Enhancing leak detection through digital monitoring and operational expertise

Angelina Isler[1], Sean Malone[1], Martin Harris[1], Soon Bee Quek (Emily)[2]

1. TRILITY, Adelaide, AU

2. TRILITY, Melbourne, AU

Keywords

Early leak detection, non-revenue water, district metered areas, predictive analytics

Executive summary

The interval between a leak occurring and operator inspection is when water networks bleed. This paper closes that window by integrating flow meter data, TaKaDu's predictive analytics, and TRILITY's operational expertise. The objectives are to reduce non-revenue water through earlier detection and improved network visibility; shift from reactive inspection to proactive, data-driven maintenance; and deliver near-real-time alerting without proportional increases in operational costs.

TaKaDu's anomaly detection algorithms identify leaks within district metered areas and log alert and onset times. Detection lag is defined as Δt = Time of Alert – Time of Event Onset. Onset is identified retrospectively from baseline deviation, and alerts are triggered when dynamic thresholds are exceeded.

From a total of 401 detected events (July 2023 to April 2026):55% were water-loss events, the median water loss detection time was 5.8 hours, 75% of water-loss events were detected within 8.8 hours, and 98% of all events were detected within 3 days.

Detection lag was reduced from weeks or months - the typical interval between manual inspections - to within 3 days, with 75% of water-loss events detected within 9 hours. Continuous flow monitoring proved an effective alternative to periodic inspections, demonstrating a viable path to proactive network management.

Introduction

Water utilities worldwide are under increasing pressure to reduce non-revenue water (NRW), improve operational resilience and do more with less - yet smaller regional utilities often lack the resources and expertise to adopt the advanced solutions that make this possible.

This paper explores the implementation of an early leak detection system for a utility serving over 5,000 residents. The utility faced persistent challenges with undetected leaks, which contributed to water scarcity, financial losses, and elevated operational risks. Traditional

detection methods, such as periodic inspections, customer reports, manual analysis and reactive alarms, struggled to detect low-magnitude or developing leaks in time. To bridge this gap, a data-driven event detection system, TaKaDu's Central Event Management (CEM) platform, was implemented to pull flow and consumption data from District Metered Areas (DMAs) and apply automated anomaly-detection algorithms to surface actionable insights.

A key differentiator of this Knowledge-as-a-Service (KaaS) offering is the integration of analyst expertise through TRILITY's centralised control centre. Network analysts assess, validate, and classify detected events, ensuring that only actionable insights are escalated to the utility's operational teams. This paper investigates event detection speed, accuracy, operational effectiveness, and future potential.

The implementation of the KaaS offering aims to deliver the following operational and strategic outcomes:

- Reduce non-revenue water through early detection and improved network visibility
- Improve system performance with near real-time, high-quality data
- Support the transition from reactive maintenance to proactive, data-driven decision-making
- Enhance long-term network resilience without significantly increasing operational costs

Methodology/process

The two steps to this process are implementation, CEM setup and calibration, and analysis of the data captured within the system.

Implementation

The system leverages DMAs and historical flow and consumption data to establish baseline supply and consumption patterns and detect anomalies such as flow increases, consumption changes, and system faults. The DMA is a discrete segment of a water distribution network in which the total supply can be calculated from one or more flow meters and validated against consumption. The CEM software was configured with 12 months of historical data from the existing flow meters to learn historical patterns and expected flow variance. Then, statistical thresholds were set and fine-tuned on the anomaly detection engine so that minute variances in flow would not trigger an event alert.

The CEM system detects a range of event types, including flow increases and decreases, flow trends, consumption anomalies, meter faults, communication failures, and negative readings. Flow increases may indicate bursts, leaks, or unexpected usage, while decreases can signal reduced supply or consumption. Flow trends track gradual rises in the night line, often

indicative of slow-developing hidden leaks. Meter faults, missing data, and negative readings typically stem from calibration errors, meter malfunctions, or data transmission issues.

As shown below in Figure 2. A flow increase event was detected for a DMA. The yellow region indicates the period during which the system has determined the event occurred. The label 'A' indicates the start of the event, the label 'E' indicates the end of the event, and the hash '#' indicates the peak magnitude at 20l/s. Although the event started at 7/04/26 9:00 pm, the system as shown in Figure 1. Notified the control centre 8/04/26 1:09 am.

For this utility, the data transmission from the flow metres is every hour, so that delay must also be considered when viewing the results.

Analysis methodology

The performance of the KaaS service was assessed by extracting all events from July 2023 to April 2026 to determine the event-detection time for all event types. Within this data, each event has a detection time of an event, the point at which a user is alerted, and an initial start time of the event, the point at which the anomaly began appearing. The results were divided into different event types based on the detection criteria.

Event Detection Definition:
Detection Time (Δt) = Time of Alert Generation – Time of Event Onset

Event onset is retrospectively determined based on deviation from baseline. Alert generation occurs automatically when calculated ad-hoc thresholds are exceeded.
A benefit of the events being monitored and interpreted by data analysts within the control centre is that each event is assessed by skilled TRILITY personnel to verify that it has actionable outcomes and to cleanse any potential data misinterpretation. The recorded actions and feedback from the data analysts to the system then allow the system to self-learn from previous classifications and improve future detection accuracy.

Results

A total of 401 events were analysed across all categories. Table 1 shows that flow-increase events are most indicative of leaks, with a median detection time of 5.8 hours and 75% detected within 8.8 hours. It also shows that 219 out of all 401 events, approximately 55%, were detected as flow events. Flow trend events exhibited longer detection times, ~ 1,513 hours or 63 days, reflecting the challenge of detecting gradual leakage. The second notable high detection time comes from the data transmission failure events, which had values up to 241 hours (10 days). The flow increase event type has one outlier at 94.13 hours due to a permanent network change in the corresponding DMA, which was excluded from this table. For the remaining event types, flow increase, decrease, consumption usage and fault events, the maximum time to identify the event was approximately 3 days, and the minimum time was 2 hours.

The two key event types for early identification of leaks are flow increases and leak events; their detection times were plotted against the magnitude of the corresponding event. As shown in Figure 3, there is a negative correlation between detection time and magnitude. This means that higher-magnitude events are identified more quickly than low-magnitude events.

As shown in Figure 4, the distribution of detection times for flow events typically fall below 15 hours, whereas consumption events may take up to 65 hours in some cases.

Discussion

The results demonstrate that digital monitoring systems can significantly improve the speed and consistency of leak detection compared with traditional reactive approaches. Detection performance is influenced by event magnitude, DMA characteristics, and data resolution and transmission frequency.

While automated systems provide continuous monitoring, effective operational outcomes depend on translating detected anomalies into reliable, actionable insights. In this implementation, structured validation of detected events improved confidence in alerts and supported more targeted field response.

Evidence of impact includes a reduction in NRW volume from an initial 25% loss, a reduction in response time to field actions from weeks or months to less than 9 hours for 70% of flow-increase events, and a reduction in unnecessary investigations or field-response dispatches. Limitations include detection delays for low-magnitude or gradual leaks, which are easily identified by data analysts in the control room via the CEM, dependence on data quality and DMA configuration, and a limited sample size for certain event types.

Conclusion

This study demonstrates that integrated digital monitoring systems using a KaaS model can significantly improve early leak detection within water distribution networks.

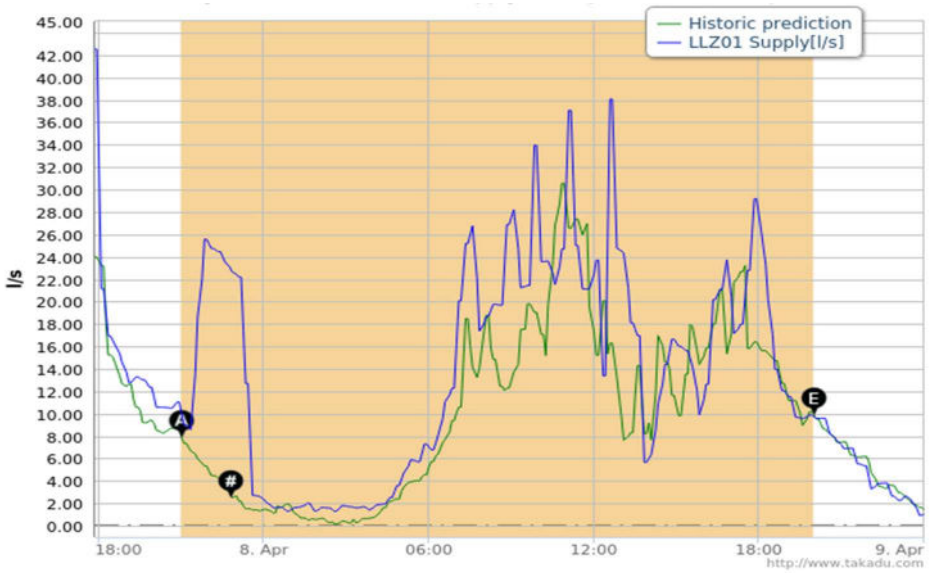
Key outcomes:

- Possible leak detection time for flow events has a median of 5.8 hours, and with 75% detected under 8.8 hours

- reduction in leak detection time from weeks or months for regular maintenance checks to remote detection within 3 days for 98% of detected events

In contrast to traditional weekly or monthly maintenance tasks that involve physical inspection of flowmeters or network assets, the KaaS model enables significantly faster detection with substantially reduced resource requirements. This frees internal or external resources to be scheduled for planned rectification works, rather than incurring higher costs associated with reactive breakdown responses to major bursts. This approach significantly mitigates financial, reputational and environmental losses, helping protect Australia’s

valuable potable water resources. This early-detection system provides automated event detection, continuous monitoring, event verification, and advanced data analysis to enable fast, effective notification of network leakage incidents. Rather than waiting for scheduled inspections while leaks worsen and non-revenue water quietly erodes budgets, this system continuously monitors the water distribution network, identifying issues early to safeguard reputation and both infrastructure and financial performance.



Event detected
Type is: Flow (Increase)
Status is: Open
Magnitude is: 20.00 l/s
Category updated to Actionable
Chosen prediction: Historic prediction
Based on Smartfill data
8/04/26 1:09 AM TaKaDu

Figure 1 Event Detection Log

Figure 2 Historic and transmitted DMA data - Flow Increase Event

Table 1 Time difference between Event Start and Event Detected (hrs)

Type of event	Count of Events	Average	Median	Max	Min
Consumption Increase	51	36.63	34.12	65.07	22.05
Consumption Decrease	7	36.84	37.35	49.30	29.18
Fault	25	21.04	19.62	74.42	2.00
Flow Decrease	17	11.37	10.33	31.17	4.65
Flow Increase	219	7.88	5.77	48.83	1.80
Flow Trend	3	1514.26	1514.13	1515.35	1513.30
Negative	29	8.80	6.33	43.47	4.32
Usage	40	9.43	7.43	29.07	2.95
no data	7	126.10	123.70	241.30	50.25
Leak	3	2.79	2.93	3.17	2.27

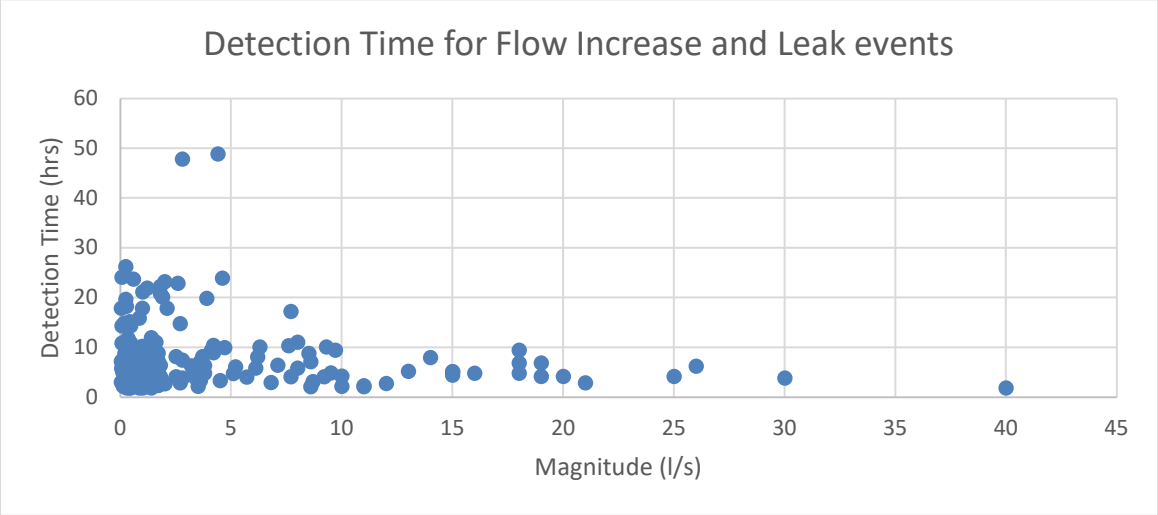


Figure 3 Detection Time for Flow events over magnitude

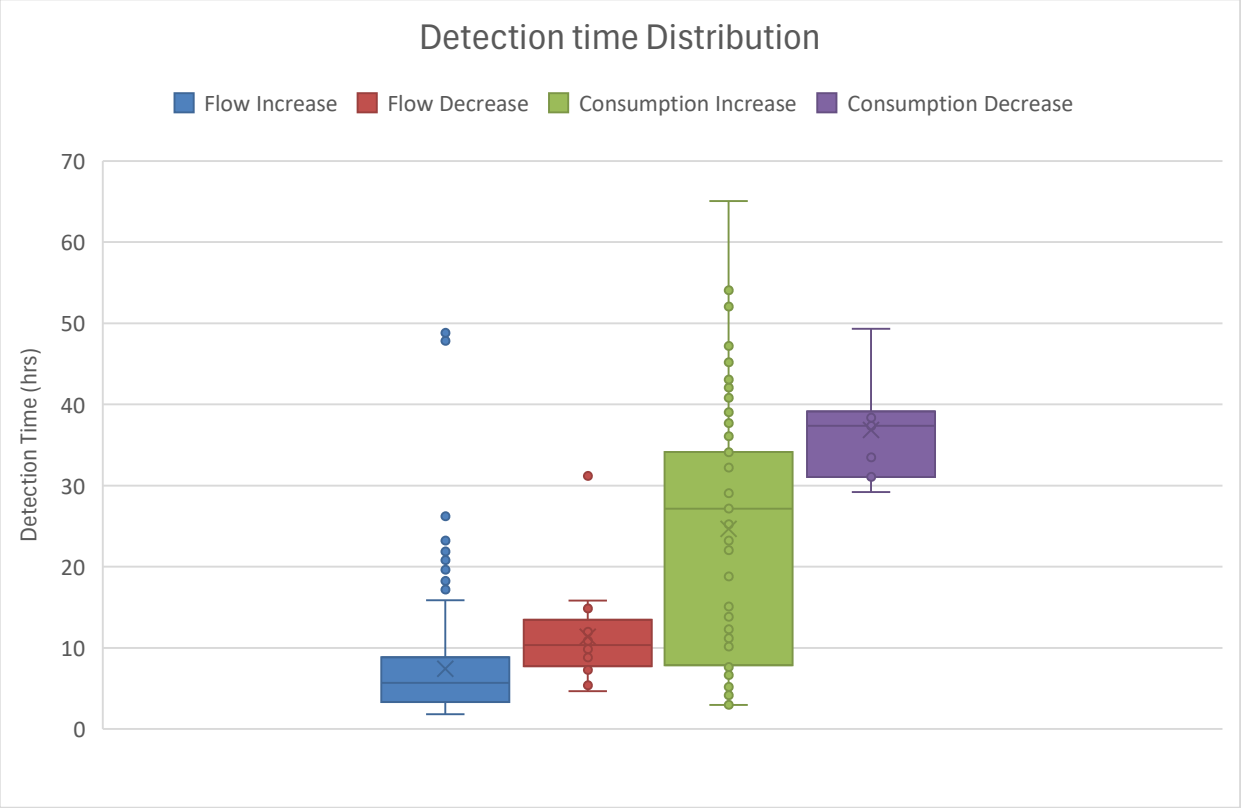


Figure 4 Detection Time Distribution for flow and consumption events