pipe deterioration models across heterogeneous Water Distribution Networks (WDNs) located in Northern and Southern Italy. A unified modelling framework, based on a common set of physical and hydraulic predictors and implemented through four classification algorithms, is applied to explore how network specific characteristics affect predictive performance. The findings reveal significant accuracy discrepancies among all models when applied to the networks, pointing to the influence of differing deterioration dynamics, operational contexts, and data quality. These outcomes highlight the importance of explicitly considering network heterogeneity when designing predictive models for WDN asset management.

Keywords: Data-driven modelling; Network heterogeneity; Pipe failure; Deterioration ranking; Water distribution networks.

1 Introduction

Water Distribution Networks (WDNs) are critical infrastructures that ensure the continuous delivery of potable water to consumers. Their reliability is challenged by structural defects arising from pipe properties, environmental factors, operational conditions, and external loads [1], which may lead to failures with significant economic, environmental, and social impacts [2]. Predictive modelling has therefore become a key decision-support tool, enabling the identification of pipes most susceptible to failure and supporting prioritization of inspection, maintenance, and replacement activities. Over time, forecasting approaches have evolved from heuristic and physically based formulations to statistical and machine learning methods [3]. However, heterogeneity in data quality, feature availability, and deterioration dynamics across WDNs poses significant challenges to model generalization [4].

To address this issue, the present work applies a common data-driven modelling framework to real WDNs located in Northern and Southern Italy. By evaluating model performance in different operational and structural contexts, the study provides insight into how network heterogeneity affects predictive accuracy.

2 Materials and Methods

Pipe deterioration is analysed from a ranking perspective, with the objective of identifying the pipes most likely to fail within a defined prediction horizon. The problem is formulated as a binary classification task and addressed using four machine-learning algorithms: Logistic Regression [5], Support Vector Machine [6], Random Forest [7], and eXtreme Gradient Boosting [8].

A central aspect of the study is the comparison between real WDNs in Northern and Southern Italy. Although both serve similar functional requirements, they differ in structural layout and hydraulic behaviour, offering an ideal testbed to investigate how heterogeneous network characteristics influence model performance. To guarantee comparability, an identical feature set is consistently adopted, incorporating structural variables (such as material type, length and diameter) alongside hydraulic variables obtained through numerical modelling that capture pressure and velocity variability.

Moreover, variables capturing the environmental and socio-contextual conditions in which WDNs are embedded may also be incorporated.

Variables undergo normalization, while categorical information is encoded through one-hot encoding. A spatially aware 70/30 train–test split is applied to both datasets. Model performance is evaluated through ranking-oriented metrics: the Concordance Index (C-Index) [9], which measures the correctness of predicted orderings, and the Failure Detection Rate [10], which quantifies the models' ability to correctly identify high-risk pipes.

3 Results and Discussion

When applied to the Italian WDNs, models trained on the common feature set display marked variations in predictive accuracy, highlighting the influence of local deterioration dynamics, operational conditions, and underlying data characteristics. Beyond purely evaluating predictive performance, the literature emphasizes the importance of understanding the contribution of individual variables to model outputs. Techniques such as sensitivity analysis, feature importance in tree-based models, and methods like SHAP (SHapley Additive exPlanations) enhance model transparency and interpretability. Overall, the study compares multiple classification models across two distinct contexts to understand how their performance diverges and to derive insights into the impact of network heterogeneity on data-driven pipe deterioration modelling.

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