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AI-Driven Leakage Detection & Water Network Analytics

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Abstract

Water utilities are under growing pressure to improve operational performance and service levels while conserving energy and resources. Predictive analytics—including time series forecasting, anomaly detection, leakage detection, and leakage prediction—can inform data-driven decision-making for smart distribution systems. The overall research is designed to explore and implement predictive analytics for smart water distribution systems and leakage detection, with key contributions including a temporal analysis framework to extract time-dependent patterns from management-relevant data streams, and techniques for the detection of anomalies in flushing patterns, as well as the detection and prediction of leaks.

Water losses from ageing infrastructure, corporate theft, infiltration, and leakage combine to impose economic, social, and environmental costs. Although regulation is often a key driver for leakage detection and mitigation, proactive management is typically more cost-effective than responding to external pressure. Indeed, decision support tools can facilitate the identification of optimal solutions with respect to detection priority, repair timing, and budget allocation. Predictive analytics—including time series forecasting, anomaly detection, leakage detection, and leakage prediction—can support data-driven decision-making for smart distribution systems by exploiting existing data streams that are often recorded at high frequency.

Keywords: Water Utilities, Predictive Analytics, Smart Distribution, Leakage Detection, Leakage Prediction, Time Series, Anomaly Detection, Data Streams, Infrastructure Aging, Water Losses, Decision Support, Resource Optimization, Energy Efficiency, Data Driven, Forecasting Models, Pattern Analysis, High Frequency, System Monitoring, Repair Planning, Budget Allocation.

1. Introduction

Water supply and distribution systems fulfil a fundamental mission of society, but the challenge of aging, inefficient, and loss-prone infrastructure urgently calls for innovative

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solutions. Smart Water Systems rely on timely and accurate monitoring, modelling, and predictive analytics. Artificial Intelligence offers tools to enhance components of the water cycle in a predictive manner. Such components include predictive models for water demand, supply availability, and supply quality; anomaly detection for monitoring pressure and quality signals; leakage detection schemes; and smart distribution management tools capable of controlling these systems. Timeliness, reliability, and cost-impact are proposed as general criteria to guide the implementation of predictive analytics research at all levels and scales of Smart Water Systems.

AI-driven predictive analytics encompass all levels of Smart Water Systems, including water demand, supply, distribution and control, operational management, and asset renewals. Different sets of predictive techniques are suitable for different applications. Common predictive models such as Artificial Neural Networks or Gradient Boosting Machines can be used for forecasting water demand and predicting raw-water quality. Time Series Analysis methods such as ARIMA or Prophet are suitable modelling techniques for capturing temporal patterns, seasonality, or the trend component of the time series. Anomaly detection approaches using Unsupervised or Supervised Learning can provide early warning signals of fault conditions in pressure or quality signals. Leakage detection schemes and control strategies for Smart Water Distribution Systems can be built around Residual-Based, Statistical, and Machine-Learning Based Indicators computed on the flow-pressure-velocity signals stream, and Operational Management models can be developed to support real-time decision making and long-term asset renewal investments.

2. Background and Context

Predictive analytics are the most sought-after methods for developing a smarter water distribution system, as these systems can minimize water losses and support economic activity. An intelligent water distribution system detects, predicts, and prevents distribution anomalies that result in service interruption and loss of human life. The system must forecast both water demand and the occurrence of distribution anomalies, such as leaks, bursts, or contamination. Predictive analytics can help focus corrective action on these anticipated anomalies and, for demand, utilize available resources more effectively and reliably.

To meet the utility requirements, the predictive engine should have several capabilities such as modeling system time series for short-, medium-, and long-term horizons, detecting anomalies early enough to minimize consequences, supplying temporally reliable and accurate

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predictions that recognize seasonal patterns and trends, and providing predictors of model quality and uncertainty. These aspects also underpin predictive analytics success across other domains.

2.1. Historical Context and Framework Analysis

The introduction of smart water systems was motivated by the need for a more comprehensive approach for water resources management. In to address these needs it is necessary to overcome three main limitations of both traditional and smart systems concerning management dumping of water infrastructures, telematics, and anomalies control. Geographical information as basis for SWM historical data analysis, forecasting and simulated data are the bases for “beyond mean” models. In the prediction of normally distributed variables it is suggested to use the simple but still powerful normal distribution, while anomaly detection can be modelled in many other non-teleconnected or even in simulated-based frameworks. Consequently, these and several other analytical SWM aspects combined with prediction, anomaly and supervised early-stage leakage detection together can contribute towards a really predictive smart water system management. These characteristics are finally mapped to a novel predictive smart water management framework.

The evolution of smart water technologies has led to a wide range of methods, models, and systems for enhanced water services. Nevertheless little attention has been given to the combination of predictive and analytical methods into a single framework and consequently to the progressive transition towards a predictive smart water system directly managing dumping of water infrastructures and anomalies. The presented contributions help to fill this gap and represent further steps toward the dream of the predictive smart water system able to manage both forecasting and anomaly detection . The combination of predictive and analytical methods together progresses towards the implementation of a predictive smart water management system able to progressively predict and control new floods or droughts according to the latest and most probable weather forecasts and to detect anomalies within the water system.

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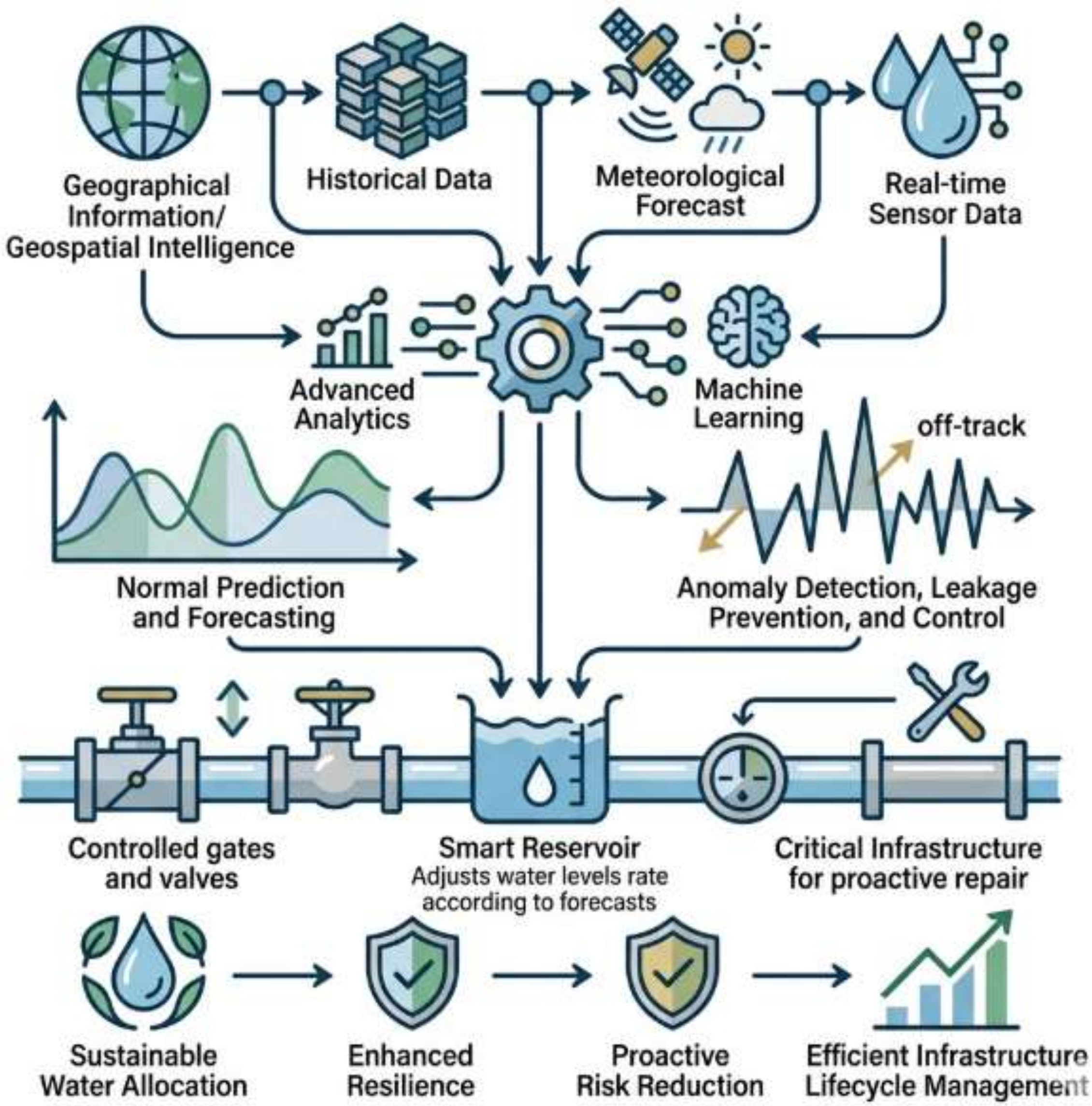

Fig 1: Harnessing Geospatial Intelligence and Advanced Analytics for Predictive Smart Water Systems: An Integrated Approach to Forecasting and Anomaly Control

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3. Methodology

The study employs the scientific method, follows an exploratory design, and uses a mix of qualitative and quantitative approaches. Quantitative data are collected from multiple websites and telemetry datasets. A preliminary data analysis involves visualizations utilising Python libraries. Seasonal autoregressive integrated moving average (SARIMA) models, Facebook Prophet, long short-term memory (LSTM) neural networks, isolation forest, one-class support vector machine, dynamic time warping, and multiple classification techniques from supervised machine learning are applied. The implementation of a data-driven framework progresses through feature engineering, automated model configuration, training-validation-testing data partitions, grid search for hyperparameter tuning, and model evaluation; standardised packages and functions encapsulate the extended solutions. The main hypothesis is that, through the use of advanced temporal analysis techniques informed by relevant datasets, predictive analytics can deliver information for smart water systems that helps prevent and mitigate service disruption due to flooding, leaks, and pipe bursts.

The main steps in the research are: examining the required temporal analyses; identifying the modelling options, applied models, and supporting data; detailing a framework for detecting leaks and bursts; and considering the application of analysis results in controlling water-distribution networks. Temporal-sequence, time-series-analysis, and anomaly-detection techniques are applied to a range of spatiotemporal data sources, including telemetry data from the water agencies of three metropolitan areas of South America. The ultimate goal is to support decision-making in advanced smart water systems through methods that accurately, timely, and reliably predict possible future occurrences of vital events, in compliance with cost and privacy constraints.

3.1. Methodological Framework and Approach

The study, though ideally empirical, relies on secondary data sources. A framework for predictive analytics is developed and tailored using publicly available datasets from the city of Barcelona, Spain, and the region of Flanders, Belgium. Despite several assumptions imposed by the data, the findings contribute evidence supporting five research hypotheses and answering six key questions. The results shed light on the role of predictive analytics in smart water distribution and leakage detection and offer practical guidelines for implementation.

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Data-based research is organized around six overarching tasks and sub-steps. A suitable temporal analysis technique is employed to identify time-dependent patterns, seasonal cycles, and trend components in sensor time series. Predictive modeling options are collated, along with criteria for model selection. Models capable of capturing time-dependent patterns and tendencies are tested and benchmarked for horizontal integration with the broader class of smart water system data. The contribution of additional features to supervised modeling applications on anomalies is investigated, and a hybrid modeling approach is defined. Finally, a framework for leak detection—including models, data sources triggering the detection engine, and detection architecture—is established based on data availability and guidance from the literature.

Equation 1) SARIMA model: full derivation

For seasonal period s, seasonal differencing is:

$$\nabla_s y_t = y_t - y_{t-s} = (1 - L^s) y_t$$

If seasonal differencing order is D:

$$\nabla_s^D y_t = (1 - L^s)^D y_t$$

Now combine:

- nonseasonal AR: $\phi(L)$
- nonseasonal differencing: $(1 - L)^d$
- seasonal AR: $\Phi(L^s)$
- seasonal differencing: $(1 - L^s)^D$
- nonseasonal MA: $\theta(L)$
- seasonal MA: $\Theta(L^s)$

The SARIMA model becomes:

$$\Phi(L^s)\phi(L)(1 - L)^d(1 - L^s)^D y_t = c + \Theta(L^s)\theta(L)\varepsilon_t$$

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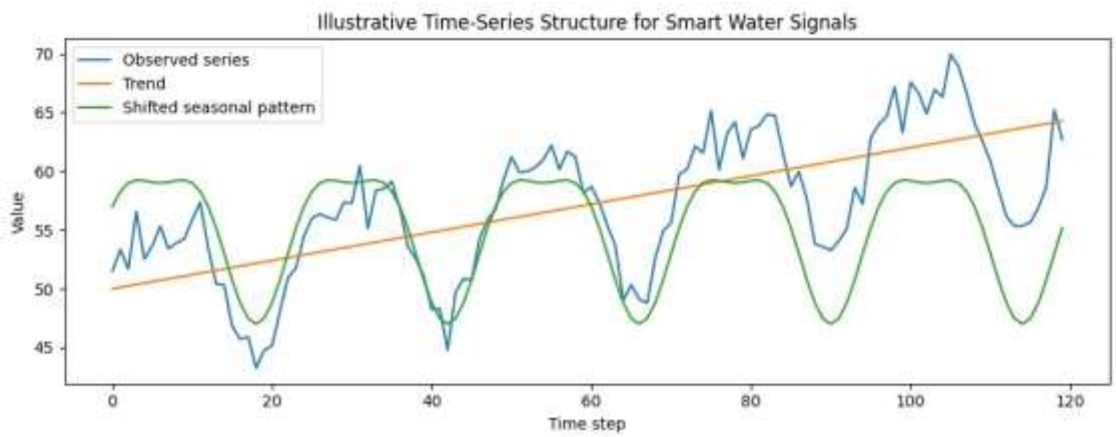
This is SARIMA$(p, d, q) \times (P, D, Q)_s$.

Example expansion

Take SARIMA$(1,1,1) \times (1,1,1)_{24}$:

$$(1 - \Phi_1 L^{24})(1 - \phi_1 L)(1 - L)(1 - L^{24}) y_t = c + (1 + \Theta_1 L^{24})(1 + \theta_1 L)\varepsilon_t$$



4. Objectives of the Study

The main purpose of the research is to develop AI-based predictive analytics methods, encompassing predictive techniques, anomaly detection, leakage detection frameworks, and predictive leakage indicators, to support optimized, resilient, and safe operation of water distribution systems. A secondary objective is to serve as a reference framework for integrating predictive analytics, propensity models, and creep-stress testing in smart water distribution systems during operation.

Predictive techniques ascertain the timing and probable magnitude of events from different data streams, crucial for timely, cost-effective management, for ensuring resilience to uncertainties, and for guiding operational decisions that reduce the system's carbon footprint. Detecting anomalous conditions in system operation ensures reliability, contributes to safety, and lowers overall operational costs and leakage rates. Condition-specific models, trained on historic

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events, give the best performance and diagnosed conditions without triggering alarms indicate situations that merit focused monitoring. Empirical predictive leakage indicators ease direct and remote investment decision-making, while automatically monitored indicators support predictive maintenance.

4.1. Temporal Analysis Techniques

Acknowledging the temporality embedded within water system data, statistical methods are deployed to capture time-dependent patterns, seasonality, and trend components for advanced modelling and anomaly detection. Time series decomposition divides a signal into components associated with seasonality, trend and irregularity, thereby exposing the seasonal and trend signals, forming the basis for subsequent predictive models. The seasonal component captures regular fluctuations that recur in the same season of each year/month/week/day. The trend signal accounts for systematic propagation over time, representing slowly-varying change in signal level. The irregular component contains the information not explicitly captured by the seasonal or trend signals, arising from non-recurring events and phenomena. Decomposed seasonal and trend signals can be subsequently used in various modelling tasks.

Seasonal and time-dependent signals can also be specified by Fourier basis representation. Fourier terms can be defined for both, aperiodic periodic functions, at any time resolution. These can be applied as fundamental components for capturing seasonality in predictive models or feature representation in anomaly detection techniques over a wide variety of data sources. Other temporal analysis techniques—including dynamic time warping, Seasonal-Trend decomposition using LOESS and the Seasonal-Harmonic Generalized Autoregressive Conditional Heteroskedasticity model—enable representation of non-linear and non-linear temporal patterns, leading to improved accuracy in predictive analytics. Joint Time-Frequency Analysis techniques such as Short-Time Fourier Transform, Wavelet Transform and S-Transform can be employed for Any-Time Abnormal Event Recognition and Any-Automatic Water Quality Event Classification.

5. Research Summary

The proposed research considers the application of predictive analytics to water distribution systems with specific focus on water loss detection. Predictive analytics can be beneficial as part of the decision-support system for these water systems as it can augment the

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exposure of anomalies, support the anticipation of events and enable the preparation of infrastructures for conditions that can increase the risk of failure. Yet, while predictive analytics has an established place within the field of machine learning, its practical use in urban water distribution systems remains reduced.

The proposed investigations address the use of predictive techniques in different aspects of an urban water system, including leakage detection, anomaly detection, time-series forecasting and predictive modelling. The resulting operational models will support and provide the basis for deploying predictive analytics within their predictive monitoring contexts. The different processes will be benchmarked and validated against established methods and datasets, ensuring representative and reliable results.

6. Predictive Modeling Techniques

A wide range of predictive modeling techniques is available, each suited to specific applications and also offering support for systems and processes. Selection depends on the accuracy and reliability required, their appropriateness for the specific application, as well as for the geographic area where they are to be applied. One of the primary requirements of a predictive model is to accurately forecast near-future behavior of the variables historically generated. In most cases, one is interested in forecasting a variable that, together with the forecasts of other variables, can serve as an input to a higher-than-one-step-ahead predictive model such as a

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predictive control model or to the real-time control system.

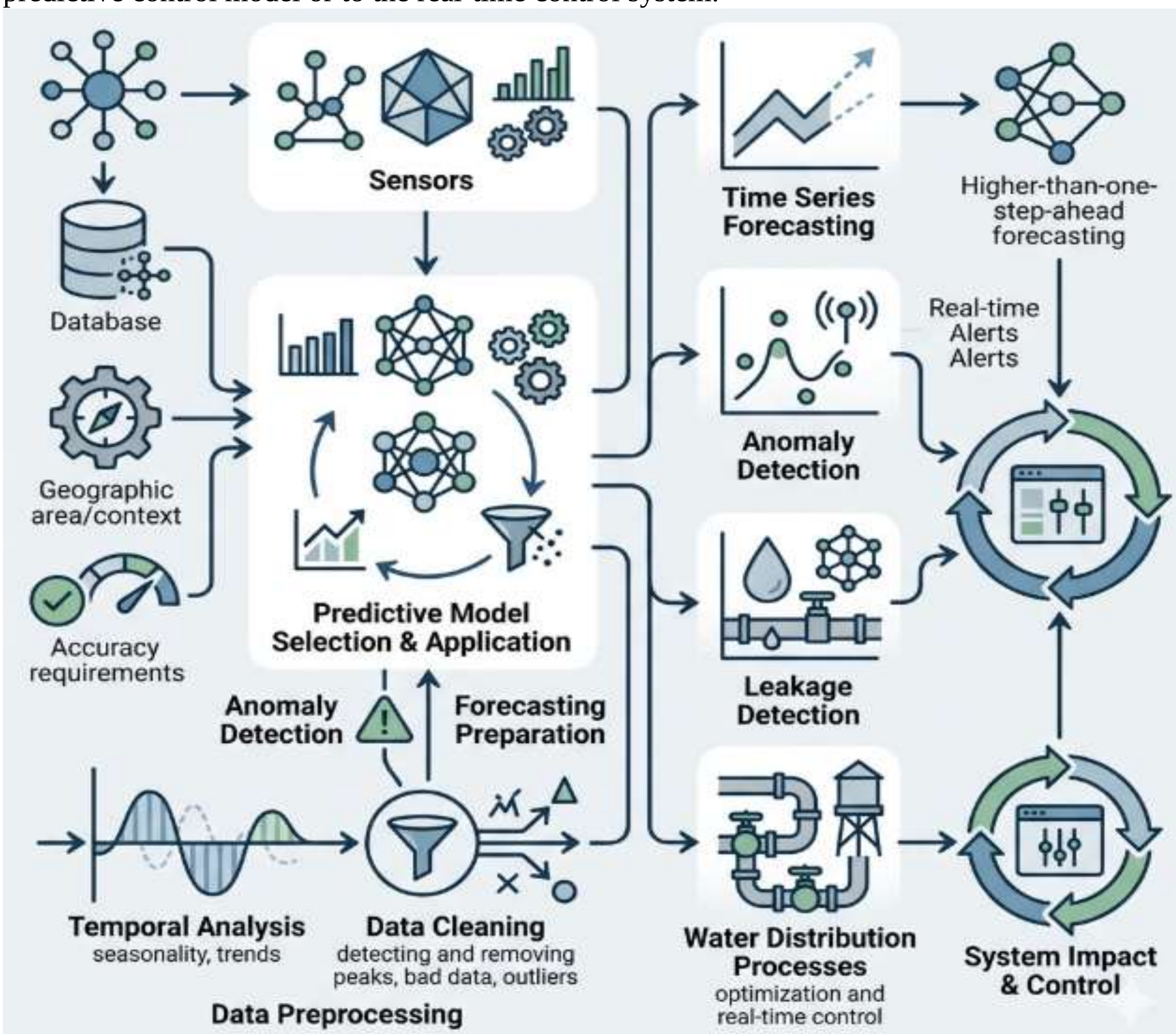

Fig 2: Integrated Predictive Modeling Framework for Resilient Smart Water Systems: Applications in Time Series Forecasting and Anomaly Detection

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For smart water systems predictive analytics, prediction is broadly applied to four main areas: time series forecasting; anomaly detection; leakage detection; and other processes associated with water distribution. Time series forecasting involves the early description of a variable using its history. Other time-related aspects, such as seasonality or trend components, may also be captured using temporal analysis techniques before the forecasting model is employed. Time series data anomalies (e.g., peaks, bad-quality data, unusual values during a period, and sudden changes) are detected and removed before a forecasting model is fitted. Unsupervised or supervised anomaly detection approaches may be adopted.

6.1. Time Series Forecasting

Appropriate models for time series forecasting include generalised autoregressive integrated moving average (ARIMA), Facebook Prophet, and long short-term memory (LSTM) neural networks. Inputs can come from historical values or upper-level analytics. Forecast monitoring remains crucial for timely and reliable predictions. Forthcoming violations of prediction quality can be detected using statistics of past prediction errors. Performance measures span accuracy, timeliness, and reliability. Time series prediction of the next lags for important indicators (e.g., water imbalance, inflow, outflow errors) is highly beneficial and enables the definition of additional operational budgets of available, inflated, or depleted resources, potentially indicating a latent anomaly.

Forecasting techniques can capture explicit patterns in time series data covering seasonal characteristics and trend components with advances in data mining and artificial intelligence. Time series anomalies can be detected by using elevation or reduction values for all annotated time series. The historical pattern of prediction errors can also be a valuable source of information, both for early warning of decreasing prediction quality and for dynamically controlling other components relying on forecasts. Time series models are especially important when the residuals of higher-level predictions are monitored for abrupt deviations.

Equation 2) Core signal model for smart water data

Let

- y_t = observed signal at time t

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- This may be pressure, flow, demand, velocity, inflow, or imbalance

The most basic decomposition discussed in the article is:

$$y_t = T_t + S_t + I_t$$

where

- T_t = trend
- S_t = seasonal component
- I_t = irregular/noise component

This is the **additive decomposition** form.

If seasonal amplitude scales with the level, then the multiplicative form is used:

$$y_t = T_t \cdot S_t \cdot I_t$$

Taking logs:

$$\log y_t = \log T_t + \log S_t + \log I_t$$

6.2. Anomaly Detection

Anomalies can indicate underlying issues in water distribution systems. Detecting such anomalies can aid water utilities in timely diagnosis of incidents requiring maintenance. Anomalies can be detected as they occur or during a post-analysis. Unsupervised Anomaly Detection does not require historical data about anomalous behaviors. Instead, models learn normal behavior as the temporal signatures or distributions of the input features, such as pressure, flow, velocity, etc. The obtained pattern, when applied to new data, can label examples as normal or anomalous according to their distances to the learnt signatures or distributions. Normally, the distance should quantify the possibility of belonging to the normal behavior. Learning normal behavior does not require the input features to be normal or isolated (outliers) but only needs that most of the data belong to the normal category. If a few percentage of labeled anomalous data are available, supervised anomaly detection also can be used.

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Supervised Anomaly Detection methods, like classification, need historical labeled data containing both normal and anomalous behaviors for training. Unsupervised Anomaly Detection requires only labelled normal data for training. Both detection approaches can use the same data stream in parallel, and the recovered abnormal behaviors can be correlated with the cause for diagnosis. In the subsequent analyses, only the pressure and velocity features are retained, and unsupervised and supervised Anomaly Detector models are trained on the same temporal period. These two models can be used as candidate Anomaly Detectors in practical applications.

7. Leakage Detection Frameworks

Detecting leaks in water supply networks is crucial for effective-service provision. Leakage detection is typically performed through regular physical inspections, checking the irrigation systems, or through predictive maintenance. However, if the infrastructure is large and supply pressure is strictly controlled, it is nearly impossible to detect leaks on time due to low flows. The impact of leaks on water loss can be minimized if early warning and detection are implemented.

The architecture of such a framework is presented, which is based on the integrated use of a SCADA system in combination with advanced data mining techniques. It operates in two steps: a first step that performs an anomaly detection on pressure and flow measurements and a second step that compares the flow h−1 data of the distribution network with that of the pump station(s) supplying the district. The data analyzed in the first stage of the model are parameters generally available in a SCADA system, while the second part requires the use of flow in one or more locations.

The factors influencing the performance of the described detection mechanisms are also discussed. As the time needed for a leak to be detected increased, seasonality more strongly influenced the possibility of earlier detection. In a scenario of two critical leaks, an improvement in performance was related to the existence of a clearer pressure drop. . A second model is described that detects hard-to-discover leaks using supervised funnel-type classifiers. The monitored anomalous signals of these rare events are supported by engineered features: (i) pressure; (ii) pressure trend; (iii) velocity of the supply flow; (iv) univariate detection scores based on thresholds related to flow and pressure; (v) multivariate detection scores from unsupervised learning techniques; and (vi) speeding up of the supply flow.

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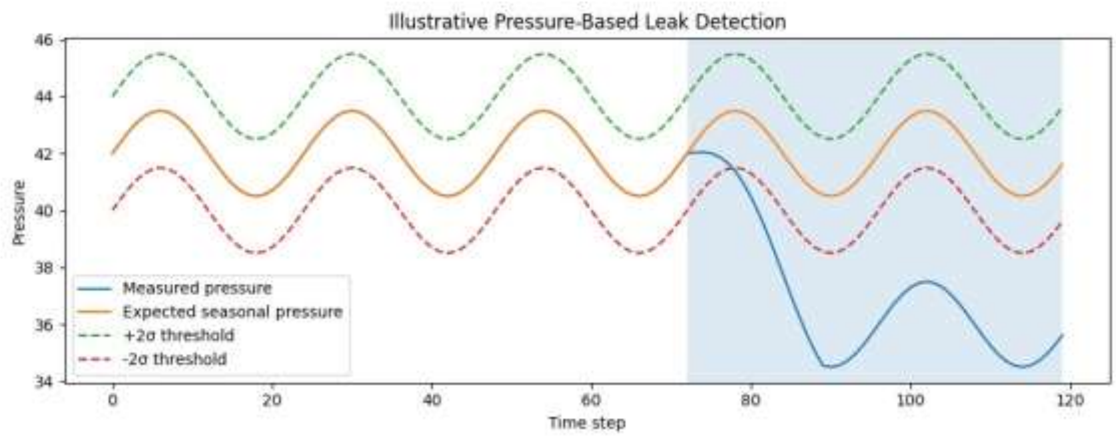

Equation 3) Step-by-step derivation of time-series decomposition

3.1 Additive decomposition

Start from the assumption:

$$y_t = T_t + S_t + I_t$$

We want to estimate each part.

Step 1: Estimate trend

A centered moving average over period m:

$$\hat{T}_t = \frac{1}{m} \sum_{j=-k}^{k} y_{t+j}$$

where $m = 2k + 1$.

For example, if hourly data has daily seasonality, then $m = 24$.

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Step 2: Remove trend

$$d_t = y_t - \hat{T}_t$$

Now d_t contains mainly seasonality plus irregularity:

$$d_t \approx S_t + I_t$$

Step 3: Estimate seasonality

For a seasonal period m, average all detrended values at the same position in the cycle:

$$\hat{S}_r = \frac{1}{N_r} \sum_{t \equiv r \pmod{m}} d_t$$

for $r = 1,2, \dots, m$.

That gives a seasonal template $\hat{S}_1, \dots, \hat{S}_m$.

Step 4: Enforce zero-mean seasonal component

For additive decomposition, seasonality should sum to zero over one cycle:

$$\sum_{r=1}^{m} \hat{S}_r = 0$$

If not, normalize:

$$\hat{S}_r^* = \hat{S}_r - \frac{1}{m} \sum_{j=1}^{m} \hat{S}_j$$

Step 5: Estimate irregular component

$$\hat{I}_t = y_t - \hat{T}_t - \hat{S}_t$$

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So finally:

$$y_t = \hat{T}_t + \hat{S}_t + \hat{I}_t$$

7.1. Feature Engineering for Leaks

Statistical Leakage Indicators. Three statistical indicators, suitable for a variety of water systems, allow detection of anomalies in pressure, flow, velocity, and their interrelations. Each indicator exploits the temporal correlation pattern in the data and signals when it deviates significantly from the expected behavior. Tuning these detectors requires estimating threshold values for accepted deviations from seasonally decomposed and smoothed historical data.

Pressure Indicator. The pressure indicator quantifies the variation of pressure with respect to its expected seasonal pattern; pressure anomalies outside ±mσ (smoothing threshold) of the seasonally decomposed signal are flagged. Flow and Velocity Indicators. Two gross flow detectors are defined. The flow indicator measures the correlation of flow between the inlet and outlet of a subnetwork/nodal zone, while the velocity indicator measures the correlation of flow and cross-sectional velocity in the same direction in each segment traversed by the flow. Seasonally decomposed and smoothed historical data are used to tune the thresholds ±kσ. For flow detection, tying-flow meters may be exposed to large temporal variance due to inevitable changes along the water cycle. When correlations deviate from ±1, the expected range is therefore ±0.5; otherwise, it is within ±0.2. In principle, any non-significant correlation should raise a flag.

7.2. Statistical and ML-Based Leakage Indicators

Leak detection systems can consist of multiple detectors monitoring various feature streams with a single point of decision-making triggered when all indicators provide evidence of a leak. Alternatively, systems can be based on statistical and machine learning (ML) models, featuring separate detectors and aligned decision-making processes capable of identifying the nature of the detected leakage, such as quantity and/or location. Within this framework, the analysis considers different avenues for capturing leakage-related information, triggering events from the different detectors, and enabling layered decision-making depending on model types. Statistical detectors typically use statistical thresholds based on univariate approaches, while unsupervised machine learning models trigger alarms by detecting an anomaly. The usage of

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supervised machine learning models requires labelled datasets enriched with pressure loss, flow gain, velocity gain, or the presence and quantity of leaks, thus being more challenging to cover for the main topologies of a given water distribution network.

Statistical and ML-based indicators are separate from the aforementioned unsupervised/autoencoder leakage detectors, aiming at complementing their findings with additional leakage-related information when available, and potentially revealing more minor leakage events. Moreover, the information provided can be used for layered decision-making. The models take as inputs the full set of feature streams generated during the preprocessing phase. The statistical models are based on a statistical threshold and consider dotted point process traffic streams as the input, while the unsupervised and supervised methods are based on anomaly-detection modelling.

8. Smart Distribution Optimization

Control strategies for leakage-prone water distribution networks seek to optimize the distribution system and control network resilience when uncertainties arise. The respective models and approaches are crucial for decision-makers to respond to probable future scenarios. The impacts of climate change threaten water supply crises, with a strong relationship between anomalous climate behavior and the depletion of sources. Simulated predictions indicate that extreme conditions are intensifying. Leak allowance, as a critical variable in the supply-demand equilibrium of exploited resources, can be seen as a margin of safety. Networks with high vulnerability towards water losses require stricter leakage control. The simulation-optimization framework accounts for both corrective and preventive control measures. Pressure control can be established as an operating practice.

Controlling the piezometric level in the network is of paramount importance to reduce service outages. Decision control rules are classified into pressure management control at the exit boundary of the network and maintenance. To guarantee the operability of the system, an input–output feedback control structure allows a dynamic adjustment of the control law according to the external conditions. Simplistic pressure control models can now be relied upon, where service levels in pressure-prone regions are maintained in the lower range of acceptable values. When operating regulations tolerate pressure set points in the acceptable range, the pressure control rule is not decisive for operating management.

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Block	What the article says	Mathematical form usually used
Time-series forecasting	ARIMA/SARIMA, Prophet, LSTM	y_t, lag operators, seasonal terms, neural recurrence
Anomaly detection	Isolation Forest, One-Class SVM, residual thresholds	anomaly score $s(x)$, margin function $f(x)$, thresholding
Leakage detection	pressure, flow, velocity indicators	residuals, correlations, standardized deviations
Evaluation	accuracy, timeliness, reliability, AUC-ROC, MAPE	classification and forecast error metrics

8.1. Pressure Modelling and Control

Pressure control ensures that drinking water flows through the distribution network and is available when needed, at an appropriate level and quality for the user, and does not exceed the limits of the system. Valve settings, pump characteristics, and other related control variables can usually be tuned once per season and may not require long-term predictive control. Nevertheless, pressures within the system can vary during the course of a day due to changes in demand, creating the risk of insufficient service delivery or damage to customer property (e.g., burst pipes and pumps); planning these demands and the setting of these controls can be supported by prediction.

Dynamic pressure demand modelling combines demand data with hydraulic data from the distribution system. Supply pressure varies with the firing of pumps and the filling of elevated storage; therefore, pressure demand modelling can be split into the temporal variation of supply pressure and the estimation of the associated service level for a given pipe size and discharge capacity. The service-level requirement may also vary with time and can be related to the daily cycle of electricity supply.

Equation 4) Fourier representation of seasonality

$$S_t = \sum_{k=1}^{K} \left[a_k \cos\left(\frac{2\pi kt}{P}\right) + b_k \sin\left(\frac{2\pi kt}{P}\right) \right]$$

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Why this works

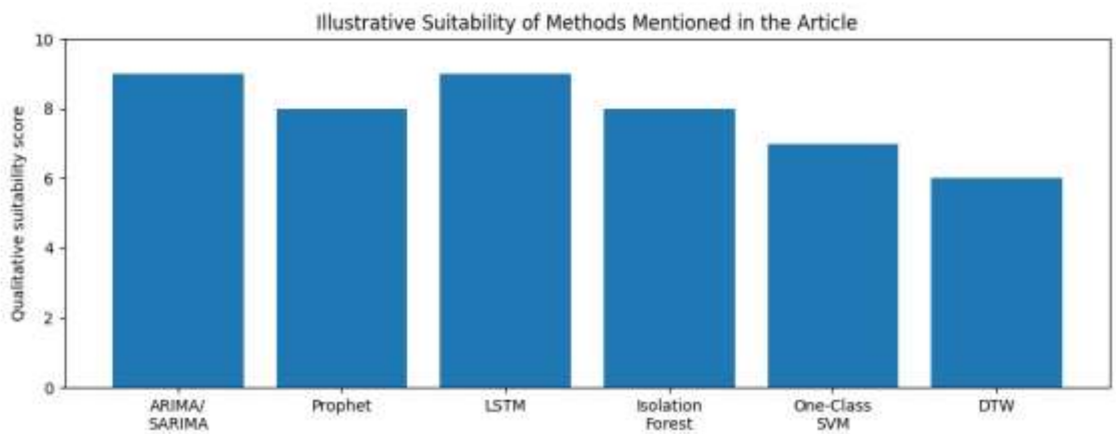
Any periodic signal can be written as a sum of sinusoids.

For one harmonic:

$$S_t^{(1)} = a_1 \cos\left(\frac{2\pi t}{P}\right) + b_1 \sin\left(\frac{2\pi t}{P}\right)$$

For two harmonics:

$$S_t^{(2)} = a_1 \cos\left(\frac{2\pi t}{P}\right) + b_1 \sin\left(\frac{2\pi t}{P}\right) + a_2 \cos\left(\frac{4\pi t}{P}\right) + b_2 \sin\left(\frac{4\pi t}{P}\right)$$



8.2. Network Optimization under Uncertainty

Distribution systems must be designed to ensure service continuity at all time, particularly for emergency situations where system failures occur. Routing and pumping scheduling strategies need to be defined to optimise the usage of the network during these periods. In this situation and despite uncertainty regarding water demands and bursts, pumping schedules need to be prepared to avoid serious economical and environmental costs. Paths for the pumps should also be defined to fulfil the demands and restore normal conditions in the network as quickly as possible. These two strategies provide demand satisfaction in the short term,

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allowing concentration on mid- and long-term strategies such as network optimisation on a cost basis. Optimal Pumping Scheduling is a time-critical optimisation action, usually executed under uncertainty.

Routing strategies in water supply systems aim to minimise the expected cost of water supply during a particular period. Networks must be able to satisfy demand efficiently during normative and disruptive scenarios. Normative scenarios involve deterministic conditions, while disruptive scenarios incorporate stochastic demand and burst conditions. The optimal routing procedures are applicable to both cases but are developed here for the disruptive situation.

9. Evaluation and Validation

Defining protocols for assessing model performance and generalization complements the choice of predictive methods. For analytical forecasting, accuracy, timeliness, and reliability indicators underpin performance evaluation, whereas cost impacts are also relevant for modelling and predictive control. For anomaly detection, the area under the receiver operating characteristic curve (AUC-ROC) indicates discriminative capacity, and the accuracy, precision, and recall of

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the prediction can highlight the overall performance and partly address class imbalance.

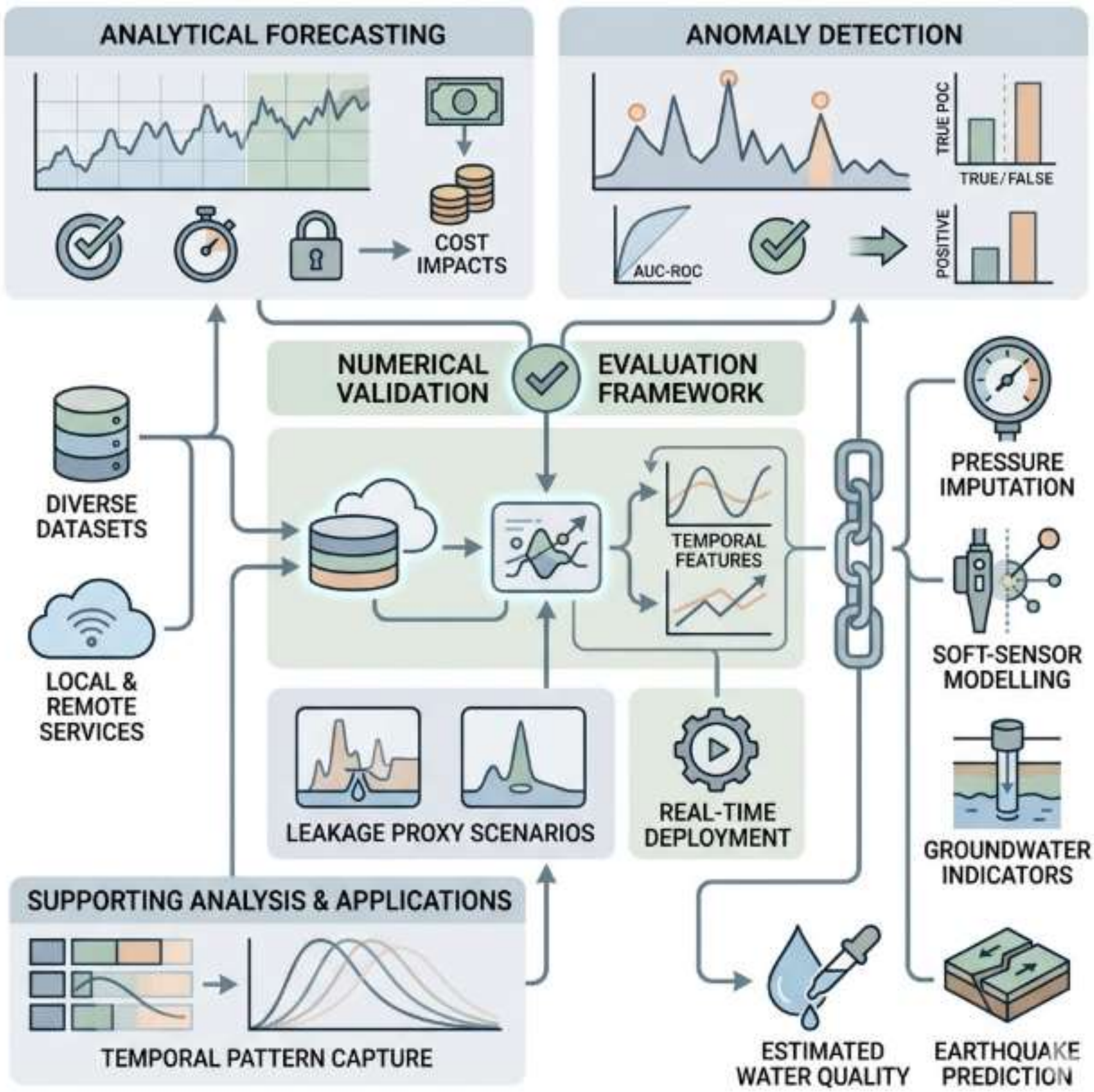

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Fig 3: A Multi-Faceted Evaluation Framework for Predictive Water Management: Integrating Forecasting, Anomaly Detection, and Control Systems

Numerical validation aims to benchmark predictive analytic components and constitutive models across multiple sites. The assessment draws on diverse datasets for time series forecasting and leakage detection but maintains a similar control scheme and architecture. Temporal features for seasonal trend decomposition and leaky conditions are derived from the systems used and are not inherently included in the corresponding predictive analytic models. The framework integrates local and remote datasets and services, supporting real-time deployment and simulating leakage under two proxy scenarios.

Supporting analysis of predictive modelling, temporal patterns are captured through suitable techniques for time series signals, seasonality, and trend components. For time series forecasting, windowed data or temporal decay can serve as model input, with predictive analytics accuracy assessed through precision, MAPE, and AUC-ROC where applicable. The prediction of pressure omits cost but provides a base for imputation and soft-sensor modelling in other water management tasks. Groundwater state indicators, estimated water quality, and earthquake predictions may also benefit predictive outage analytics.

9.1. Benchmarking and Datasets

Benchmarking predictive analytics for smart water management requires datasets that reflect the challenges faced by real-world systems. Anomalies must be captured in both flow and pressure measurements, and both normal operation and periods of stress and failure should be included. Where predictive models are used for simulation, active leak styling should be employed. Datasets from two previous studies on separate urban areas offer such variety by combining distinct yet complementary strengths. At one site, New York City, USA, a large urban area with a complex water supply system is monitored with extensive pressure measurements, though without leakage detection. At the other site from Southern Europe, Emilia-Romagna, Italy, a smaller area has limited pressure supervision but an unsupervised leakage detection system based on flow, pressure, and velocity anomalies. Predictive models perform the tasks emulating all observed stream and label the pressure dataset.

The predictive models are benchmarked using datasets for anomaly detection from another previous study, with additional methods that leverage the time-dependent nature of the

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data. The suitability of ARIMA, Prophet, and LSTM models in combination with seasonal decomposition and autocorrelation is examined through cross-validation. Performance is measured with the Normalized Mean Absolute Error and Normalized Dynamic Time Warping distance, assisted by K-Folds. One optimization deploys the models jointly, while a second runs them sequentially, with temporal cross-validation. The capability to carry, pattern, and load prediction within a common framework promotes accuracy across the board.

9.2. Performance Metrics for Predictive Analytics

To evaluate the performance of predictive analytics, it is crucial to define comprehensive quality criteria. Properly constructed predictive models are anticipated to accurately characterize the monitored context and anticipate future conditions, while providing reliable, updated forecasts at consistent time intervals. Furthermore, timely forecast delivery is crucial to enable informed decision-making. Frequently updated predictive models that are combined as part of a larger smart system should be capable of maintaining a satisfactory overall quality level. Local models, which rely on historical data and cover a limited horizon, should deliver reliable results on a regular basis, facilitating their integration into subsequent analytical stages.

Quality metrics must also account for the impact that predictive model performance has on the operation of the larger predictive system. Individual models should therefore be assessed in terms of their ability to offer useful predictions, and expressed in a common, configurable economic dimension. Quantifying the economic impact of predictive analytics is crucial during implementation, but it is exceptionally difficult. A basic approach consists of estimating the expected costs for each model type, relating them to the specific outcome they aim to achieve, accounting for the costs associated with prediction misses, and establishing whether the expected benefits are higher than the expected costs. This cost-benefit analysis can be supplemented by additional evaluation metrics to comprehensively assess predictive modeling quality.

10. Deployment Considerations

The deployment of predictive models in monitoring and decision-making requires further consideration of implementation challenges. Evidence of these considerations can be observed in various areas. First, the integration of predictive models into a coherent system and operational environment necessitates architectural design, technical interfaces, internal protocols, and management of data pipelines. Second, decision-making responsibilities and authorisations need

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to be defined along with data privacy policies and governance frameworks. These aspects involve specifying data ownership rights and determining how, when, and by whom data are shared. The internal governance rules and frameworks must meet the legal, regulatory, and policy requirements applicable to the organisation and country.

The architecture of the predictive analytics system is characterised by the model requirements defined in previous sections and the proposed approach to maintain and monitor water systems. For the architectural design, the type of decision-making considered is tactical in nature. Consequently, the organisation is responsible for developing, maintaining, and controlling the various models involved in predictive analytics. With this final assumption clarified, the subsequent subsections elaborate the areas of system architecture and interoperability and data governance and privacy. Together, they define the deployment aspects of predictive analytics for water distribution systems.

Equation 5) ARIMA model: full derivation

5.1 AR model

For an autoregressive model of order p:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

where ε_t is white noise.

Using lag operator L, where $Ly_t = y_{t-1}$:

$$\phi(L) y_t = c + \varepsilon_t$$

with

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$$

5.2 MA model

A moving-average model of order q:

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$$y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$

Using lag operator:

$$y_t = \mu + \theta(L)\varepsilon_t$$

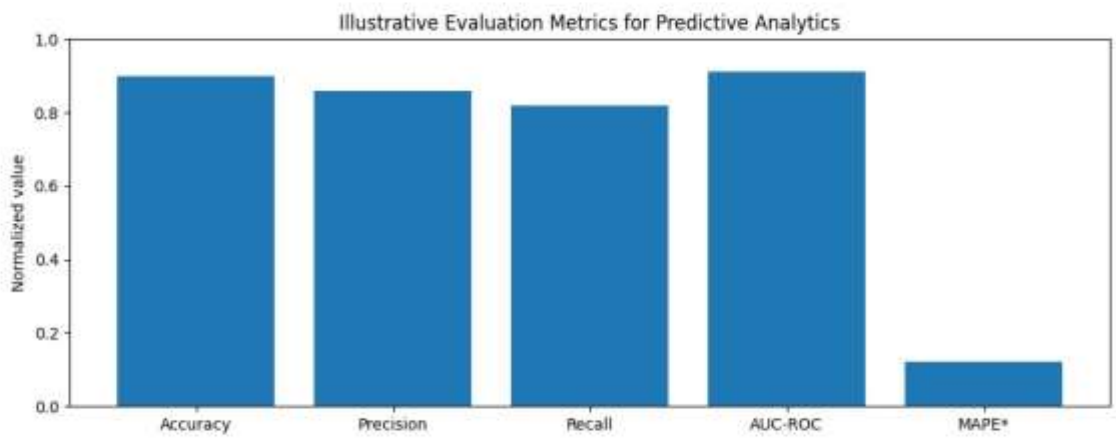
where

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$$

5.3 ARMA model

Combining AR and MA:

$$\phi(L) y_t = c + \theta(L)\varepsilon_t$$



10.1. System Architecture and Interoperability

A side schematic outlines how the four main operational blocks are linked. The application can be decomposed into three types of modules covering (1) predictive and anomaly detection analytics, (2) leakage detection or leakage-prone change detection modules, and (3) optimization support, including operational control functions. Depending on availability and

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compatibility of APIs, the modules can be operated separately or integrated directly into a larger water distribution system management platform for deployment. Presence of a module-enabled system and open data/hydraulic information-sharing agreements among municipalities can reduce redundancy and enhance capabilities in regions where such analytics do not currently exist. The system and its analytics are intended to scale to serve additional municipalities that provide interconnectivity information on the hydraulic model or that support open data sharing.

Focused solely on predictive analytics, a simplified architecture consists of three main components, also shown in the previous figure in the context of an anomaly-detection module. (1) The predictive analyst maintains the models and supports the downstream application—certain predictive-analytics tasks must be performed per site. (2) The wider-data manager encompasses the two tasks required to ensure timely detection of out-of-control conditions in the shared-hydraulic information and at least one type of prediction during a period of interest. Successful deployment relies on appropriate attention to both components. When at least the core functions of these components are properly enabled, a community of administrative entities can jointly benefit from forecasting and predictive-analytics tasks without further resource investment.

10.2. Data Governance and Privacy

Timely and reliable access to data and analytics is at the heart of any AI-powered water application, yet both access and use must be governed to ensure compliance with legal frameworks and other policy requirements. Data owner’s policies determine how data from surveillance systems installed in the water system can be accessed and used. The monitoring layer of smart city applications collects vast amounts of sensory data that must be kept secure, retained only as long as necessary, and made accessible only to privileged users. Such policies define the technical and institutional set up of data and analytics pipelines, operational procedures, and sharing agreements that stipulate how long data needs to be retained, for which purposes, by whom, in what format, and under which conditions. Data owners are expected to establish a retention policy for each data stream, taking into consideration their attribute’s nature, the cost of storing them, the risk of not keeping them, and the probability they will be used in the future.

However, much nuanced controls are required to ensure that personal, sensitive, or confidential data do not fall into the wrong hands through careless or malicious act. Access to

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data is governed through role-based access control, a mechanism for restricting access to authorized users, roles, or groups of users. Identity and access management provides a single sign-on interface for privileged users to retrieve the different types of data needed for the different AI-powered water applications. Data access for model training is orchestrated by operators. Data ownership, access, retention, and use must comply with country law, relevant regulations such as the GDPR, and any other internal information security policies to which data owner is subject.

11. Policy and Stakeholder Implications

The transition to smart water systems has been driven by regulatory frameworks aiming for the sector's sustainability. For analytics to support the realization of regulation objectives, decision makers, and utility companies need to be aware of possible legal and economic impacts. Further, the application requires the involvement of different actors who actively take on defined roles. In the context of predictive analytics, the relevant impact points are the already-mentioned regulatory compliance and Data Governance and Privacy issues, as well as a framework underpinning the overall approach for adopting an analytics face supporting predictive control or predictive management.

Regulatory pressure in combination with the positive aspects of optimizing water management should ensure the economic benefits of predictive analytics in water management. However, it can result in inequity for less developed regions as implementation usually requires higher investments. Consequently, the public acceptance of the technology plays an important role in practical transfer. The technology should not receive any resistance during its implementation, but rather be viewed as a progress for the habitat and climate environment.

11.1. Regulatory Compliance and Standards

Smart Water Distribution Systems (SWDS) are susceptible to the leakage of valuable water resources. Monitoring solutions based on telemetric sensors and information technology (IT) systems are being deployed, making it possible to integrate existing solutions to define high-level SWDS models. Smart Water Control Systems (SWCS) exploit the opportunities of these new technologies, but they remain in the demonstration phase and must prove their reliability, effectiveness, and scalability. Such systems assist in predicting both the amount of water entering the distribution network and its required demand at a spatial level in order to optimize

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water flows. Seasonal and temporal prediction has received a lot of attention, but little attention has been paid to anomalous behaviour and detection at spatial resolutions that can trigger the control functions of a remote monitoring SWCS. An SWCS can improve the monitoring of water leakage, allowing control over the pressure to maintain service levels and preventing future failure events in the system.

The architecture of the SWCS is based on monitoring the expected water flow entering the distribution network and the expected demand at user level. Quantifying both aspects is crucial for leak detection. Different methods exist to achieve seasonality and temporal prediction, and expected water flow can be used as input to anomaly detection methods. Spatial models exploit information from neighbouring zones to detect leaks with tested reliability. Recent works suggested exploiting a combination of unsupervised anomalous behaviour detection and supervised anomaly classification to provide high-resolution leakage detection outputs. Supervisors comply with these proposals, providing strong statistical evidence for different anomaly detection approaches and for different sets of features, as well as considering new feature proposals such as velocity or combining temporal and anomalous behaviour.

11.2. Economic and Social Impacts

Smart water systems have far-reaching effects on cities, both directly and indirectly. Alongside the direct economic benefits, a reduction in leak occurrence will engender self-evident socio-economic gains: leak-free distribution systems do not disrupt services to customers, do not pollute potable water, and are not costly to repair; destruction of public property (roads, urban gardens, the valuable green) is avoided; and insurance costs decline. Central to achieving sustainable water systems is the rigorous testing of approaches and associated economic analysis. Cost and economic discussion should focus on smart water solutions that are either not already in widespread use or not proven to operate successfully across a wide range of applications.

The development and a first operational deployment of predictive analytics for smart water distribution have the potential to be exploited and sustained over time, positioning their solution within the definitions and properties of Local Smart Water Solutions that are addressing real needs and providing added value. Predictive analytics for smart water are positioned as open-source software for the community and public domain, enabling their free use for non-commercial operations—an important aspect that must be highlighted alongside the recognised potential for group-responsibility endorsement of public access. The only revenue stemming

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from predictive use should come from the reduced costs associated with system leaks or with corrective actions for pressure, flow, and pluviosity deviations. These, however, are indirect and probable economic impacts that should be tested via proper use of smart water solutions throughout an extended period of time.

12. Results

Predictive Analytics for Smart Water Distribution and Leakage Detection Predictive analytics for water systems predicts pressure, volume, seasonal consumption, leaks, and other anomalous behaviours. Such predictions enable efficient and resilient operation, particularly during periods of uncertainty (e.g., extreme weather). Accuracy, timely availability, reliability, and assessment of the cost impact of predictions are thus paramount.

Leaking water distribution networks affect service reliability and public health. Conventional detection methods rely on field observations or visual assessments, yet continuous monitoring enables detection of real leaks rather than potential ones. In addition to concentrated effort devoted to leak detection, both supervised algorithms (using actual leakage events) and unsupervised models (without such examples) have been trained to detect leaks on the basis of

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pipeline-feeding pressure, flow rate, and leakage-flow velocity.

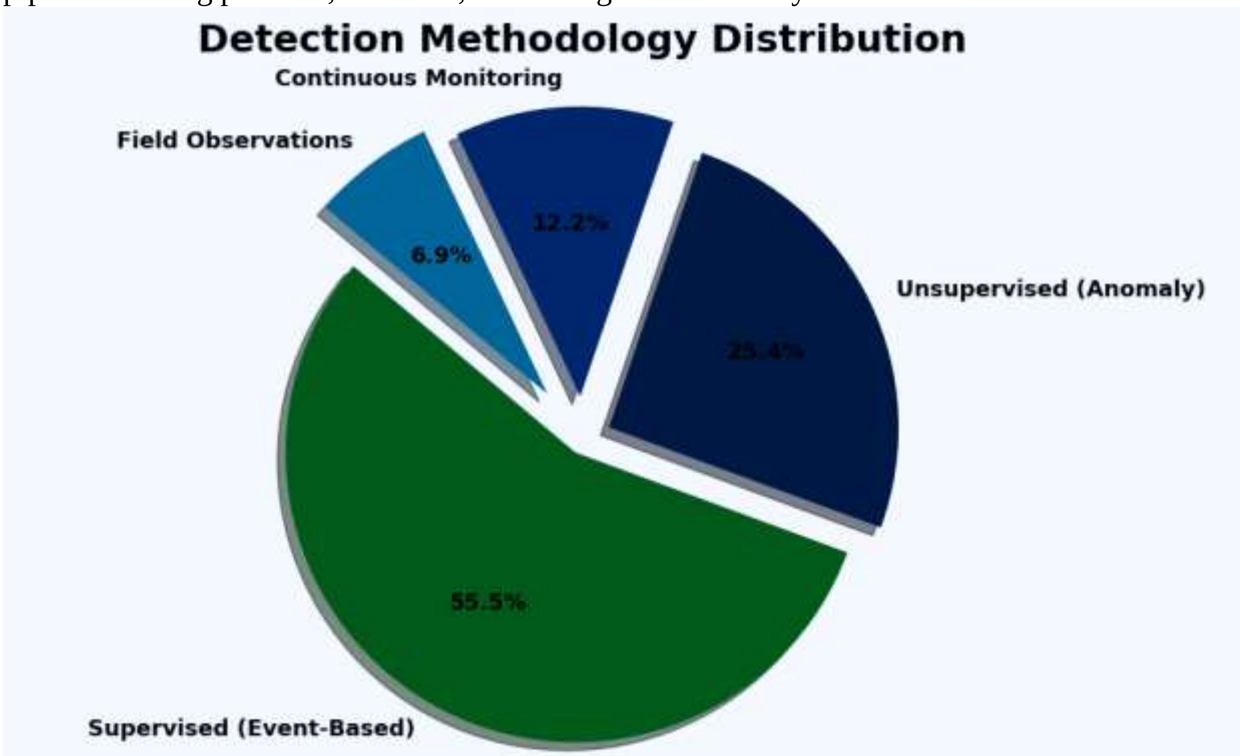

Fig 4: Detection Methodology Distribution

Anomaly detection in water flow allows service and operating technicians to focus on apparent problems rather than planned monitoring along the whole network. Unsupervised learning models also indicate potential problems in other flows, predicting instances of service that may need attention. In this case, caution is recommended: the first-level approximation may unclog pipes but not prevent clogging recurrence. For operators, incidence prediction is as valuable as prediction of the incident itself.

13. Conclusion

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Predictive analytics are critical for managing water systems in cities, yet practical methods and deployment considerations are often overlooked. This study introduces predictive techniques to support anomaly detection, leakage detection, network optimisation, predictive distribution, dynamic supply, and pressure modelling in water supply systems. Methods include time series forecasting, unsupervised and supervised anomaly detection, pressure level modelling and adaptation, pressure network optimisation under uncertainty, and leak detection featuring soft sensor development, supervised classifiers, and statistical leak indicators. A multi-level delivery framework addresses safety, resilience, and uncertainty. The impact of applying predictive analytics on providing smart water services is evaluated, enabling practical comparisons of five predictive models on a high-frequency dataset, ranging from prediction scores and timing to influence on water consumption and costs.

Predictive models can facilitate smart water management—detection, analysis, preparation, and mitigation of undesirable problems through timely predictions. Leakage detection, for instance, requires timely identification of pressure flows and leakages. The presence of leaks, together with pressure and flow conditions, can trigger the supervision of water supply networks. Consequently, predictive models of anomaly detection depict the occurrence of pressures or flows considered abnormal. Unsupervised models expose long-term patterns, while supervised classifiers provide midterm forecasting. Both analysis types can prevent or mitigate undesirable problems in water networks: flooding, economic losses, and service disconnections for pressure drops. Predictive models applied in time series of consumptions, flow meters, or pressure measurements forecast water-distribution network behaviour for upcoming hours and days by detecting sudden consumption increments at short time scales.

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