Machine-learning-based fresh water service reservoir outflow data logging system and virtual outlet flowmeter

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ABSTRACT

This paper presents the implementation of a Virtual Outlet Flowmeter (VOF) and a Service Reservoir Outflow Data Logging System (SRODLS) in a Fresh Water Service Reservoir (FWSR). A VOF offers a cost-effective solution for estimating outlet flow rates without physical meters. SRODLS improves the data quality by providing continuous logging and remote access to critical data, facilitating efficient fault detection and troubleshooting. The paper also explores machine learning anomaly detection systems to identify data inconsistencies and potential issues in water flow data. By leveraging historical data and advanced algorithms, the system can detect unusual patterns that may indicate problems such as leaks or infrastructure failures. The application of machine learning in forecasting and anomaly detection is seen as a significant step forward in water resource management. The results show that the implementation of VOFs and SRODLS in pilot FWSRs has been successful, contributing to better planning and management of water resources with minimal operational impact. The paper concludes with the potential for future developments, including the analysis of minimum night flow and the creation of APIs for hydraulic modelling, to further enhance water loss detection and resource management.

KEYWORDS Water supply; data analytics; virtual metering; machine learning; water resources, control automation and instrumentation

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1. Introduction

1.1. Background

Water is one of the most valuable resources across the globe. The Water Supplies Department (WSD) aims to provide reliable and adequate supplies of high-quality water to a population of about 7.5 million people in Hong Kong.

With no natural lakes, large rivers, or underground water, Hong Kong faces the challenging task of securing an adequate and sustainable supply of water to meet its development needs. Over the years, Hong Kong has developed an extensive rainwater collection and storage system. About one-third of Hong Kong's land is designated as water gathering grounds where surface runoff is collected for storage. Most of the gathering grounds fall within country parks, and are thus protected by the Country Parks Ordinance.

Fresh water service reservoirs (FWSRs) play an important role in water resource management by providing transient storage for fresh water to cope with the peak demand and help manage the supply water pressure. They also serve as a buffer for maintaining supply when the trunk mains are not operating (e.g., during maintenance). FWSRs are normally constructed on high ground so that gravity will help assert enough pressure to supply water to customers through the distribution network.

Monitoring the water resource in FWSRs not only ensures reliable water supplies to customers, but also provides insights into water leakage in the FWSRs.

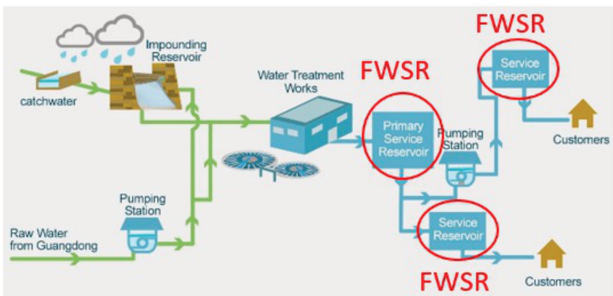

Figure 1. Hong Kong fresh water supply schematic.

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1.2. Existing Instrumentation Standard Design of a Service Reservoir

The current standard design for instrumentation, widely utilised in service reservoirs, comprises the following measuring instruments:

(a) Water level instruments; and

(b) Water flow instruments.

In the domain of industrial instrumentation and measurement, two primary categories of signals are recognised: analogue and digital. The former utilises a 4-20mA direct current (d.c.) signal, predominantly employed for signals exhibiting continuous variation, such as water level and flow rate. In contrast, digital signals are represented by the open or closed state of a pair of dry contacts, primarily utilised for signals with discrete variation, including overflow level, equipment start/stop control, and alarms.

In the recent period, with the technological advancements in the design of electromagnetic (EM) flowmeter converters, digital communication protocols such as Fieldbus and HART (Highway Addressable Remote Transducer) have garnered substantial prominence and are extensively implemented in new flowmeter installations or during flowmeter replacements. These protocols offer multifarious advantages over conventional analogue signals, encompassing enhanced precision, dependability, and adaptability.

The standard provision for a monitoring and control system for FWSRs is summarised in the following Table 1.

Table 1. Summary of standard provision of monitoring and control at a service reservoir.

Standard Provision	Monitoring	Control	Alarm	Equipment
(a) FWSR water level	X			Level Transmitter
		X		Electrode controller
			X	Float switch
(b) FWSR inflow Rate	X			Inlet flowmeter
		X		Valve actuator Pump control
(c) FWSR outflow rate	X			EM Outlet flowmeter /Virtual Outlet flowmeter

1.2.1. Water level instruments

Water level instruments include pressure sensing instruments, submersible-type level transmitters, and ultrasonic level instruments (Loizou & Koutroulis, 2016). Readings from a level transmitter provide a momentary portrayal (snapshot) of the level status at a specific point in time. Factors like inflow and outflow may cause rapid level fluctuations. In typical FWSRs, submersible-type level transmitters and ultrasonic level instruments are used due to their reliability and accuracy (Shenoy & Venkata, 2025).

1.2.2. Water flow instruments

There are various water flow measuring instruments such as differential pressure flowmeter, open channel EM flowmeter, ultrasonic flowmeter, float flowmeter, and vortex flowmeter in the market (Sun, Chen, Liu et al., 2020). In FWSRs, EM flowmeters and Virtual Outlet Flowmeter (VOF) are implemented in consideration of site constraints and complexity of works.

In a typical FWSR, a flowmeter is installed at the inlet to measure the inlet flow rate of the FWSR. In the past, dall tubes were widely adopted for this purpose (Baker, 2016). With EM flowmeters becoming more cost-effective, EM flowmeters have dominated such applications. The EM flowmeter utilises the principle of EM induction to measure the flow of conductive fluids (Wu et al., 2018). EM flowmeters have less stringent straight pipe requirements, typically 10D upstream and 5D downstream where D is the diameter of the pipeline (Fowles & Boyes, 2010), which enables them to be predominantly installed at locations where the available length of straight pipe is a constraint.

In the majority of service reservoirs, the instantaneous flow rate signal is still transmitted utilising an analogue signal of 4-20mA d.c. An integrator (counter) is implemented to determine the totalised flow rate. This value is subsequently communicated to the SCADA system in the form of pulse signals for statistical analysis.

In new flowmeter installations and replacements, electromagnetic (EM) flowmeters equipped with converters supporting communication protocols such as Fieldbus and HART are gradually being adopted (Shercliff, 2022). The accuracy of the field signal transmission, in both analogue and statistical values, can be directly read from the registers of the EM flowmeters. This eliminates the need for analogue-to-digital conversion or current-to-pulse integration at the flow converter, which inevitably introduces errors during the data conversion process.

1.3. Data retrieval methods

Two primary methods could be adopted for data retrieval: report by interval (RBI) and report by exception (RBE), with existing FWSR using an RBE mechanism on WSD Supervisory Control And Data Acquisition (SCADA) systems for overall monitoring and control of pumping stations and FWSR territory wide. RBE only passes on data to SCADA if the readings from the instruments have changed by more than a specified amount.

The widespread adoption of RBE in WSD's SCADA system is rooted in historical necessity. During the 1990s, when the SCADA system was first developed, communication networks were significantly less advanced than today. Bandwidth scarcity and unreliable communication channels posed major challenges. In this environment, RBE emerged as a revolutionary solution, demonstrably optimising bandwidth usage. Its focus on transmitting only critical information—alarms, events, and changes in parameters—proved to be a game changer for SCADA systems, enabling efficient data communication despite limitations in the underlying infrastructure.

RBE offers a more efficient alternative by only transmitting data when a data point's status or value changes. This trigger-event-driven approach optimises bandwidth usage by sending data only when necessary. Benefits include:

- Reduced Network Traffic: By eliminating unnecessary data transmissions, RBE minimises network strain and promotes a more reliable system.
- Improved Operator Efficiency: Operators receive alerts only for changes, allowing them to focus on critical events and prioritise tasks. Faster response times for critical situations translate to minimised damage and downtime. Additionally, knowing the exact time of an event enhances situational awareness and facilitates more effective diagnosis. However, RBE presents challenges in data pattern analysis limitations: the discontinuous nature of RBE data, with different data types having varying time intervals, can complicate analysis and limit the insights derived, potentially hindering its suitability for data pattern analysis.

RBI transmits data at predetermined intervals, regardless of changes in data point status or value. This ensures a steady stream for consistent monitoring and analysis, particularly beneficial for data pattern analysis.

Figure 2 shows the use of RBI data and RBE data for an inlet flowmeter. Unfortunately, RBE is unable to show a meaningful trend for analysis.

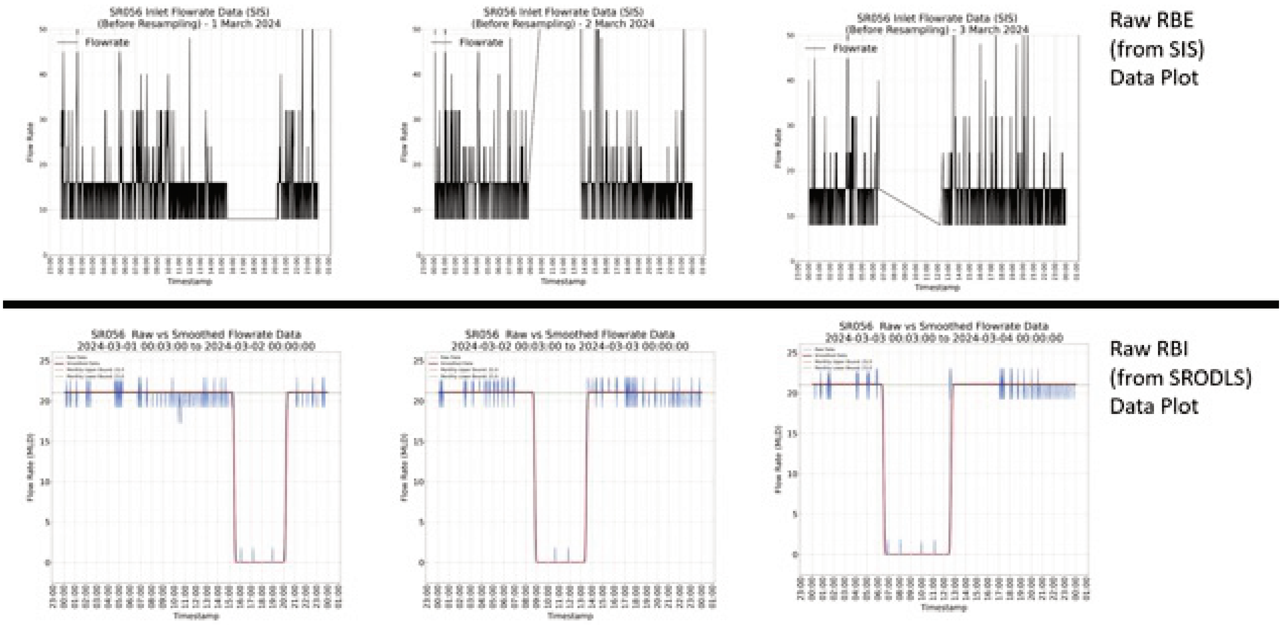


Figure 2. Comparison of RBI data and RBE data for an inlet flowmeter.

1.4. Limitation on outlet EM flowmeter installation

The absence of outlet EM flowmeters in most FWSRs is primarily attributed to spatial constraints as described in Section 1.2.2. Nonetheless, outlet flowmeters offer valuable insights into consumption patterns within the supply zone. This information is pivotal for water demand forecasting and detecting and monitoring trunk main or distribution main leakages, especially under minimum night flow conditions, when compared against the inlet flow of downstream FWSRs or data obtained from District Metering Areas (DMAs).

Identifying suitable locations for outlet flowmeter installation in existing FWSRs is challenging. Even when space permits, installation and replacement require temporary suspension of the water supply, making it prohibitively difficult or operationally unacceptable to install outlet flowmeters in existing FWSRs.

1.5. Objective of this project

There were three main objectives of the project:

(1) Continuous logging of FWSR outflow with regular timestamps;

(2) Formulate a historian database of FWSR outflow for water loss analysis; and

(3) Detect anomalies of instruments in FWSRs.

2. Methodology and technology

2.1. Virtual flow metering

To overcome the physical limitation of installing outlet flowmeter at existing FWSRs and minimise service interruption, virtual flow metering was selected. Virtual flow metering is an increasingly attractive method for the estimation of flowrates without using expensive metering devices (Bikmukhametov et al., 2020). A virtual flow meter is a mathematical model that uses process conditions to estimate flow rates instead of using a physical meter. By adopting the concept of virtual flow metering, a native VOF was designed for FWSRs.

A VOF is a software-based system that measures the outlet flow of FWSRs without requiring in-situ physical flowmeters (Nikolai, 2018). It leverages periodic snapshots of inlet flow and volume changes in the FWSR to calculate the outlet flow. A VOF panel consists of a Programmable Logic Controller (PLC) equipped with dedicated software and add-on modules designed to compute the virtual outlet flow of the FWSR.

The quality of VOF computation relies heavily on precise inlet flowmeters, level transmitters, and meticulously calibrated FWSR capacity lookup tables. Data quality issues may arise due to discrepancies in inlet flowmeter or level sensor data, leading to inaccuracies in the computed virtual outlet flow. The only hardware-related error associated with a VOF panel is a PLC malfunction resulting from electronic component failure.

Unlike physical EM flowmeters, a volumetric test for VOF calibration is impractical because a VOF is a virtual system that depends on data inputs rather than direct physical measurements. VOF troubleshooting primarily involves ensuring the accuracy of input devices and conducting periodic PLC inspections. VOF troubleshooting involves data logging the readings of input devices in snapshot mode at regular intervals for a predetermined period, replicating the computation process, and identifying any PLC errors or input-related issues.

The VOF panels are installed on the FWSR without any EM outlet flowmeter for local VOF calculation works. The VOF panel computes the outlet flow based on the instantaneous inlet flow and the change in volume within the FWSR, obviating the need for a physical flowmeter at the site. A VOF consists of a PLC equipped with a software program and the requisite add-on modules necessary for calculating the FWSR outlet flow. The reading of a VOF is stored in the PLC flow counter of the VOF panel.

The outlet flow is calculated using the formula in Figure 3 below, where the outlet flow is obtained from the difference between the inlet flow and volume change in the FWSR. With the calculated outlet flow of the FWSR, it is equivalent to virtually installing an outlet flowmeter for the FWSR. Given that FWSRs are well covered and loss of water due to evaporation or groundwater loss is limited in short periods, the calculation is performed in 3-minute intervals.

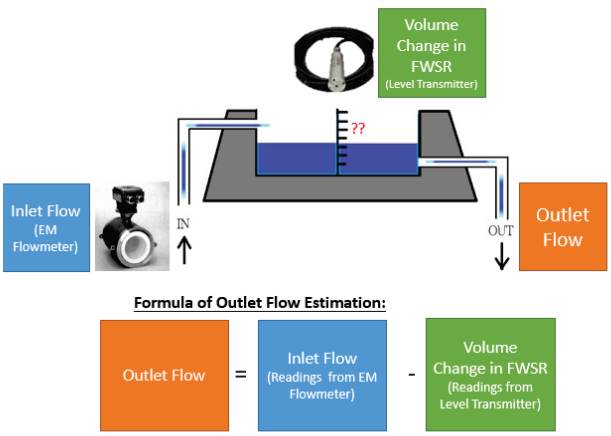


Figure 3. Formula for outlet flow used in the virtual outlet flowmeter.

2.2. Service Reservoir Outflow Data Logging System (SRODLS)

While SCADA historical data, including FWSR instrument data, is stored in the SCADA Information System (SIS), it cannot be utilised for VOF troubleshooting efficiently due to the report-by-exception data retrieval mechanism employed by the SCADA system. This discontinuous and irregular data logging results in inconsistent timestamps for inlet flow, water level, and VOF data, making it a headache to replicate the computation in the VOF panel and diagnose the root causes of data anomalies and abnormal patterns in VOF data. Additionally, given the rural locations of many FWSRs, VOF troubleshooting tasks can become repetitive and resource intensive without a remote data logging system.

To address these challenges, the SRODLS was developed. The SRODLS provides continuous data logging at specified intervals and enables remote access to the inlet flowmeter, level transmitter, and VOF data at consistent and regular timestamps. This system facilitates efficient monitoring, fault detection, and remote troubleshooting. The SRODLS eliminates the need for manual data logging and thus reduces the frequency of site visits, saving time, manpower, and resources. Moreover, the SRODLS can identify data anomalies and abnormal patterns through the application of anomaly detection algorithms.

The SRODLS comprises Projected Time Modeller (PTM) panels at the FWSR and a Virtual Machine (VM) Master Station hosted in a VM server at the WSD office. The PTM panels interface with the VM Master Station by utilising cellular networks via secure Virtual Private Network (VPN) tunnelling.

Figure 4 shows the system architecture of the SRODLS, where the PTM panels collects the measurement data from the inlet flowmeter and level transmitter in the FWSR and transmits the data to the SRODLS panel for data logging. The calculation of outlet flow is done at both the PTM panels and SRODLS panel for counterchecking of calculation error.

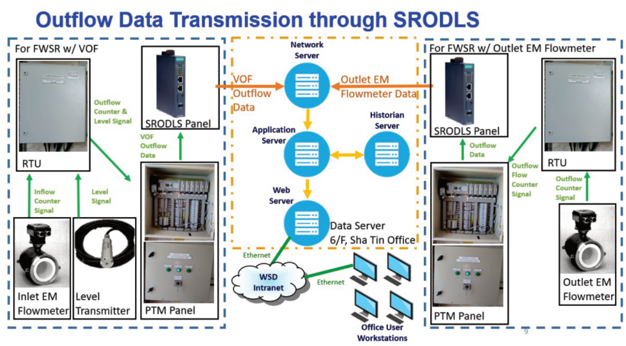


Figure 4. System architecture of the SRODLS.

Table 2. Components of the system.

Data Collection Devices	
Component	**Functions**
PTM panel	• Collects data from the inlet EM flowmeter and level transmitter of SRs; • Performs calculations of the VOF; and • Calculates the Projected Time to Fullness, Projected Time to Emptiness, and Projected Time to Level Low of an FWSR
SRODLS panel	• Consists of 4G router, edge PC. Ignition Edge in Moxa edge PC; • Calculates the VOF using the data collected from the PLC and transmits results to the server via 4G cellular connection; • Collects historical data of the VOF; and • Records data locally for up to 1 week, and backs up data to the remote server
Application server	A VM Master Station processes the following data from each SRODLS panel of the FWSRs: • Inflow counter signal is generated from the Inlet EM flowmeter; • Level signal is generated from the Level transmitter; • VOF outflow data is generated from the PTM panel; and • Outflow counter signal is generated from the Outlet EM flowmeter
Historian server	• Storage of FWSR outflow data in 3-min and 15-min intervals
Web server	• Provides a web interface to allow users to view the real-time FWSR outflow, extract the historical outflow data for analysis, and generate dashboard charts

2.3. Machine learning anomaly detection system

Common types of anomalies which may occur in flowmeter data include spikes and dips, flat lines, and zero offsets in the analysis of weekly data for EM flowmeters and level transmitters in an FWSR. These anomalies will be reflected in the VOF calculated as spikes and dips, flatline, and irregular patterns. The anomaly data provides insights on the condition of an FWSR.

2.3.1. Inflow anomaly detection

• Zero flow time > 95% detection

The algorithm identifies whether more than 95% of the inflow data points within a week are zero values.

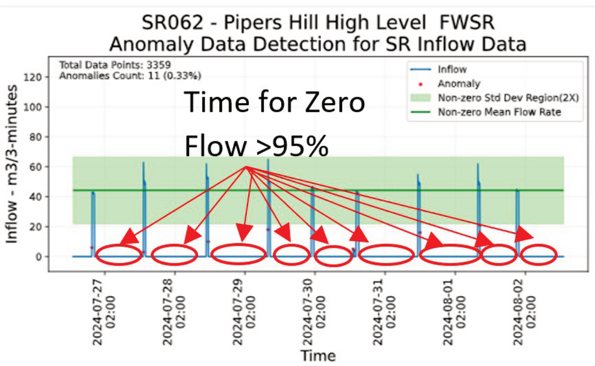
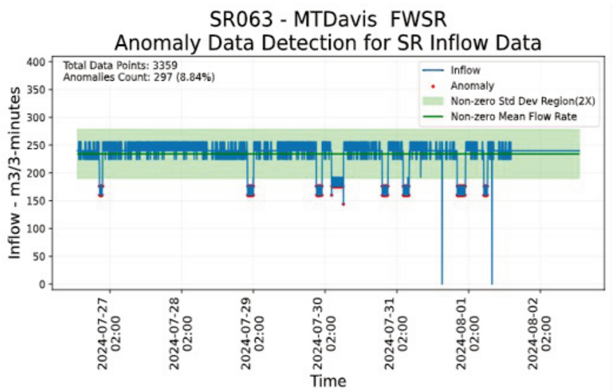


Figure 5. Example from Pipers Hill High Level FWSR (SR062) for zero flow time > 95% detection.

• Statistical outlier detection

To address scenarios where varied data is recorded due to electromagnetic (EM) wave interfering instruments or instrumental random error, a statistical outlier detection algorithm is created. The statistical outlier detection algorithm identifies data that falls outside the range of 2 σ (two times larger than the standard deviation of the dataset).

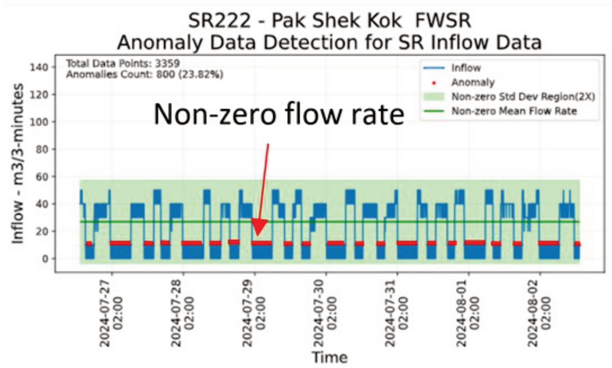


*Red spot indicates the anomaly.

Figure 6. Example from Mount Davis FWSR (SR063) for Statistical Outlier Detection.

• Zero offset anomaly detection

To address the inaccuracies during the calibration process of an instrument, Zero offset anomaly detection is created. The detection algorithm evaluates inflow data within a specified timeframe to determine if it primarily consists of zero values. Any non-zero values within this window are classified as zero offset anomalies.



*Red spot indicates the anomaly.
Figure 7. Example from Pak Shek Kok FWSR (SR222) for Zero Offset Anomaly Detection.

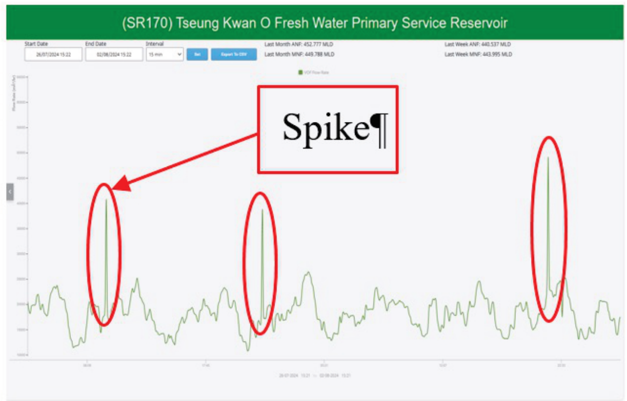
2.3.2. Outflow anomaly detection

Similar to the detection of an inflow anomaly, the detection of an outflow anomaly is summarised in Table 3.

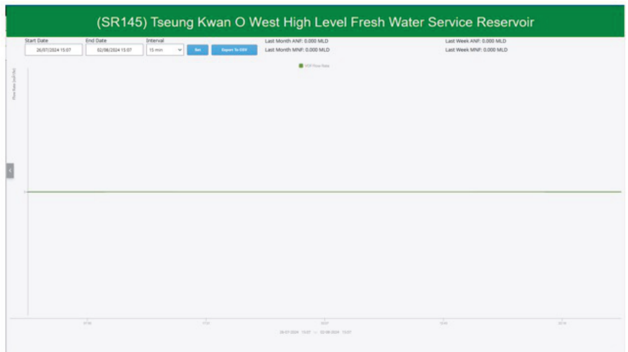
Table 3. Summarisation of the outflow anomaly

Anomaly	Pattern Description	Causes
Spikes & Dips	Sudden and sharp increases/decreases in flow rate	VOF • Incorrect data input EM flowmeter • Faulty flowmeter • Electrical noise or interference
Flatline	Periods when flow rate remains constant or nearly constant	VOF • Incorrect data input EM flowmeter • Faulty flowmeter • No flow through flowmeter
Irregular Pattern	• The daily patterns are not close to the major pattern of other days. • Cannot establish a major pattern.	VOF • Incorrect data input EM flowmeter • Faulty flowmeter

(a)



(b)



(c)

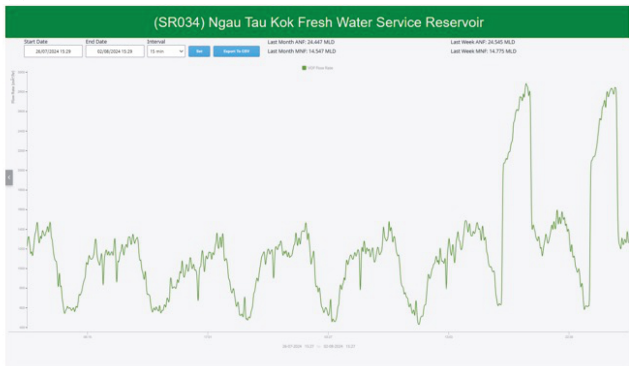


Figure 8. Example of (a) spikes, (b) flatline, and (c) irregular pattern of the outflow anomaly.

Unlike FWSR inlet flow, there are several factors that influence FWSR outlet flow rates, including daily usage patterns, pipe network infrastructure, elevation variations, and seasonal changes. Traditional methods like standard deviation have limitations in analysing FWSR outlet flow data due to its non-normal distribution and insensitivity to specific usage patterns.

Unsupervised learning offers a more robust approach for anomaly detection in water flow data. Unsupervised learning algorithms like Prophet can identify deviations from normal usage patterns without requiring labelled data.

By leveraging unsupervised learning's ability to recognise complex patterns and facilitate real-time monitoring, water utilities can gain a deeper understanding of their water supply zones. This allows for proactive identification of potential issues and optimisation of water distribution, ultimately ensuring a reliable and efficient water supply for the community.

Among candidate machine learning models—including Long Short-Term Memory (LSTM) and Auto Regressive Integrated Moving Average (ARIMA)—Prophet was selected for yielding the lowest mean squared error in water consumption forecasting (Udhbhav et al., 2024). This performance underscores its suitability for medium-term predictions influenced by seasonal fluctuations and persistent trends (Sulaiman et al., 2023).

Prophet was developed by Facebook as an algorithm for the in-house prediction of time series values for different business applications. Therefore, it is specifically designed for the prediction of business time series (Taylor & Letham, 2017).

It is an additive model consisting of four components:

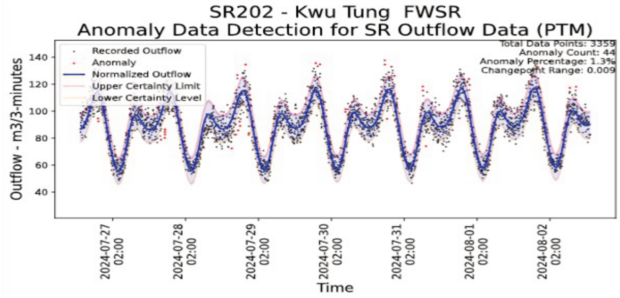
$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t. \quad (1)$$

- g(t) represents the trend, and the objective is to capture the general trend of the series. For example, the number of advertisement views on Facebook is likely to increase over time as more people join the network.
- s(t) is the Seasonality component. The number of advertisement views might also depend on the season. For example, in the Northern hemisphere during the summer months, people are likely to spend more time outdoors and less time in with their computers. Such seasonal fluctuations can be very different for different business time series. The second component is thus a function that models seasonal trends.
- h(t) is the Holidays component. The information for holidays has a clear impact on most business time series. Note that holidays vary between years, countries, etc. and therefore, the information needs to be explicitly provided to the model.
- The error term ε_t stands for random fluctuations that cannot be explained by the model. As usual, it is assumed that ε_t follows a normal distribution N $(0, \sigma^2)$ with zero mean and unknown variance σ that has to be derived from the data.

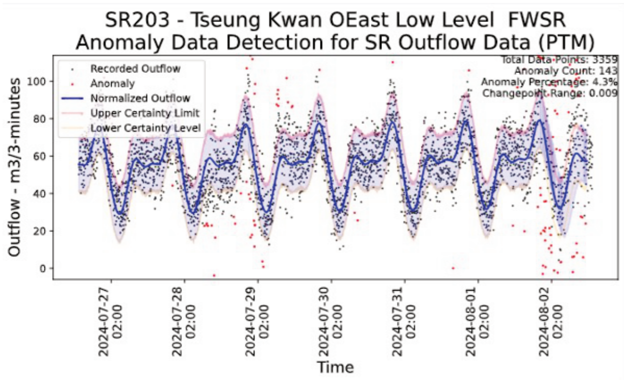
By leveraging historical data, Prophet offers a data-driven approach to anomaly detection. It isolates the underlying trend by removing the effects of seasonality, allowing for the identification of anomalies that deviate from the expected range. These anomalies can indicate issues such as leaks, bursts, unauthorised use, or flowmeter malfunctions.

The Prophet model provides the upper and lower certainty limit of the nominal outflow value. The anomaly detection counts the number of data falling outside the limit within the past 7 days. If the count is greater than 5% of the total counts of outflow, it is then considered as having faulty instruments.

(a)



(b)



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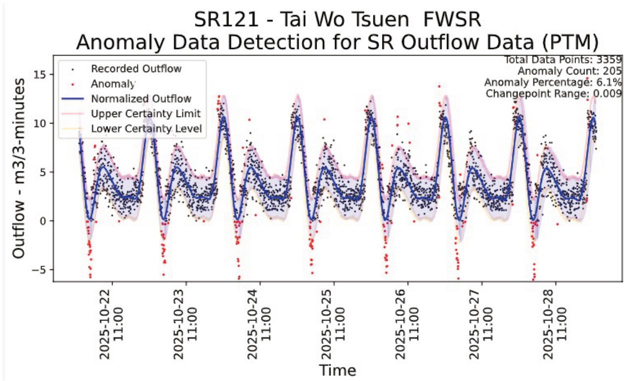

Figure 9. Example for (a) Pattern Anomaly Detection (High) in Kwu Tung FWSR (SR202); (b) Pattern Anomaly Detection (Tolerable) in Tseung Kwan O East Low Level FWSR (SR203); and (c) Pattern Anomaly Detection (Under Maintenance) in Tai Wo Tsuen FWSR (SR121).

3. Validation of VOFs and SRODLSs

To validate the accuracy of a VOF, a comparison of measurement data from DMA (bottom-up approach by summing the flow rate of downstream flowmeters to the FWSR) was made at Tui Min Hoi FWSR. The data of four days illustrated that the VOF data and DMA data has a reasonable correlation of (R^2 value) 0.8. This demonstrates that the VOF can estimate the outlet flow with sufficient accuracy for water balance analysis.

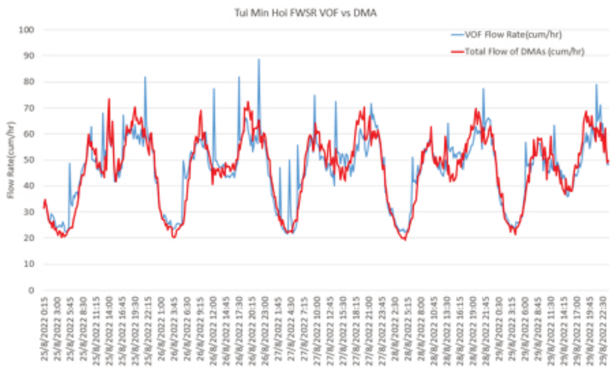

Figure 10. Comparison of VOF data and DMA data for Tui Min Hoi FWSR.

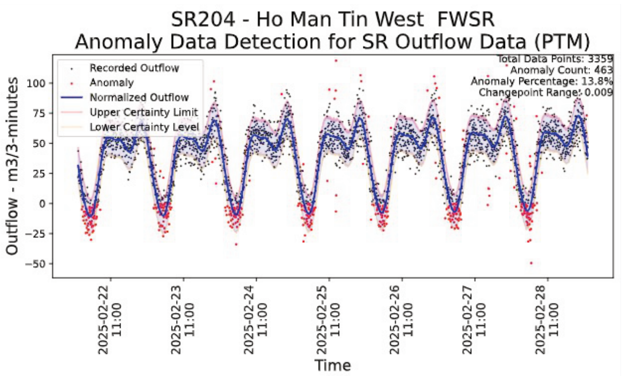

Figure 11. Pattern Anomaly Detection in Ho Man Tin West FWSR (SR204).

Figure 11 illustrates an example where the outflow recorded is a negative value. This implies that the SRODLS detects faulty instruments (i.e., EM flowmeter or level transmitter or PLC error) in FWSRs. A further site check confirmed that the concerned FWSR inlet flowmeter was faulty. This provides a proactive monitoring approach to detect instrument errors in FWSRs.

4. Results and discussion

A dashboard of anomaly detection was created to keep track of the data quality and compare the PTM result and calculated formula of capacity of the FWSR. The VOF data was analysed daily using the past week's history. Anomalies <3% were considered as good quality data, anomalies of 3% - 5% were considered as tolerable quality data, and anomalies > 5% were considered as poor quality data, and the SRODLS would convert the FWSR into "under maintenance" mode.

The summary of VOF data quality of 47 FWSRs is shown below: the results showed that 51% of VOF data was of good quality, while 11% was tolerable, 17% was poor quality due to operational implication (e.g., maintenance works at FWSR), and 21% was poor quality.

The tolerable data quality was mostly due to an inconsistent inlet/outlet flow pattern as compared with the past week. The tolerable data quality would be of good data quality if the operational pattern returns to normal.

The 21% poor data quality was due to a software bug and inlet EM flowmeter transient measurement data.

5. Limitation and Way forward

The measurement of outlet flow of FWSRs alone cannot deduce the water loss at FWSRs. There are two potential methods to achieve this target in the future:

- Nighttime consumption of water is much lower than that in the daytime. A baseline of minimum night flow shall be set up for each FWSR. The analysis of trends in minimum night flow via machine learning algorithms could be implemented such that if there is a gradual increase in the minimum night flow of FWSRs, an alarm will be triggered to draw users' attention to the potential water loss in an FWSR and/or fresh water supply zone.
- Development is needed of an Application Programming Interface (API) on the SRODLS for outputting the outflow data at regular time intervals for separate water distribution hydraulic models to identify the potential water loss areas. Combining the readings on water flow and pressure sensors in distribution network, water loss in fresh water supply zones can be deduced.

VOFs and SRODLSs could be further utilised in salt water service reservoirs and other reservoirs for the detection of instrument errors and potential water loss.

6. Conclusion

The successful deployment of the VOF and SRODLS implementation in pilot FWSRs enables the WSD to achieve better planning of water resources in FWSRs and identifying the potential water loss at FWSRs and fresh water supply zones in the future, while without needing to interrupt the water supply services to customers and with minimal installation cost as compared with conventional EM flowmeters. The integrated machine learning module provides proactive instrument monitoring and automated data cleansing, significantly reducing manual inspection efforts.

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