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NRW ESTIMATION AND LOCALIZATION IN WATER DISTRIBUTION NETWORKS VIA HYDRAULIC MODEL CALIBRATION USING 24/7 MONITORING DATA

Alvin Wei Ze Chew[1]; Zheng Yi Wu[2]; Rony Kalfarisi[3]; Meng Xue[4]; Jocelyn Pok[5]; Jianping Cai[6]; Kah Cheong Lai[7], Sock Fang Hew[8], Jia Jie Wong[9]

[1, 3,4,5,6] Bentley Systems Singapore Pte Ltd, 1 Harbourfront Pl, Singapore 098633
[2] Bentley Systems, 76 Watertown Rd, Thomaston, CT 06787, USA
[7,8,9]Water Supply (Network) Department, Public Utilities Board (PUB), Singapore

[1]*Alvin.Chew@bentley.com,* [2]*Zheng.Wu@bentley.com,* [3]*Rony.Kalfarisi@bentley.com,*
[4]*Meng.Xue@bentley.com,* [5]*Jocelyn.Pok@bentley.com,* [6]*Jianping.Cai@bentley.com,*
[7]*Lai_Kah_Cheong@pub.gov.sg,* [8]*Hew_Sock_Fang@pub.gov.sg,* [9]*Wong_Jia_Jie@pub.gov.sg.*

Abstract

Operations of water distribution networks (WDNs) are monitored daily via installed data loggers, where the collated hydraulic data can be leveraged to improve the system's operations over time, and to minimize total economic losses due to non-revenue water (NRW). In collaboration with Public Utility Board (PUB), Singapore's National Water Agency, a practically novel model calibration approach using 24/7 monitoring flow and pressure data has been developed to facilitate PUB's Smart Water Grid (SWG). The approach is developed as a generic integrated solution process to conduct a series of systematic analyses for daily WDN model calibration, namely: (1) estimating the system's daily NRW contributions; (2) performing flow calibration that involves net demand consumption calibration, adjusting pumps operational configurations and localizing NRW sources when the system's daily estimated NRW volume exceeds its assumed background volume; (3) performing energy calibration by rectifying possible drifting in monitored pressure head data and calibrating other physical properties which include, but not limited to, pipe roughness and valve settings, especially during peak-demand hours. The effectiveness of our proposed approach is subsequently tested on three WDN zones in Singapore, having a total pipe length of >100km, that comprises of atypical water usage patterns. The results of model calibration for one of three zones is presented in this paper. The key outcomes derived from the study are: (a) localized a reported leakage event by PUB to less than 100m; (b) calibrated the system's flow balance, to less than 1% average mean absolute percentage error (MAPE), by first identifying and addressing the system's billing data uncertainties, followed by localizing anomaly events that account for the total NRW volume estimated; and (c) calibrated the system's pipe roughness values to improve the total energy balance by achieving an average daily MAPE of 4.0%.

Keywords
water distribution networks; water losses estimation; anomaly localization; demand calibration; hydraulic model calibration; non-revenue water.

1 INTRODUCTION

Potable water is a necessity to sustain the humanity's daily livelihood. With an increasing global population, policy regulations and engineering management are expected to become more stringent to improve and ensure the supply of drinkable water to the public with minimum disruptions which, however, continue to be an engineering challenge to utility companies. For example, in the United States, an estimated volume of 6 billion gallons of treated water is reported to be lost each day [1]. On the other hand, while it may appears that managing underground water distribution networks (WDNs) in smaller countries is less complicated, Singapore, having invested in Smart Water Grid (SWG) [2] management, continues to strive to reduce their yearly non-revenue water (NRW) of around 5% of the total supplied waters. Overall, NRW components can never be fully eradicated during the real-world operations of WDNs due to the system's complexity and the presence of hidden/unknown anomaly events.

Over the years, many engineering approaches have been developed to assist operators to early detect and localize likely anomaly sources during the operations of WDNs, which can be grouped into (1) hydraulic model calibration, and (2) data-driven analytics. The former, that sets the focus of this paper, primarily leverages on physics-based simulations to calibrate the system's hydraulic properties which include flow, pressure, tank levels, pump operations, and demand patterns [3]–[7], where if appropriately calibrated, can represent the baseline operations of the WDN system as part of digital twinning [8]. The latter purely adopts data-driven/statistical methods to train anomaly detection and localization models [9]–[11], where the trained models can be combined with calibrated physics models for digital twin-based decision-supports in near real-time.

To build towards practically effective and useful calibrated hydraulic model(s), this paper identifies and addresses existing shortcomings from published calibration works, namely:

i. A common and inaccurate assumption of no water losses conditions during model calibration. As highlighted above, zero NRW component is never possible for the real-world operations of WDNs, hence the inability to model NRW as part of the calibration step may affect the baseline accuracy in representing the system's actual operations.

ii. Most works are restricted to relatively small networks with high density of sensors per area/pipeline, and leaks are usually simulated under controlled conditions to test the calibrated models for either detection or localization analysis, or both. Quite often, however, the operations of real-world WDNs have limited number of sensors deployed in large supply zones and occurring leaks are usually unknown in their physical characteristics during near real-time.

To address the above-outlined shortcomings, this work, in collaboration with PUB, Singapore, develops a practically novel daily model calibration approach that leverages on continuously monitoring flow and pressure time-series data to estimate daily NRW contributions in large WDNs by emulating near real-time, followed by performing total flow and energy calibration via calibrating the system's daily net demand consumption pattern(s) and importantly pinpointing possible anomaly events in the system which constitute to the everyday NRW volume estimated.

2 METHODOLOGY

2.1 Daily Model Calibration Approach

Figure 1 illustrates the overview of our proposed daily model calibration approach [12] that consists of 3 main systematic analyses for any operational WDN system, namely: (1) estimation of NRW components; (2) flow calibration; and (3) energy calibration. Details of each of the systematic analyses are as follows:

i. **NRW Estimation**: Leveraging on available billing data, collated via traditional metering means or advanced metering infrastructure (AMI), and daily total inflow time-series data to estimate the system's daily NRW volume and its corresponding time-series profile.

ii. **Flow Calibration**: Calibrating the system's net consumption demand pattern due to the real customers which may include accounting for varying water usage patterns due to different types of customers, adjusting available pumps operational configurations, finally performing NRW localization if the total NRW volume exceeds an assumed background NRW volume.

iii. **Energy Calibration**: After flow calibration, any remaining energy discrepancies in the system can be addressed via identifying and rectifying likely sensor drifting over time and adjusting other physical properties such as pipe roughness and valve settings, especially during the peak-demand hours, if justifiable.

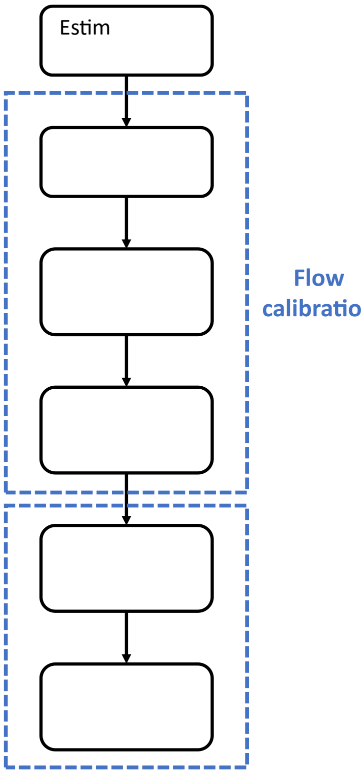


Figure 1. Overview of Daily Model Calibration Approach.

2.2 NRW Estimation

For any given day in the operational horizon, estimating its corresponding NRW is performed as follows:

i. Using either historical billing data or metered data derived from AMIs, the average daily consumption rate, termed as $Q_{c,daily}$, is first estimated, followed by approximating the total water consumption ($V_{c,daily}$) volume. For historical billing data, simple averaging techniques can be undertaken to estimate $Q_{c,daily}$ and $V_{c,daily}$ respectively. For example, if the billing data is collated monthly, then $V_{c,daily}$ is derived by averaging the total consumption volume by the total number of days for the specific month. Generally, data collected from AMIs with finer time-resolution are expected to be more accurate to estimate $V_{c,daily}$.

ii. Using daily monitoring data, the corresponding total net inflow time-series profile ($Q_{in,day}(t)$) is derived as follows:

$$Q_{in,day}(t) = Q_{R,day}(t) + Q_{AI,day}(t) - Q_{AO,day}(t) \tag{1}$$

$$V_{in,day} = \int_{t_0}^{t_1} Q_{in,day}(t)\,dt \approx \sum_{i=1}^{M} \frac{Q_{in,day}(t_i) + Q_{in,day}(t_{i+1})}{2} \Delta t_i \tag{2}$$

where $V_{in,day}$ is the total net inflow volume into the system, $Q_{R,day}(t)$ the time-series profile for the total reservoir inflows into the system, $Q_{AI,day}(t)$ the time-series profile for the total additional system inflows from the adjacent zones , and $Q_{AO,day}(t)$ the time-series profile for the total additional system outflows into the adjacent zones, excluding the billed customers in the system, t the time of the day, t_0 the starting time of the day, t_1 the ending time of the day, M total number of intervals along the time axis based on the defined time-step between t_0 and t_1, and i the time index.

iii. The total NRW volume ($V_{nrw,day}$) is then estimated as the difference between the total net inflow and daily water consumption, given as:

$$V_{nrw,day} = V_{in,day} - V_{c,daily} \tag{3}$$

If $V_{nrw,day}$ is estimated to be greater than an assumed background NRW volume, a corresponding NRW time-series profile ($Q'_{nrw}(t)$) is subsequently derived and then further deducted from $Q_{in,day}(t)$ to obtain the net demand consumption profile ($Q'_{in,day}(t)$) via the following solution procedures:

i. For a given number of pressure sensor stations (N) in the WDN system, we first estimate the average time-series pressure head profile ($P_{avg}(t)$) as:

$$P_{avg}(t) = \frac{1}{N}\sum_{i=1}^{N} P_i(t) \tag{4}$$

where $P_i(t)$ is the recorded pressure head of sensor station i at time t.

ii. Estimate an average emitter coefficient ($K_{avg,day}$) value via the well-known pressure-dependent leakage formulation (PDLD) [13] as follows:

$$V_{nrw,day} = K_{avg,day} \int_{t_0}^{t_1} \left(P_{avg}(t)\right)^n dt \tag{5}$$

$$\int_{t_0}^{t_1} \left(P_{avg}(t)\right)^n dt \approx \sum_{i=1}^{M} \frac{\left(P_{avg}(t_i)\right)^n + \left(P_{avg}(t_{i+1})\right)^n}{2} \Delta t_i \tag{6}$$

where n is the exponent, taking the common value of 0.5 for underground waterpipes.

iii. The estimated $K_{avg,day}$ from Eq. (5-6) is then used to construct the $Q'_{nrw}(t)$in Eq. (7), followed by estimating $Q'_{in,day}(t)$ using Eq. (8).

$$Q'_{nrw}(t) = K_{avg,day} \cdot \left(P_{avg}(t)\right)^n \tag{7}$$

$$Q'_{in,day}(t) = Q_{in,day}(t) - Q'_{nrw}(t) \tag{8}$$

2.3 Flow Calibration

Daily flow calibration in the operational WDN system comprising of 3 components, namely: (1) calibrating net demand consumption pattern(s) due to the real customers in the system, (2) calibrating pump operational configurations, and (3) NRW localization to account for the total estimated NRW volume.

2.3.1 Net demand consumption pattern(s) calibration

The system's daily net demand consumption pattern is calibrated via a simple Reference Averaging Approach (RAA) which leverages on the estimated $Q'_{in,day}(t)$ or $Q_{in,day}(t)$ by adhering to the following solution procedures:

i. Compute the average measured inflow value (V_{avg}) from $Q'_{in,day}(t)$ or $Q_{in,day}(t)$ using trapezoidal rule.

ii. Compute the temporal, i.e., at each time-step, ratio values between the respective monitored net inflow (due to real customers) values ($Q_m(t)$) and V_{avg} value as:

$$R(t) = \frac{Q_m(t)}{V_{avg}} \tag{9}$$

iii. The computed $R(t)$ values represent the adjusted demand multiplier values for deriving a new set of model simulated inflow values ($Q_s(t)$).

iv. Compare $Q_s(t)$ with either $Q'_{in,day}(t)$ or $Q_{in,day}(t)$ to compute a new set of temporal ratio values as:

$$R'(t) = \frac{Q_m(t)}{Q_s(t)} \tag{10}$$

v. The adjusted $R'(t)$ values obtained from Eq. (10) are then multiplied with the original $R(t)$ values to derive another set of demand multiplier values, as:

$$R''(t) = R(t) \times R'(t) \tag{11}$$

vi. The computed $R''(t)$ values are again used to derive another set of $Q_s(t)$ profile for comparing with $Q'_{in,day}(t)$ or $Q_{in,day}(t)$. Note that the previously estimated $R''(t)$ values become the newly represented $R(t)$ values.

vii. Repeat steps (iii – vi) till a satisfactory goodness-of-fit is achieved between $Q_m(t)$ and $Q_s(t)$ for the selected day.

Note the above proposed procedures using RAA are used to derive a singular universal demand pattern for all customers in the system. However, there may be cases where there can be multiple water usage patterns in the same system due to different types of customers (e.g., customers who tend to consume more water during the night that differs from the traditional diurnal pattern for water consumptions). To handle such scenarios, there is thus a need to develop daily local demand pattern(s) within a given system via the following solution procedures:

i. For a selected pool of junction nodes which are affiliated to a particular water usage pattern, assign an arbitrary emitter coefficient (K > 0) value to them. Repeat this step for N number of possible water usage patterns as determined by the modeller.

ii. Transform the assumed K value(s) into unique demand pattern(s) by following the PDLD formulation from Eq. (6), where the average pressure profile is derived from a singular or selected pool of pressure sensor stations which are situated in the near proximity of the junction nodes affiliated to their corresponding water usage pattern(s).

iii. Leverage on the transformed demand pattern(s) to simulate the system's flow and pressure head profiles, followed by comparing with the monitored individual/average pressure profiles of the selected stations, and $Q'_{in,day}(t)$ or $Q_{in,day}(t)$ for mass balance considerations.

iv. Adjust the multiple demand pattern(s) appropriately by adhering to the simple principle that higher pressures are affiliated to lower water usage pattern, and vice versa.

v. Repeat steps (ii-iv) till good agreement (<< 5% error) is achieved for comparing the simulated and monitored values for $Q'_{in,day}(t)$ or $Q_{in,day}(t)$. At this stage, since energy calibration has not performed, reasonable agreement (~1m) is expected for the individual/average pressure profiles, especially for the high-demand hours.

Practically, it is expected that bulk of the customers in a given supply zone follow a universal calibrated demand pattern, while localized demand pattern(s) are expected to be applied to unique and smaller pool of customers. Hence, it is recommended that the modeller first adopts the proposed RAA method to calibrate a universal demand pattern, before performing the local demand pattern(s) calibration with multiple iterations by ensuring that mass balance for $Q'_{in,day}(t)$ or $Q_{in,day}(t)$ is attained to the highest possible extent.

2.3.2 Pump operational configurations calibration

During the process of calibrating the net demand consumption pattern(s), it is equally important to also check that the internal pump flows within the system are properly calibrated against available monitored pump outflows to ensure the correct distribution of the pump energies to the different junction nodes. To do so, the modeller is required to calibrate the pump operating curves and control statuses. For the latter, it mainly involves adjusting the pumps' operational state of either fixed- or variable-speed characteristics. For fixed-speed pumps, their operational states can only be taken as a binary option of either “on” or “off”, while the operational states of variable-speed pumps range between 0.0 (fully switched off) and 1.0 (fully switched on).

2.3.3 NRW localization

If the estimated daily NRW volume is greater the assumed background NRW volume, NRW localization will be performed by using the same PDLD method [13]. The method generally enables the modeler to select and aggregate any combination of junction nodes into a demand group within the network. In each demand group, a given number of the junction nodes will then be identified as potential anomaly hotspots via suitable emitter coefficients which contribute “additional” flow demand to the system, hence emulating the estimated NRW volume for the specific day. Before NRW localization, it is expected that the system’s pipe connectivity, valve settings, pump configurations, if available, and net demand consumption pattern(s) are taken to be calibrated, to the best possible extent.

The PDLD method can be formulated as an implicit non-linear search problem which determines the pool of junction nodes having positive K values to emulate the leakage hotspots in the system. The PDLD method is integrated with the optimization-based model calibration tool [14], [15],which can be executed repetitively for the same anomaly event. The optimization run for the non-linear implicit search problem is then performed with the competent genetic algorithm [16]. To determine the optimal steady-state timings from the minimum night flow (MNF) hours (2am – 4am) for the NRW localization analysis, the computed discrepancies between the model simulated and monitored values for the flow and average pressure head parameters, respectively, are considered to estimate the average hydraulic power ($W_{NRW}(t)$) due to the estimated daily NRW volume in the system, defined as:

$$W_{NRW}(t) = |P_{avg}(t) - P_s(t)| \times (Q_m(t) - Q_s(t)) \qquad (12)$$

where $P_{avg}(t)$ and $Q_m(t)$ respectively represent the monitored average pressure head and flow values at a specific steady-state timestamp, while $P_s(t)$ and $Q_s(t)$ respectively represent the simulated average pressure head and flow values at the same timestamp.

Note that $W_{NRW}(t)$ represents the average temporal NRW hydraulic power profile for the selected day. The modeller can then inspect the estimated power values for the same MNF period to identify the top (e.g., top 3) power values and their corresponding timings (e.g., 2.30am) to perform the required NRW localization analysis. The greater the power values, the NRW contributions are expected to be more significant in their hydraulic characteristics.

2.4 Energy Calibration

At this stage, the system’s initial energy discrepancy is addressed, to an extent, by the completed flow calibration. Any remaining energy discrepancy across the multiple stations in the same system are then managed via (1) identifying and rectifying likely drifting(s) in the monitored pressure values of individual sensor stations in the system, and (2) calibrating other physical properties which include, but not limited to, pipe roughness and valve settings within the system.

2.4.1 Rectifying sensor drifting

For any given pressure sensor station, the most obvious indication of sensor drifting is a near-constant deviation value observed between the simulated and monitored pressure values at all timestamps for a specific day. In the practical field context, sensor drifting may be caused by environmental disturbances to the positions of the deployed sensors underground, low operating power of the sensors, and initial calibration of the sensors goes out of range. Rectifying the sensor drifting thus involves adjusting the drifted monitored pressures values, across all hours of the selected day, by an approximated offset value.

2.4.2 Calibrating physical properties

After completing the NRW localization analysis, the WDN system's average pressure head discrepancy is expected to be most minimum for the MNF hours as compared to the peak-demand hours (e.g., 9am-11am) as the observed velocities in the underground pipes during the former hours are expected to be much less than 1.0 m/s, hence friction losses in the pipes are expected to be relatively insignificant to that of the latter hours.

To appropriately calibrate physical properties which account for the remaining energy discrepancies in the system, especially during the peak-demand hours, we progressively calibrate the pressure profiles for pressure sensor stations located nearest to the upstream reservoirs/tanks and gradually moving towards the furthest stations. Typically, for real-world WDN systems, we would expect that the valve settings to be well-calibrated with respect to the available Geographic Information System (GIS) information as provided by the utility company. Hence, the most typical physical property to be calibrated is the system's pipe roughness by systematically adjusting the initial C-factor values for the different pool of connected pipes between the reservoirs/tanks and the respective pressure sensor stations. The final adjustments to the different segments of connected pipes in the system are then evaluated via the level of goodness-of-fit between the model simulated and monitored pressure head values for all stations. Finally, we note that calibration of the relevant physical properties in a given system is usually conducted once for the initial hydraulic model having not undergone any prior calibration.

3 CASE STUDY

3.1 Description of WDN system

In collaboration with PUB, Singapore's National Water Agency, a real-world WDN system that serves industrial consumers is undertaken to verify our proposed calibration approach. The selected system consists of underground water pipes having a total length of 331.3km, 1 service reservoir, 11796 junction nodes, 35 pressure sensor stations, as illustrated in Figure 2. No operating pumps are installed in this network. The pipe diameters in the system range between 15.0mm and 1400.0mm, with an average value of 204.0mm. Due to data confidentiality information, the exact naming, and locations of the different hydraulic properties in the system cannot be revealed.

Historical flow and pressure SCADA data for the operational week of 19-25 Apr 2021 is thus leveraged to verify our proposed approach by emulating the near real-time context. For the selected week, a single leak event is reported on 21 Apr 2021. Again, we underline that the leak sizes of are often unknown in the near real-time context. Also, the initial hydraulic model configuration as provided by PUB has already been pre-constructed, to an extent, to represent the actual pipe connectivity and valve settings in the system.

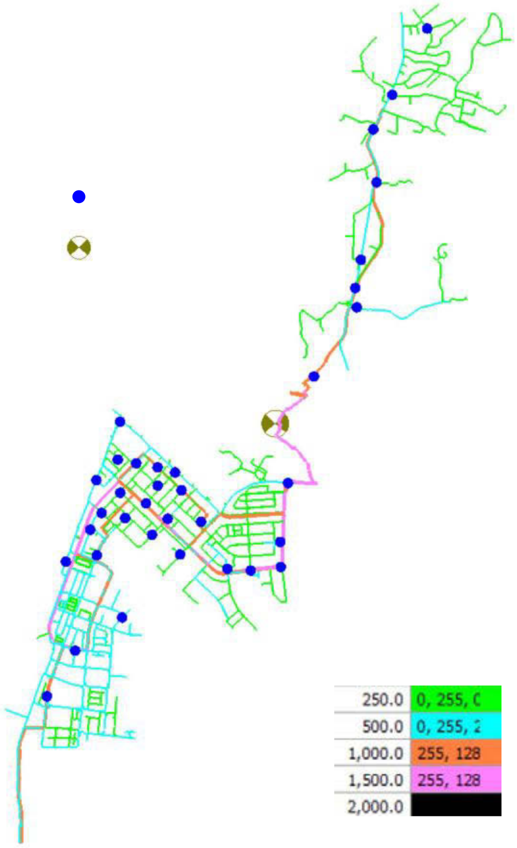
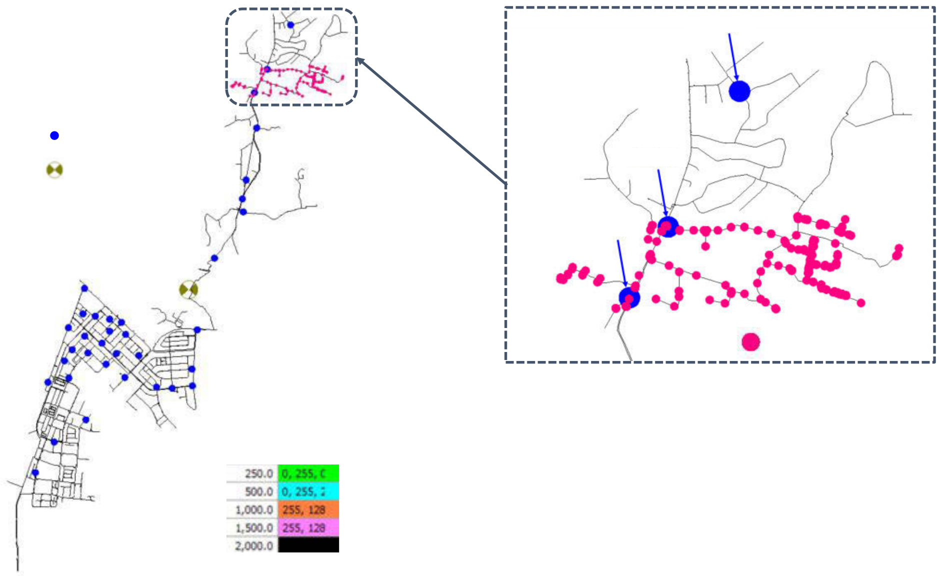


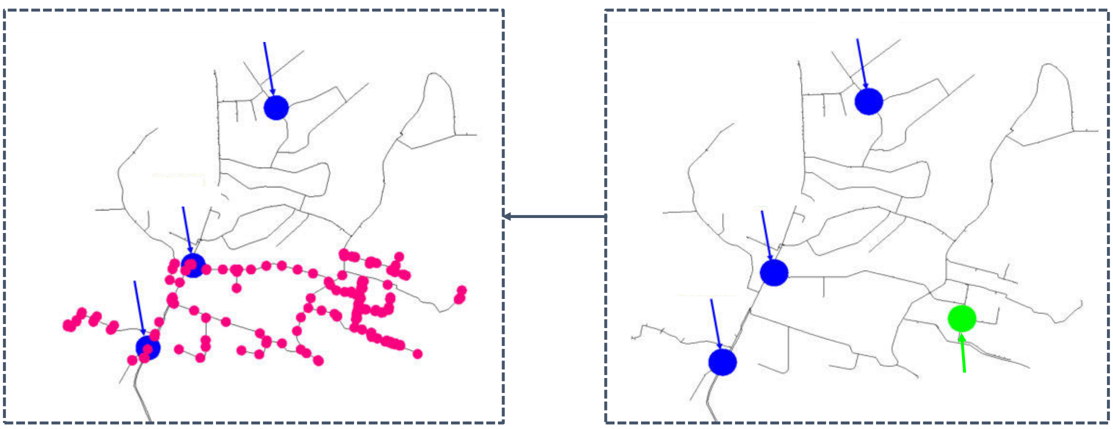
Figure 2. Case study WDN system in Singapore

For the selected system, it has been found that there are 2 sets of unique demand consumption patterns where one follows the traditional diurnal (TD) usage pattern, i.e., low usage during the night and high usage during the day, and the other follows the exact opposite trend (NTD). The latter appears to correspond to a segment of farms located towards the north of the network itself, as shown in Figure 3a, where STN_J pressure readings has been found to best represent the observed water usage pattern for the identified farms in that area. For engineering simplicity, a singular junction node, as indicated in Figure 3b, is thus assumed to aggregate the total demand consumption by the known farms in the same area, where the assigned node is located in the near center of the available farms. The junction nodes (majority) in the other segments of the system, which are not situated near to the farms, are regarded to follow the TD pattern.

For illustrations, Figure 4a and 4b represent the typical normalized pressure profiles under the TD and NTD water usage patterns, respectively, for the system's Monday operations. As discussed, the lower normalized pressures for NTD's pattern during the MNF hours are due to the higher water usage by the available farms in the identified area (Figure 3a-3b), and vice versa during the typical peak-demand hours when compared to that of the TD's pattern.



(a)



(b)

Figure 3. Representation of junction nodes affiliated to farms' water usage pattern: (a) identified pool of nodes; and (b) aggregated junction node for engineering simplicity.

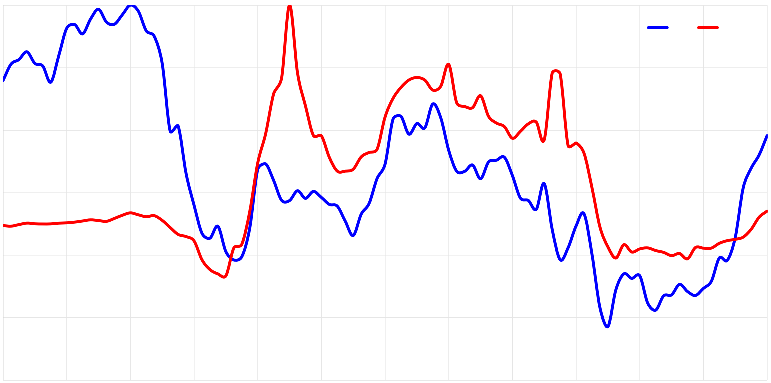


Figure 4. Normalized pressure profiles for TD vs NTD water usage patterns (Monday's example).

3.2 Flow Calibration

By following our proposed solution procedures to calibrate TD (via RAA) and NTD (localized) demand consumption patterns, Figure 5 represents their respective final calibrated patterns for Monday-Sunday in the selected week of 19 Apr 2021. These calibrated patterns are associated with the real customers in the system, by removing the NRW contributions at this stage. Following on, by developing the unique NTD pattern, we can better estimate the actual NRW volume, in percentage values, for the respective days as shown in Figure 6, by leveraging on the total net inflow and historical billing data records for the selected month.

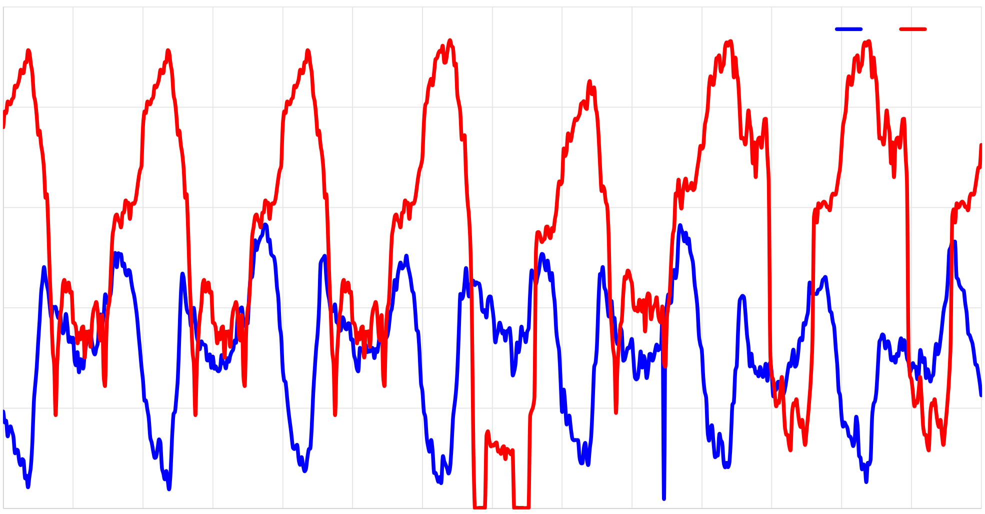


Figure 5. Calibrated demand consumption patterns for TD – bulk of customers in system, and NTD – local farms.

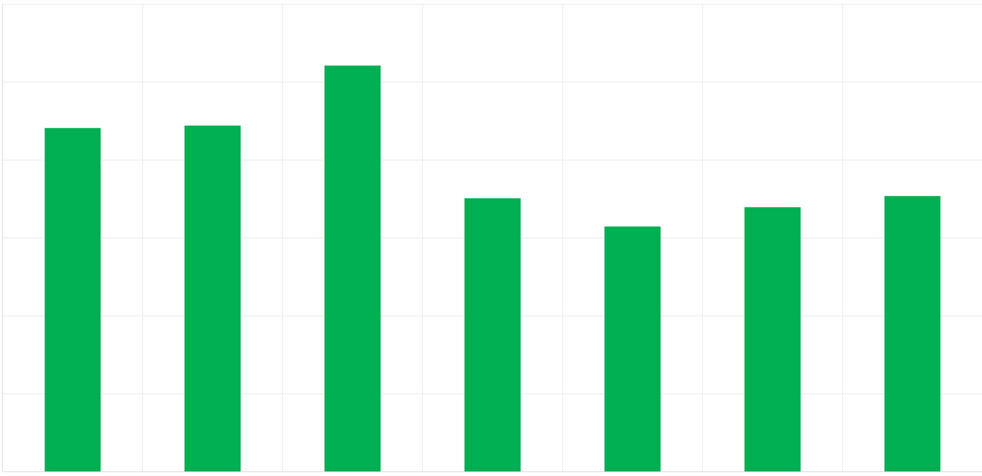


Figure 6. Estimated NRW volume in system for selected week of 19 Apr 2021.

The estimated NRW volumes are then localized as possible anomaly events which may include, but not limited to, hidden/unreported and background leak events and billing data uncertainties. Figures 7a-7g summarize the localized nodes, with a range of estimated emitter coefficient (K) values, within the network for the respective days (19-25 Apr) by using their corresponding MNF timestamp having the highest anomaly hydraulic power, with respect to Eq. (12). At this stage, the following key observations can be derived, namely:

- Figure 7h compares the model simulated and monitored total net inflow values for the selected system, where an average of 0.5% MAPE can be derived across the selected week.
- Across all 7 days, the NRW localization analysis constantly localize several anomaly nodes in around the same area of the network, as shown in Figures 7a-7g, hence indicating a strong likelihood of anomaly events (hidden leaks, demand uncertainties, etc.) taking place in that localized area.
- The approach could localize an actual reported event by PUB to less than 100m on 23 Apr 2021 with a maximum delayed time of 1 day, while also localizing the other possible anomalies which constitute to the respective NRW (%) volume estimated daily.

(a) (b) (c)

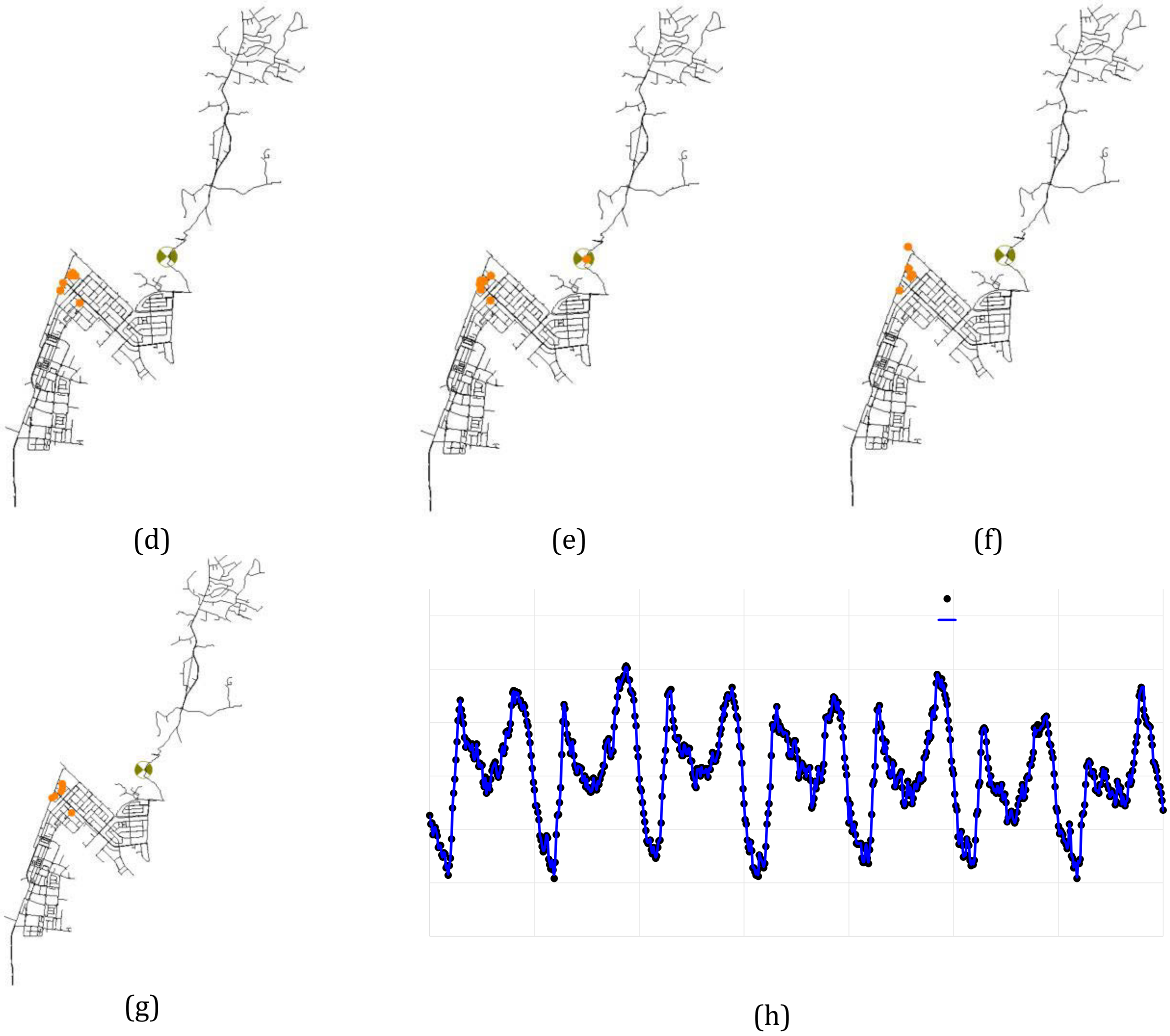


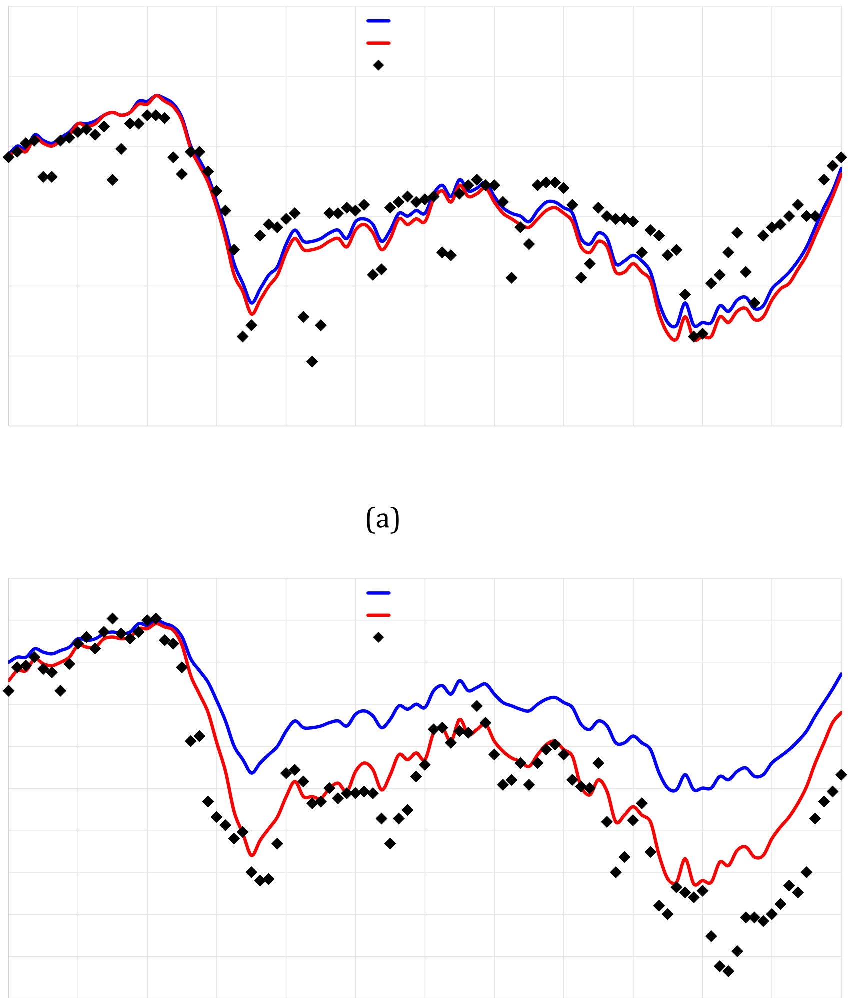
Figure 7. Localized anomaly nodes in network across different days of selected 19 Apr 2021 week: (a) 19 Apr – 3.30am; (b) 20 Apr – 2.45am; (c) 21 Apr – 2.30am; (d) 22 Apr – 2.15am; (e) 23 Apr – 2.15am; (f) 24 Apr – 3.15am; (g) 25 Apr – 2.15am; (h) total net inflow comparison after demand calibration and NRW localization.

3.3 Energy Calibration

Upon completing the NRW localization analysis for each day in the selected week, we proceed to first identify and rectify any likely drifting(s) in the recorded pressure data for the available sensor stations in the network. For the present analysis, it has been found that rectifying any sensor drifting(s) is done once on Monday (19 Apr 2021), and the same adjusted pressure head values can subsequently be maintained for the remaining of the same week. As discussed, since the valve settings are expected to well-calibrated by PUB beforehand, emphasis is thus placed on calibrating the system's pipe roughness values on the same Monday while maintaining the calibrated roughness values for the remaining days.

We thus progressively calibrate the system's pipe roughness from the nearest to the furthest pressure sensor stations from the upstream reservoir. Building upon the completed NRW localization scenario from Monday (19 Apr 2021), Figures 8a and 8b illustrate the before- and aftereffects of the pipe roughness calibration for the nearest and furthest stations respectively. Performing the systematic pipe roughness calibration for all available stations, excluding stations having "bad" monitored data such as missing data, negative/zero pressure values for the selected week, Figure 9 summarizes the MAPE (%) scores for the respective stations across the entire week where the average daily MAPE score is approximately 4%. Likewise, several key observations can be derived, namely:

- Stations, such as STN_D, STN_E and STN_Y, located furthest away from the reservoirs, tend to have higher daily average MAPE scores of between 4-6%. This could be caused by the accumulated calibration errors as stations move away from the reservoirs.
- The reasonably good agreement (~2% MAPE on average) obtained for the energy comparison for STN_I, STN_J especially, and STN_K, together with the prior good agreement achieved for the flow calibration, justifies the proposed local demand calibration by iterating against the daily monitored pressure values from STN_J, as the reference station, and a singular junction node to aggregate the demands for the local farms in the identified area.



(a)

(b)

Figure 8. Before- and aftereffects of pipe roughness calibration on pressure head values for Monday's (19 Apr 2021) analysis: (a) STN_M-nearest station; and (b) STN_E-furthest station.

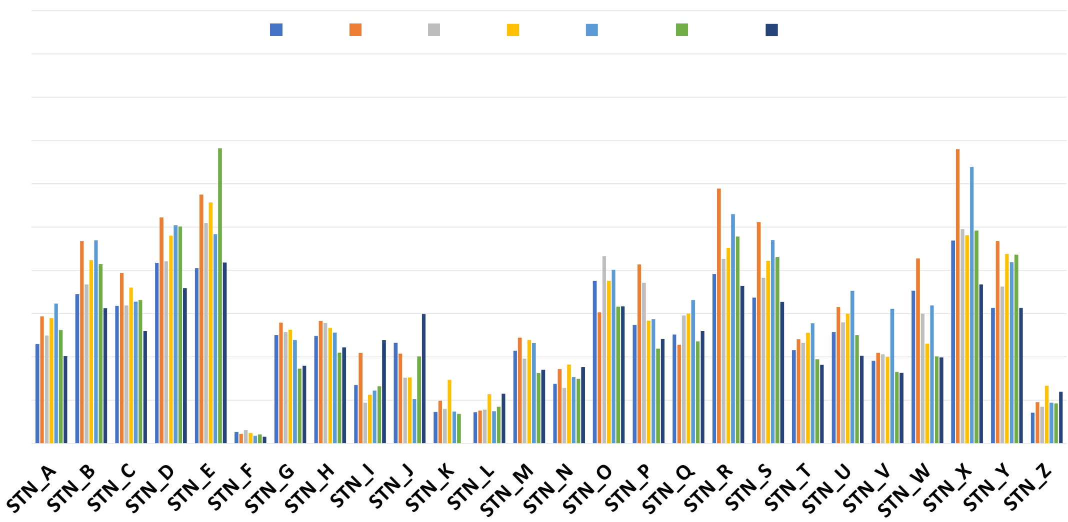


Figure 9. MAPE (%) scores for pressure head comparison across stations (excluding stations having "bad" data such as missing data, negative pressure, etc.) in WDN system for 19 Apr 2021 selected week.

4 CONCLUSIONS

This paper develops a practically novel daily model calibration approach for the real-world operations of water distribution networks (WDNs) by encompassing 3 main systematic components of (1) estimation of NRW contributions, (2) flow calibration, and (3) energy calibration. It is believed that the proposed approach is capable to calibrate real-world large WDN systems by leveraging on monitoring flow and pressure data which are collected 24/7 in the underground water pipelines. In collaboration with PUB, Singapore's National Water Agency, the hypothesis has since been verified by testing the approach on three WDN zones in Singapore having more than 1000km of underground pipes with varying demand consumption pattern(s), pertaining to different groups of customers, where the calibrated hydraulic model achieves daily average mean absolute percentage error (MAPE) scores of <1.0% and 4.0% approximately for the total flow and energy calibrations, respectively. Overall, the calibration approach serves as integral component to PUB's Smart Water Grid management, where a resulting well-calibrated model provides the baseline physics-based environment to facilitate a two-way data/information communication between the physical and digital working environments which can enhance the daily operations of WDNs. Acknowledgements

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