Hybrid Statistical Process Control Method for Water Distribution Pipe Burst Detection

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Abstract: Statistical process control (SPC) identifies any nonrandom patterns in the system output variables of a water distribution system (WDS) by comparing them to their normal historic mean and variance. While each SPC method has different performance characteristics, there has been little effort expended to develop a hybrid method that combines the different characteristics. This paper proposes a hybrid SPC method that combines a modified Western Electric Company (WECO) method and the cumulative sum (CUSUM) method. First, the original WECO method is modified to incorporate a user-defined parameter c that manipulates the tolerance for warning and control limits to fit the specific network of interest. Then, the best parameter set is identified for each of the two individual methods so that coupling them should not increase false alarms. The detection effectiveness and efficiency of the WECO, CUSUM, and hybrid methods were compared by using common data sets obtained from a hydraulic model of the Austin network. The results showed that a simple coupling of individual SPC methods with different detection characteristics can significantly improve pipe burst detection probability while reducing false alarm rates and average detection time. **DOI: 10.1061/(ASCE)WR.1943-5452.0001104.**

Introduction

Water distribution pipe burst occurs when a pipe ruptures from pipe deterioration, excessive pressure, and ground shifting due to temperature changes and earthquakes or a combination of these factors; the pipe burst causes a water loss (Q_{loss}) to escape the water distribution system (WDS). With the exception of large pipe bursts, customers cannot clearly recognize the occurrence of a burst pipe until they receive a notice from the water utility and continue with their normal usage (Q_{normal}). The overall head losses in the pipes increase owing to the increased total quantity of water ($Q_{\text{loss}} + Q_{\text{normal}}$) flowing through the system (Jung et al. 2015). When a pipe bursts, customers can experience consistent service interruptions due to low pressure. A burst pipe can cause liquefaction of the surrounding soil and eventually collateral damage, such as sinkholes. In addition, soil particles can enter the water distribution system through the damaged portion of the pipe and cause water discoloration. Therefore, burst pipes should be rapidly detected to prevent these negative effects on the water system and water quality, which lead to customer complaints and dissatisfaction.

Once detected, the ruptured pipe should either be repaired or replaced. Therefore, the main challenges in pipe burst detection are determining whether a burst has actually occurred and then pinpointing the exact location. The effective and efficient detection of a burst pipe is the most critical first step in returning the system to normal. The repair team of the water utility is dispatched to shut down the valves close to the failed pipe in order to isolate the damaged section (Jun and Loganathan 2007). Locating burst pipes is beyond the scope of this study.

During the last two decades, many data-driven methods have been proposed for detecting pipe burst through an analysis of the affected system output data (i.e., the pressure and pipe flow rate in a WDS) (Puust et al. 2010; Wu and Liu 2017). Mounce and Machell (2006) proposed two artificial neural network (ANN) models with different time-delay schemes to identify abnormal patterns in pipe flow data. Ye and Fenner (2011) introduced a linear Kalman filter (LKF) model to detect burst pipes by comparing the estimated and measured system output variables (SOVs). Romano et al. (2014) proposed a comprehensive pipe burst detection model based on ANN, statistical process control (SPC), and the Bayesian inference system. Other methods applied have included the expectation maximization method (Romano et al. 2013) and time series model-based approach (Mounce et al. 2011b). While most previous methodologies can only be applied to consistent operating conditions (or many false alarms will be triggered because measurements are affected by changes in operating conditions), Jung and Lansey (2015) developed a nonlinear Kalman filter (NKF) method to estimate nodal group demand and pipe flow rates and detect burst pipes under varying operating conditions. The most widely used detection method is SPC, which identifies any nonrandom patterns in SOVs by comparing them to their normal historic mean and variance (Jung et al. 2015).

Jung et al. (2015) compared seven SPC methods by using a common data set with respect to their detection effectiveness and efficiency. Detection effectiveness indicates how well a method detects burst pipes and avoids false alarms, and efficiency refers to the expected time required for detection. The detection probability (DP) and rate of false alarms (RF) were used as indicators for the former, whereas the average detection time (ADT) was calculated for the latter. Three univariate methods—Western Electric Company (WECO) rules, the cumulative sum (CUSUM) method, and the exponentially weighted moving average (EWMA) method—were compared to multivariate methods. The results showed that the univariate methods outperformed the multivariate methods overall. While no significant benefits are derived from utilizing the correlation between meter data obtained with the latter method,

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the former method, with a long memory of past data (i.e., CUSUM and EWMA methods), even detected small bursts and avoided false alarms while having shorter ADTs than the other methods (Jung et al. 2015).

Hagos et al. (2016) introduced a linear-programming-based model to optimize the meter locations for WDS pipe burst detection and investigated the pipe burst characteristics for detectability with the WECO method. Their investigations, based on a single pipe flow and pressure meter's performance, confirmed that the WECO method can quickly detect short-term large mean shifts in the pressure and pipe flow rate despite the relatively high RF. Therefore, an interesting research topic is the degree of improvement that can be achieved by combining multiple SPC methods with different performance characteristics.

Given that the period during which an abnormal signal clearly remains in the system, output data differs for burst magnitude, timing, location, and demand randomness in a neighborhood area. A hybrid SPC method (consisting of individual methods with different detection characteristics) has the potential to rapidly detect burst pipes of various magnitudes and characteristics (i.e., to provide highly sensitive and consistent detection). However, few efforts have been made to develop a hybrid SPC method that incorporates the mechanisms of different SPC methods.

An alternative way of improving detectability, rather than using a high-detectability method, is to increase the amount of information available; this is affected by the amount of high-quality data available, the sampling frequency, number of meters, type of meter, and meter location, among other factors. While many data sampling approaches have been proposed to select and provide quality data for pipe burst detection (Farley et al. 2010, 2013; Huang et al. 2012; Zheng and Yuan 2012), the basis of the data sampling design is to analyze the sensitivity of the data sampling frequency in terms of detectability and determine the best frequency (Mounce et al. 2011a). Therefore, another research question is the degree to which the data sampling frequency affects the detectability of individual and hybrid SPC methods and the optimal frequency.

In order to answer the preceding two research questions, this paper proposes a hybrid SPC method that combines a modified WECO method and the CUSUM method. First, the original WECO method is modified to incorporate a user-defined parameter c that manipulates the tolerance for warning and control limits to fit the specific network of interest. Then, the best parameter set is identified for each of the two individual methods so that coupling them should not increase the false alarms of the proposed hybrid method. The detection effectiveness and efficiency of the three detection methods were compared by using common data sets obtained from a hydraulic model of the Austin network: (1) a long time series of pipe flow rates was generated at five meter locations at 5-min time intervals with and without pipe bursts; and (2) data from one to five meters were provided to the methods with five different data sampling intervals ($dt = 5$, 10, 15, 30, and 60 min).

Methodology

The details of the normalization, modified WECO method, CUSUM method, proposed hybrid method, and data generation for comparing the three methods are presented here. Refer to Jung et al. (2015) for the formulation of the three measures: DP, RF, and ADT.

Normalization

SPC is based on the Shewhart control chart, which plots the mean values (centerline) of an SOV, warning limits (WLs), and control limits (CLs) (Shewhart 1930). While WLs are generally multiples of the standard deviation of the SOV, CLs are thresholds beyond which an alarm is issued. In a dynamic system (e.g., a WDS), the Shewhart control chart has a time-varying centerline and limits. Therefore, the measured value of each SOV is normalized by

$$z_i = \frac{x_i - \bar{x}_i}{\sigma_i} \tag{1}$$

where z_i = standard score of an SOV at time i; x_i = measured value at the ith time period; and $\bar{x}_i$ and σ_i = mean and standard deviation, respectively, of the SOV's value at the ith time period.

Modified WECO Method

Jung et al. (2015) confirmed that the original WECO method (Romano et al. 2014) has higher DP and RF than multivariate methods. In order to be employed in a hybrid detection method, the original WECO method should first be modified to eliminate the risk of false alarms while maintaining high DP. The modified WECO method applies the following four decision rules to detect pipe bursts:

1. Any single standard score is beyond $\pm 4c\sigma$ CL.
2. Two of three consecutive standard scores are beyond the $\pm 3c\sigma$ WL.
3. Four of five consecutive standard scores are beyond the $\pm 2c\sigma$ WL.
4. Eight consecutive standard scores are beyond the $\pm 1c\sigma$ WL.

In this method, c is a user-defined parameter that manipulates the widths of the WLs and CLs (tolerance for alarm) for the specific WDS of interest. The original WECO method (Romano et al. 2014) consists of the four rules with $c = 1$. The rules are applied to one side of the centerline ($z_i = 0$) at a time. Therefore, a score immediately followed by another score on the other side of the centerline outside the WLs will not be considered as a nonrandom pattern.

The best value of c should be identified a priori by calculating detectability measures with varying c values. In the proposed hybrid method, the modified WECO method serves to capture short-term large bursts. Because including the WECO method should not increase the false alarms of the hybrid method, the main goal of the parameter estimation is to find the value of c that produces an RF of 0% and reasonably high DP. The original and modified WECO methods can consider eight consecutive past measurements at most when used to make a detection decision. The probability that eight consecutive measurements are beyond 1σ WL is approximately 0.01% ($= 0.3173^8 \times 100\%$).

CUSUM Method

While the standard score of SOV measurements is directly used as an anomaly indicator in the WECO method, the CUSUM method collects the residual difference between the standard score and user-defined reference value K over time (Jung et al. 2015; Misiunas et al. 2006). The CUSUM method uses upper and lower CUSUM control charts on one side to calculate SUM_i^+ and SUM_i^-, respectively, as

$$\mathrm{SUM}_i^+ = \max[0, \mathrm{SUM}_{i-1}^+ + z_i - K] \tag{2}$$

$$\mathrm{SUM}_i^- = \max[0, \mathrm{SUM}_{i-1}^- - z_i - K] \tag{3}$$

where $\mathrm{SUM}_0^+ = \mathrm{SUM}_0^- = 0$. If either SUM_i^+ or SUM_i^- exceeds the user-defined decision interval H, the system is considered to be out of control (i.e., pipe burst). The two parameters K and H should be estimated for the specific network to apply the method.

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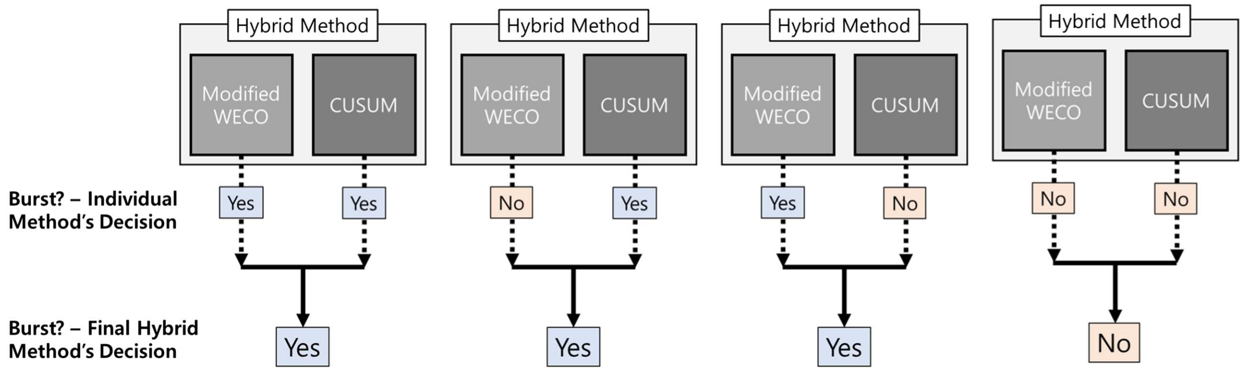

Fig. 1. Four potential final decision flows in the proposed hybrid method for pipe burst detection.

The CUSUM method can consider all past measurements before the cumulative sums are reset to zero [Eqs. (2) and (3)]. Therefore, the CUSUM method has a much longer memory of past data than the WECO method, so it can detect even small mean shifts in the values of SOVs (Jung et al. 2015).

Proposed Hybrid Detection Method

The proposed hybrid detection method uses the (1) modified WECO method to promptly detect short-term large bursts and (2) CUSUM method to identify long-term small bursts. The two individual methods are simply combined because each is tuned so that coupling them should not increase the rate of false alarms of the hybrid method. The final decision on detection is made based on ensembles (combinations) of detection decisions made with the two individual methods (Fig. 1). A sophisticated decision support method is not employed to derive the final decision in the event that the modified WECO and CUSUM methods disagree (e.g., no alarm with WECO but an alarm with CUSUM). Therefore, a WDS is considered to be out of control when either the modified WECO or CUSUM method issues an alarm (Fig. 1).

Two speculations were formulated that were later confirmed by the results: (1) DP increases if the two individual methods detect different sets of pipe burst events (i.e., the events detected by WECO are not subsets of those detected by CUSUM method); and (2) ADT decreases if the two detection strategies are actually adopted in the hybrid method.

Data Generation

The performances of the modified WECO, CUSUM, and hybrid methods were compared with regard to DP, RF, and ADT by using common data sets generated with an EPANET hydraulic model (Rossman 2000). Two data sets were generated: control and out-of-control data. The control data represented the measured SOV under normal naturally random system conditions and were generated based on randomness in nodal demands. RF was computed by using the control data set. In contrast, the out-of-control data were generated based on demand randomness and pipe bursts. DP and ADT were calculated with the control data.

The emitter discharge coefficient C of the orifice equation ($q = Cp^a$, where q is the burst flow, p is the nodal pressure, and a is the emitter pressure exponent) in EPANET was randomly selected within a predefined range to produce random pipe bursts. The location, magnitude, and timing characteristics of the pipe bursts were randomized. The advantage of using synthetic data is that the performances can be tested under various burst conditions (e.g., with respect to magnitude and timing) with exact information on the pipe burst and system conditions. Most previous pipe burst detection studies on real-life events in a network structuralized into district metering areas were based on a limited set of pipe bursts [e.g., burst sizes mostly ranged between 5% and 50% of the mean total system demand (Wu and Liu 2017)]. For more details on the data generation, refer to Jung et al. (2015) and Hagos et al. (2016).

Study Network

The three detection methods were tested on burst pipes generated from the Austin network with 126 nodes and 90 pipes (Fig. 2) (Brion and Mays 1991; Jung et al. 2015). The mean total demand of the Austin network was 726 L/s. A long time series of pipe flow rates with and without pipe bursts was generated at a 5-min time interval with the network's hydraulic model. Nodal demands were randomly sampled from a normal distribution with a coefficient of variation of 0.1 (Kapelan et al. 2005; Jung et al. 2014; Surendran and Tota-Maharaj 2015). It was assumed that the demands had a strong temporal correlation because of diurnal patterns but no spatial correlation. One hundred of the events within a 2-day period (5-min intervals and 576 time steps) were simulated for each of the control and out-of-control conditions used in quantifying the three performance measures. The emitter coefficient C was assumed

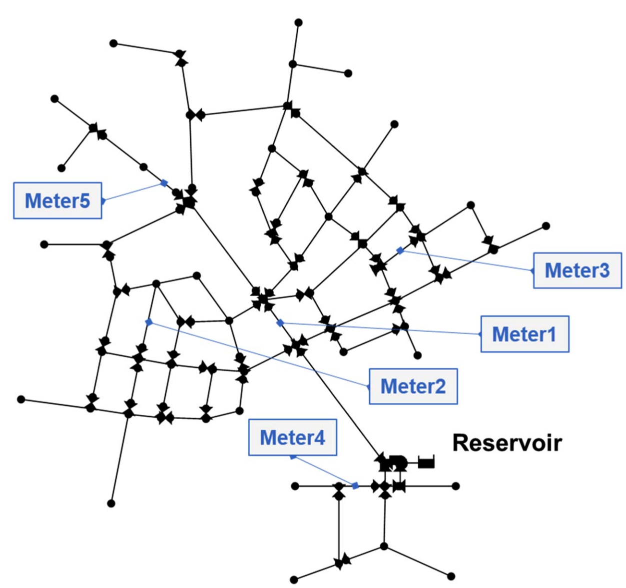

Fig. 2. Austin network and pipe flowmeter locations.

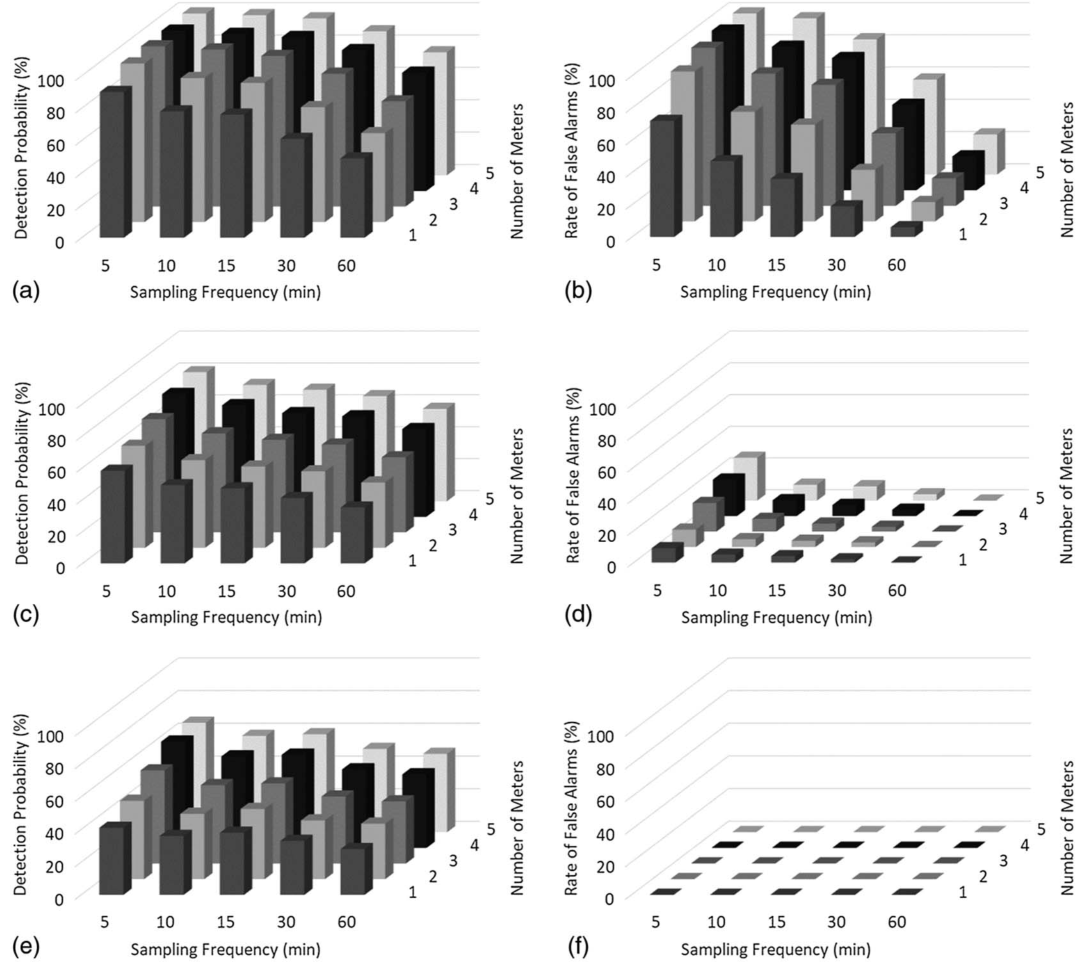

Fig. 3. (a, c, and e) Detection probability and (b, d, and f) false alarm rate of the modified WECO method with different c values: (a and b) $c = 0.8$; (c and d) $c = 1.0$ (the original WECO method); and (e and f) $c = 1.2$.

to follow a uniform distribution over the range of 1–50, which resulted in burst magnitudes of 0.1%–3.3% of the mean total system demand.

Data from one to five meters (Fig. 2) were generated to investigate the impact of the number of meters on detectability. Then, the data were sampled at five different sampling intervals ($dt = 5$, 10, 15, 30, and 60 min) to examine the sampling frequency's impact on detectability. A burst that was not detected within 48 h was assumed to be a nondetected burst; only one burst existed within each 48 h. For more details on the study network, meter locations, and assumptions, refer to Jung et al. (2015).

Application Results

Parameter Estimation of the Modified WECO and CUSUM Methods

First, the best value for the parameter c of the modified WECO method was identified through a sensitivity analysis, in which the DP, RF, and ADT were calculated with $c = 0.8$, 1.0, 1.2, 1.4, and 1.6 at the five different sampling frequencies. Fig. 3 and Table 1 include part of the sensitivity analysis results. The modified WECO method with $c = 1.0$ was equivalent to the original method. The best value had the highest DP with the RF constrained to 0% (no false alarms). ADT was also computed as a reference for selection if the single best parameter could not be determined based on DP and RF. Taking longer to detect a burst pipe was preferred to failing to detect the burst pipe at all.

Table 1. ADT (h) of the modified WECO method with different c values

Meters	$c = 0.8$	$c = 1.0$	$c = 1.2$
1	9.4	10.5	6.9
1, 2	8.5	9.1	5.3
1, 2, 3	8.4	8.7	6.4
1, 2, 3, 4	6.1	8.2	6.2
1, 2, 3, 4, 5	4.8	8.0	6.0

Note: Data were sampled every 10 min.

Fig. 3 shows the DP and RF of the modified WECO method with different c values [Figs. 3(a and b) for $c = 0.8$; Figs. 3(c and d) for $c = 1.0$; and Figs. 3(e and f) for $c = 1.2$]. Overall, DP and RF were confirmed to decrease with increasing c. In other words, as the tolerance for the warning and control limits increased, the sensitivity of the modified WECO method to burst pipes and the risk of false alarms decreased. DP and RF were also confirmed to increase with the amount of data as the (1) data sampling frequency and (2) number of meters were increased (Fig. 3). Using the parameter values of 1.4 and 1.6 resulted in no false alarm but lower DP than the case of $c = 1.2$. Overall, ADT was longest when $c = 1.0$ and shortest when $c = 1.2$ (Table 1).

Table 2. ADT (h) of the two SPC methods with sampling intervals of 5 and 60 min

Meters	Modified WECO ($c = 1.2$) 5 min	Modified WECO ($c = 1.2$) 60 min	CUSUM ($K = 0.1$, $H = 45$) 5 min	CUSUM ($K = 0.1$, $H = 45$) 60 min
1	5.8	12.5	7.9	28.2
1, 2	5.7	9.4	7.1	24.2
1, 2, 3	6.1	9.3	6.7	24.2
1, 2, 3, 4	5.9	9.2	6.7	24.2
1, 2, 3, 4, 5	5.6	8.4	6.4	23.0

Therefore, the best value for the control parameter c of the modified WECO method was determined to be 1.2, which produced DP = 41%–67% and no false alarm when data from one to five meters were used in 5-min intervals [Figs. 3(e and f)]. The detection effectiveness of the original method was significantly improved by incorporating the user-defined control parameter and fine-tuning the warning and control limits to fit the specific network of interest (RF was 8.2%–11% with the original WECO method ($c = 1.0$) given the same data set [Fig. 3(d)]).

For the parameter estimation of the CUSUM method, the values for the parameters K and H were discretized within the ranges of 0.05–0.1 and 35–45. The three detectability measures DP, RF, and ADT were then quantified for different combinations of the two parameters. The best parameter set was selected as $K = 0.1$ and $H = 45$, which resulted in DP $= 72\%$ and RF $= 0\%$–1% when one to five meters' data were used at 5-min intervals. Pipe flowmeters installed in a local area detected the subset of the burst event detected by Meter 1 on a transmission line (Fig. 1). ADT decreased from 7.9 to 6.4 h as the number of meters was increased (Table 2).

The detection rapidity was significantly degraded for the CUSUM method as the data sampling frequency was decreased from 5 to 60 min. The degradation was more severe than for the modified WECO method (Table 2). For example, ADT was 23 h when data of five meters with a sampling frequency of 60 min were used, which is a 262% increase compared to the case with a 5-min sampling interval (Table 2).

The preceding results indicated that the modified WECO method provides an advantage in detection efficiency (i.e., short ADT), whereas the CUSUM method provides high detection effectiveness (i.e., higher DP and equivalent RF compared to WECO). The low DP and long ADT are disadvantages of the former and the latter method, respectively, and can be supplemented by the other method.

Comparison between the Hybrid Method and Two Individual Methods

The speculations presented in the "Methodology" section were evaluated. Tables 3 and 4 present the DP and ADT of the CUSUM and hybrid methods for the five data sampling intervals. CUSUM was compared to the proposed hybrid method because it outperformed the modified WECO method with respect to DP and RF. The hybrid method provided a higher DP than the CUSUM method (Table 3). The percentage difference in DP between the two methods increased with an increasing number of meters and decreasing data sampling frequency reductions. The RF values of the hybrid and CUSUM methods were equal (0%–1%).

The hybrid method detected 28 of the smallest 48 burst events, all with the CUSUM method component (when data from a single pipe flowmeter at 5-min intervals was used). The burst magnitude of these events was less than 1.6% of the mean total system demand. On the other hand, the modified WECO method component of the hybrid method detected 77% of the burst events with a burst magnitude greater than 2.5% of the mean total system demand. This confirmed that Speculation 1 is true: The two SPC methods detect different sets of burst events, which increases the DP of the hybrid method.

Speculation 2 was also confirmed to be true. The hybrid method demonstrated a significantly reduced ADT because it incorporated the modified WECO method, which detects medium to large bursts promptly (Table 4). The percentage difference in ADT between the CUSUM and hybrid methods increased as the number of meters increased and the data sampling frequency decreased. In particular, using the proposed hybrid method decreased ADT to an acceptable level (9 h) compared to the CUSUM method when data from five pipe flowmeters were available every 15 min (Table 4).

The preceding results proved that a simple coupling of individual SPC methods with different detection characteristics can significantly improve pipe burst detectability. The prerequisite for

Table 3. DP (%) of the hybrid and CUSUM methods for different data sampling intervals

Meters	CUSUM 5 min	CUSUM 10 min	CUSUM 15 min	CUSUM 30 min	CUSUM 60 min	Hybrid 5 min	Hybrid 10 min	Hybrid 15 min	Hybrid 30 min	Hybrid 60 min
1	72	69	62	52	37	72	69	62	52	37
1, 2	72	69	64	56	41	72	69	64	56	42
1, 2, 3	72	70	64	56	41	73	71	66	59	46
1, 2, 3, 4	72	70	64	56	41	81	79	74	66	53
1, 2, 3, 4, 5	72	70	65	58	44	81	79	75	68	56

Table 4. ADT (h) of the hybrid and CUSUM methods for different data sampling intervals

Meters	CUSUM 5 min	CUSUM 10 min	CUSUM 15 min	CUSUM 30 min	CUSUM 60 min	Hybrid 5 min	Hybrid 10 min	Hybrid 15 min	Hybrid 30 min	Hybrid 60 min
1	8	13	15	22	28	8	12	14	19	20
1, 2	7	11	14	19	24	7	10	12	16	16
1, 2, 3	7	11	13	19	24	6	10	11	15	15
1, 2, 3, 4	7	11	13	19	24	6	9	10	14	14
1, 2, 3, 4, 5	6	10	12	18	23	5	8	9	13	13

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the hybrid method's superior performance is a proper parameter estimation for the individual methods in which DP is maximized while RF is minimized, rather than the implementation of a sophisticated decision support algorithm to derive the final decision when the two individual methods disagree.

Summary and Conclusions

A hybrid SPC method was proposed that combined the modified WECO method and CUSUM method. First, the original WECO method was modified to incorporate a user-defined parameter c that manipulated the tolerance for warning and control limits to fit the specific network of interest. Then, the best parameter set was identified for each of the two individual methods so that coupling them should not increase the false alarms of the proposed hybrid method. DP, RF, and ADT of the three detection methods were compared by using common data sets generated from an EPANET hydraulic model of the Austin network: (1) a long time series of pipe flow rates was generated at five meter locations at 5-min intervals with and without pipe bursts, and (2) data from one to five meters were provided at five different data sampling intervals ($dt = 5$, 10, 15, 30, and 60 min).

A sensitivity analysis confirmed that, as the tolerance for the warning and control limits increased, the sensitivity of the modified WECO method to pipe bursts and the risk of false alarms decreased in the Austin network. DP and RF increased with the data sampling frequency and number of meters. In the Austin network, the best value of $c = 1.2$ was identified, which removed the risk of false alarms with the modified WECO method. While the CUSUM method with the best parameter set of $K = 0.1$ and $H = 45$ had a higher overall detection effectiveness than the modified WECO method, it also had a longer ADT (less detection rapidity).

Finally, the proposed hybrid method was compared to the CUSUM method (the best of the two individual methods) with respect to three detectability measures in the Austin network. The hybrid method had an equivalent RF to the CUSUM method and a higher DP overall. Within the hybrid method, small bursts were detected with the CUSUM method component, which considered large amounts of past data, while relatively big bursts were rapidly identified with the modified WECO method component. This allowed the proposed hybrid method to demonstrate high detection effectiveness and efficiency compared to the CUSUM method in the network considered. A simple coupling of individual SPC methods with different detection characteristics was verified to significantly improve pipe burst detectability when using synthetically generated burst data.

Water utilities can benefit from the reduction in the number of undetected burst events and the time taken for detection, all of which help reduce overall system costs and improve water distribution services. Prompt detection of burst pipes decreases the duration of service interruptions from the low pressure caused by water loss and avoids the risk of collateral damage (e.g., sinkholes), which also has great social cost.

This study has several limitations that future research must address. First, the proposed hybrid method and comparison should be validated with real burst data. When applying the proposed method to detect real-life pipe bursts, missing data can occur that can be replaced with the historical mean or data on another location with similar characteristics. A future study could develop a missing data imputation method that fits SPC and the proposed hybrid method. In addition, the optimal value of parameter c could be compared across networks with different layouts and characteristics.

Data Availability Statement

The following data, models, or code generated or used during the study are available from the corresponding author by request: the code for the proposed hybrid SPC method in Visual Basic 6.0.

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