A DSS FOR WDS PIPE FAILURE REHABILITATION PLANNING

Cappello C.[1], Tricarico C.[1], Gargano R.[1], Leopardi A.[1]
[1] Università degli Studi di Cassino e del Lazio Meridionale, DICEM, via Di Biasio 43, 03043 Cassino, Italy
[1]*cristian.cappello@unicas.it*

ABSTRACT
Water distribution systems (WDS) are increasingly challenged by aging infrastructure, climate variability and the growing demand for sustainable operation. Pipeline failures are one of the most critical issues, resulting in service disruptions and high maintenance costs. This study proposes a machine learning (ML) framework to classify municipalities into two risk categories, “Priority” and “No Priority”, based on historical failure trends. The latter can support decision-makers in planning for the rehabilitation of WDS. A Sliding Window approach is applied to a dataset covering monthly failure records from 22 municipalities managed by a utility company in Southern Italy, spanning over seven years. Each training instance includes six months of failure rate data as input features, and the failure rate of the following month as the target variable. The failure data are normalized by network length to account for differences in system size, and class labels are assigned based on percentile thresholds. The models are trained and tested by combining hold-out and cross-validation strategies. Several algorithms are benchmarked, including decision trees, support vector machines (SVMs), logistic regression, and ensemble methods. Among all tested classifiers, the Coarse Gaussian SVM achieved the highest performance, with a test accuracy of 85.2%, a recall of 87.5%, and an F1-score of 85.6% for the “Priority” class. Cost-sensitive learning was applied to penalize false negatives more heavily, in alignment with operational needs. The comparison between the actual and predicted failure labels confirms the effectiveness of the model in estimating further maintenance in these new metered areas.

Keywords: Water Distribution System Management, Mechanical Pipe Failure, SVM.

INTRODUCTION
As water distribution systems (WDS) face mounting pressures from aging infrastructure and the imperative for sustainability in an era of climate change, their effective management has never been more crucial. These challenges demand innovative strategies to ensure the reliability and resilience of vital water services for communities now and into the future. One of the main troubles for water service managers is represented by recurrent pipeline failures and service interruptions. To effectively address this problem, it is essential to identify the areas where an increase in failures is occurring and, in such areas, to evaluate the priority of intervention. Recent advances in data availability, real-time monitoring technologies and Machine Learning (ML) techniques (e.g. [1]) have opened new opportunities to improve the reliability and resilience of water networks. Previous studies in the literature have explored the application of ML for leak detection (e.g. [2-8]) and failure prediction (e.g. [9], [10]) obtaining promising results in both controlled and real-world settings.

However, few of them (e.g. [11]) address the classification of network zones or municipalities according to their risk of future failures.
In the present work an approach is then proposed to support decision makers in planning rehabilitation interventions in large urban distribution systems, where reduced financial resources impose the scheduling of rehabilitation interventions over time. In such circumstances, improvements must be made immediately on the most deteriorated networks, which therefore have higher specific failure rates.
A supervised learning techniques is applied to classify municipalities into two risk categories: “Priority” and “No Priority”, based on temporal patterns of failure occurrences. This is particularly important for utility operators in planning maintenance activities.

CASE STUDIES AND METHODOLOGY

The proposed approach is based on a detailed and extensive failure database that effectively represents the degree of ageing of water services. The available dataset for 22 municipalities managed by a real Water Utility Company in Southern Italy (Figure 1 and Table 1) comprises monthly failure reports from January 2017 to April 2025. This results in 100-time steps per municipality, where each time step presents a monthly duration.

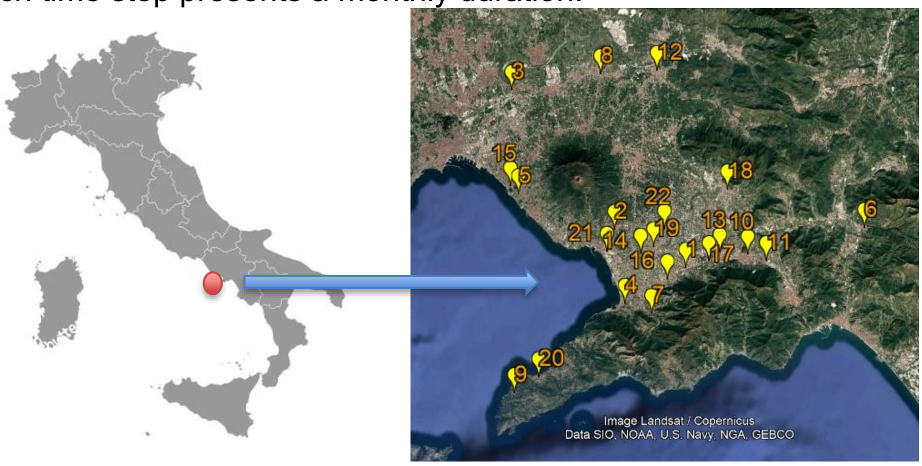

Figure 1. Territory managed by Water Utility.

Table 1: Municipality characteristics: WDS Length and Number of Users (N_{users})

N.	Municipality	WDS Length [km]	N_{users}	N.	Municipality	WDS Length [km]	N_{users}
1	ANGRI	97,54	34.176	12	NOLA	105,39	34.119
2	BOSCOREALE	87,06	25.693	13	PAGANI	37,37	35.041
3	CASALNUOVO DI NAPOLI	66,84	46.557	14	POMPEI	92,11	23.521
4	CASTELLAMMARE DI STABIA	128,29	61.982	15	PORTICI	65,52	51.293
5	ERCOLANO	84,49	49.235	16	SANT'ANTONIO ABATE	57,28	18.851
6	FISCIANO	100,39	14.145	17	SANT'EGIDIO DEL MONTE ALBINO	43,80	8.802
7	GRAGNANO	74,37	27.601	18	SARNO	93,73	30.723
8	MARIGLIANO	98,52	29.411	19	SCAFATI	181,66	47.706
9	MASSA LUBRENSE	98,99	14.129	20	SORRENTO	78,16	15.116
10	NOCERA INFERIORE	78,55	43.317	21	TORRE ANNUNZIATA	79,02	39.595
11	NOCERA SUPERIORE	91,73	23.461	22	TORRE DEL GRECO	137,44	79.055

Given the variability in size and complexity of each WDS, the absolute number of failures was normalized against the time and total length of the network. Therefore, the tendency for pipeline failure in a given municipality was expressed by the specific failure rate (λ') over a month time interval by means of:

$$\lambda' = \frac{N_{failures}}{L_{WDS} * month} \quad (1)$$

where $N_{failures}$ represents the number of recorded failures in each month, and L_{WDS} is the total length of the water network for that municipality.
In order to contribute to the classification of the WDS in terms of priority of intervention from the water utility, all these data have been classified by means of a Sliding Windows approach. Each training instance was composed by the failure rates over the past six months as input features, and the failure rate of the seventh month as the target. In so doing, 2068 instances are processed (22 municipalities × 94 windows), each with six predictors (M1 to M6) and one numerical target value.
The target variable was discretized into binary classes based on percentile thresholds. Instances with a target failure rate above the 50th percentile were labelled as "Priority", indicating a critical condition; those below were labelled "No Priority", indicating normal operational risk.
The complete dataset was split into 70% for training and 30% for testing, using a hold-out validation strategy. Model development and analysis were conducted in MATLAB. In addition to the hold-out strategy, a 5-fold cross-validation was also applied to the training set to validate the model internally and ensure its generalization during the hyperparameter tuning phase. Several classification algorithms were tested, including Decision Trees, SVM, Logistic Regression, and Ensemble, to identify the most effective model.

The best performing model is the Coarse Gaussian SVM, which achieved a test accuracy of 85.2%. To further improve classification robustness, during the training step, especially given the imbalance between the "Priority" and "No Priority" classes, a misclassification cost matrix was introduced. This matrix penalized false negatives (i.e., Priority misclassified as No Priority) more heavily, in alignment with the utility's operational priorities. An example of the adopted cost scheme is shown below in Table 2.

Table 2. Cost Matrix

		Predicted Classes	
		Priority	No Priority
True Classes	Priority	0	2
	No Priority	3	0

RESULTS AND DISCUSSION

Model performance was assessed using standard classification metrics: accuracy, precision, recall, and F1-score. While accuracy offers a general overview, it can be misleading in the presence of class imbalance. For this reason, specific attention was given to the F1-score for the "Priority" class, which balances false positives and false negatives, thus better reflecting the model's ability to detect critical conditions. The metrics are defined as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$F1-Score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{5}$$

where TP (true positives) are the correctly predicted Priority cases, TN (true negatives) are the correctly predicted No Priority case, FP (false positives) are No Priority cases incorrectly predicted as Priority, and FN (false negatives) are Priority cases misclassified as No Priority. These definitions allow for a clearer interpretation of the confusion matrices obtained during testing.
Among all the models tested the best performing one was a Support Vector Machine (SVM) based on a Gaussian kernel function. This model achieved a test accuracy of approximately 85.2%, along with a recall above 87% for the Priority class and an F1-Score of 84%, demonstrating its ability to detect critical situations with high reliability, as reported by Table 3.

Table 3. A comparative summary of model performance [%]

MODEL	**Fine Tree**	**Ensemble**	**Logistic Regression**	**Coarse Gaussian SVM**
Precision	76.65	83.71	83.44	83.74
Recall	82.05	83.97	87.18	87.50
F1-Score	79.26	83.84	85.27	85.58
Accuracy	78.39	83.71	84.84	85.16

The confusion matrix of the final SVM model confirms its effectiveness, showing that most Priority cases were classified correctly, with relatively few false negatives. The good performance of the model is partly attributable to the adoption of a misclassification cost matrix, which assigned greater weight to errors on Priority cases than on others.

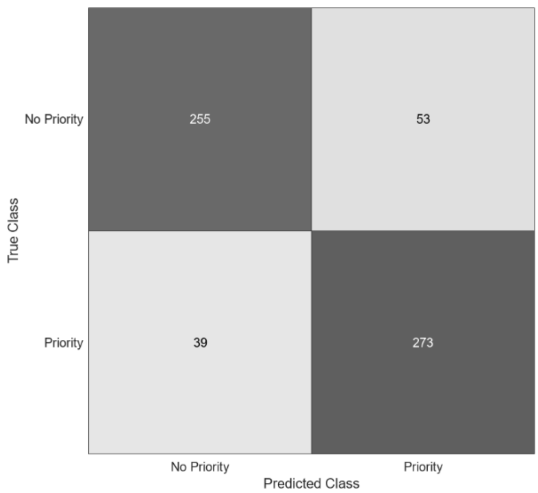

Figure 2. Confusion Test Matrix

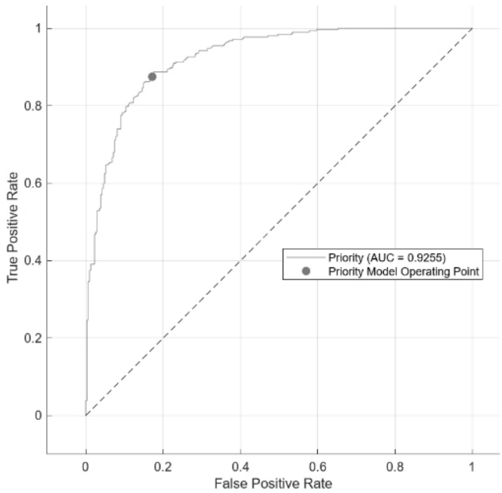

Figure 3. “Priority” ROC Curve

The model’s discriminative capability was also evaluated through the Receiver Operating Characteristic (ROC) curve. The Area Under the Curve (AUC) for the Priority class was approximately 0.92, indicating a high level of separability between classes and reinforcing the classifier’s robustness.

In terms of practical application, the model's predictions were used to generate a risk map of the municipalities under study. Each municipality was assigned a label, either "Priority" or "No Priority", based on its failure pattern over time. This output is summarized in Table 4, which can directly support water utility operational decision-making.

Table 4. List of municipalities and the predicted label assigned by the model

N.	Municipality	Criticality of intervention	N.	Municipality	Criticality of intervention
1	ANGRI	No Priority	12	NOLA	Priority
2	BOSCOREALE	No Priority	13	PAGANI	Priority
3	CASALNUOVO DI NAPOLI	Priority	14	POMPEI	No Priority
4	CASTELLAMMARE DI STABIA	No Priority	15	PORTICI	No Priority
5	ERCOLANO	Priority	16	SANT'ANTONIO ABATE	Priority
6	FISCIANO	No Priority	17	SANT'EGIDIO DEL MONTE ALBINO	Priority
7	GRAGNANO	Priority	18	SARNO	Priority
8	MARIGLIANO	No Priority	19	SCAFATI	No Priority
9	MASSA LUBRENSE	Priority	20	SORRENTO	No Priority
10	NOCERA INFERIORE	Priority	21	TORRE ANNUNZIATA	Priority
11	NOCERA SUPERIORE	No Priority	22	TORRE DEL GRECO	No Priority

To validate the meaningfulness of these predicted labels, two representative municipalities were analyzed in detail. One was assigned the Priority label (Municipality n. 10 – Nocera Inferiore) and the other No Priority (Municipality n 20 - Sorrento). Figure 4 shows the normalized monthly failure rate for two municipalities labelled, one as Priority and the other as No Priority, during the seven-year observation period. For the municipality classified as Priority, a time series with frequent and pronounced peaks is observed, justifying the high-risk classification. The other trend, on the other hand, illustrates the non-priority municipality, which shows consistently lower and stable values, with only isolated anomalies.

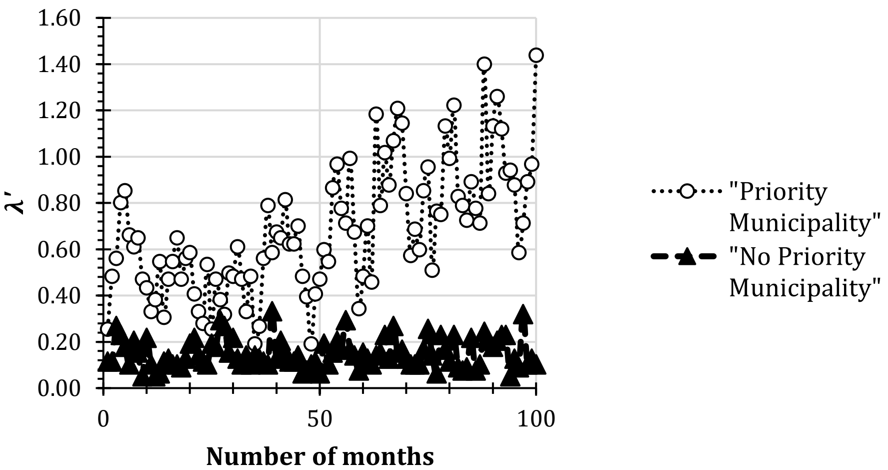

Figure 4. Comparison between Priority and No Priority municipalities

These observations confirm that the model's classifications are consistent with actual failure behaviour over time, thus offering a valuable tool for targeted maintenance planning. Indeed, this approach could enable Water Utilities to identify critical conditions and allocate resources more efficiently by combining historical failure data with a robust Machine Learning method.

CONCLUSIONS

This study presented a data-driven framework for ranking municipalities according to the risk of water network failure, using historical trends in failure rates and supervised learning techniques.

By applying a sliding-window approach and normalizing failure over network length, the proposed method allows to compare heterogeneous water distribution systems.

Among the various models tested, the Coarse Gaussian SVM demonstrated the best performance, with an accuracy of 85.2% and strong recall and F1-score values for the "Priority" class. The inclusion of a misclassification cost matrix

proved essential in addressing class imbalance and reducing the number of false “No Priority” errors, which are operationally the most critical ones.
The classification results were used to generate a predictive risk map, which confirms the consistency between the predicted class and actual failure dynamics. These findings suggest that the model can serve as a valuable decision-support tool for Utility Operators for allocating resources in revamping and/or renewing the intervention of WDSs.

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