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Diagnosing and Quantifying Post-disaster Pipe Material Cost Fluctuations

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ABSTRACT

Natural hazards pose significant threats to the integrity of pipeline networks. Rapid post-disaster reconstruction is crucial for both the safety and survival of communities. However, sudden increases in reconstruction costs following natural hazards often hamper the rapid reconstruction and rehabilitation of pipeline networks. It is essential to investigate the post-disaster fluctuations in pipe costs for a timely reconstruction of pipeline networks. The objective of this research is to quantify the pipe cost fluctuations after the 2021 Texas winter storm using cumulative sum control charts and seasonal autoregressive integrated moving average (SARIMA). The results indicate that the disaster triggered statistically significant increases in pipe costs including corrugated steel pipe costs, polyvinyl-chloride (PVC) pipe costs, ductile-iron pipe costs, and copper water tubing pipe costs. The findings of this research can assist reconstruction engineers and capital planners in quantifying post-disaster cost fluctuations, identifying vulnerable pipe costs to disasters, and enhancing pipeline reconstruction plans.

INTRODUCTION

The number and severity of natural hazards have rapidly increased over the last few decades (Ward et al. 2020). Rapid changes in global climate and atmosphere result in more severe weather-related hazards and exacerbate global socioeconomic losses from natural hazards. Communities have experienced increasing socioeconomic losses in the aftermath of large-scale disasters (Brusentsev & Vroman 2017). Large-scale disasters devastate community buildings and infrastructures, including pipeline networks, which must be repaired immediately to serve essential social services (Balaei et al. 2019). Natural hazards often threaten the integrity of pipeline networks. The pipeline networks of 1.9 million miles carry natural gas and hazardous liquid in the United States (Zhou et al. 2016). More than a half of incidents at the U.S. pipeline networks triggered by natural hazards resulted in significant damages, including fires, explosions, and property damages, leading to a substantial economic loss to communities (Girgin & Krausmann 2016). Moreover, pipeline networks such as water and natural gas pipes serve as a vital link to deliver the basic needs of communities (Chang 2016). Critical damages in pipeline networks by natural hazards can exacerbate post-disaster socioeconomic losses, decreasing recovery speed and threatening public health (Psyrras & Sextos 2018). Therefore, rapid reconstruction and rehabilitation of pipeline networks in post-disaster situations are crucial for both the safety and survival of communities.

However, reconstruction costs inflate dramatically because the demand for reconstruction resources, including construction materials and labor increases in post-disaster situations (Ahmadi & Shahandashti 2020). After a disaster, this significant reconstruction demand triggers relative scarcity of reconstruction resources and substantially increases their costs over approximately three quarters after the disaster (Esfahani & Shahandashti 2020). More than 60 percent of construction material prices published by Engineering News-Record have faced a significant statistical increase in the aftermath of recent disasters (Khodahemmati & Shahandashti 2020).

After Hurricane Katrina and Rita, asphalt unit price bids were significantly escalated in the hurricane-affected area (Baek & Ashuri 2018). The average weekly wages in construction for the Houston metropolitan area were increased by 20 percent after Hurricane Harvey (Billings et al. 2019). Sudden increases in post-disaster reconstruction costs can be one of the most significant factors that amplify socioeconomic losses in large-scale disasters (Olsen 2012).

Adequate and timely reconstruction is essential for the post-disaster recovery, survival, and long-term growth of communities after disasters (Nejat et al. 2018). However, sudden increases in pipe material costs following natural hazards often hamper the rapid reconstruction and rehabilitation of pipeline networks. It is essential to investigate the post-disaster fluctuations in pipe material costs for a timely reconstruction and rehabilitation of pipeline networks in post-disaster situations (Ahmadi & Shahandashti 2018). Existing literature for quantifying post-disaster construction cost fluctuations does not consider material cost time-series characteristics such as trends, seasonal patterns, and autocorrelations. Therefore, it is hard to tell whether post-disaster cost fluctuations for reconstructing pipelines are attributable to a disaster or simply due to a trend or seasonal changes in pipe material costs over time. The confusion about the reason for post-disaster pipe material cost fluctuations can mislead post-disaster rehabilitation decision-making.

The objective of this research is to develop a method to quantify post-disaster pipe material cost fluctuations considering regional trends and seasonal patterns and implement the method to empirically estimate post-disaster fluctuations in pipe costs after the recent 2021 Texas winter storm. The method using cumulative sum (CUSUM) control charts and seasonal autoregressive integrated moving average (SARIMA) was developed to quantify post-disaster fluctuations in pipe material costs. This method was implemented to examine regional pipe cost fluctuations after the 2021 Texas winter storm struck Dallas, Texas. The results indicate that the disaster triggered a significant increase in pipe costs. Also, the results provide information about the post-disaster recovery period and substantial changes in Dallas pipe material costs following the disaster. The findings of this research can assist reconstruction engineers, capital planners, and risk mitigation agencies in quantifying post-disaster cost fluctuations, identifying more vulnerable pipe costs to disasters, and enhancing their reconstruction and rehabilitation strategies for pipeline networks.

RESEARCH METHODS

Figure 1 presents the flow chart for quantifying post-disaster pipe material cost fluctuations after the 2021 Texas winter storm using CUSUM control charts and seasonal ARIMA models. The monthly data of Dallas pipe material costs published by ENR were collected from January 2010 to November 2021. Then, the autocorrelation among the pipe material cost time-series was assessed using Ljung-Box Q-test. If the time-series is autocorrelated, an appropriate time-series model should be developed to avoid a false signal of deviation in the CUSUM control charts. The residuals of the fitted time-series models are plotted in the CUSUM control chart to diagnose the out-of-control points in the process. If the time-series is not autocorrelated, the time-series data are plotted in the CUSUM control charts to detect the out-of-control points. CUSUM control charts are useful for detecting changes in out-of-control processes and identifying a recovery period. The recovery period is the time difference between the deviation point where a process shifts from its usual variations and the recovery point where a deviating process returns to its usual variations. The recovery periods after the Texas winter storm were estimated for each pipe cost using CUSUM control charts. The pipe material cost fluctuations were quantified during recovery periods by the difference between the actual cost data and the forecasted cost data assuming no disaster.

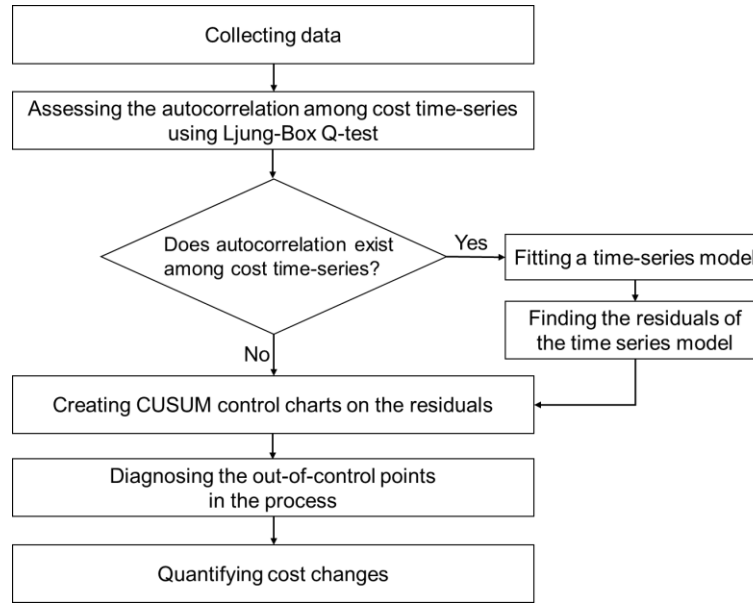


Figure 1. Flowchart for Quantifying Post-disaster Pipe Material Cost Fluctuations

Data Collection

Engineering News-Record monthly publishes different pipe material costs at the city level. Contractors and cost engineers often utilize the ENR material costs for estimating bid prices and budgets in capital projects (Kim et al. 2021a). The current research examined the pipe material cost fluctuations following the recent Texas winter storm in February 2021. Eighteen pipe material costs in Dallas were collected from 10 years before (January 2010 to December 2020) up to approximately three quarters (February 2021 to November 2021) after the Texas winter storm struck Dallas in February 2021. Table 1 shows eighteen pipe material line items collected for analysis.

Table 1. Pipe Material Line Items

Material	Line items
Reinforced concrete pipe	12" (30.48cm), 24" (60.96cm), 36" (91.44cm), 48" (121.92cm)
Corrugated steel pipe	12" (30.48cm), 36" (91.44cm), 60" (152.4cm)
Polyvinyl-chloride pipe (PVC): sewer	4" (10.16cm), 8" (20.32cm)
Polyvinyl-chloride pipe (PVC): water	6" (15.24cm), 8" (20.32cm), 12" (30.48cm)
Polyethylene pipe (PE): underdrain	4" (10.16cm)
Ductile-iron pipe (DIP)	6" (15.24cm), 8" (20.32cm), 12" (30.48cm)
Copper water tubing: type L	1/2" (1.27cm), 1 1/2" (3.81cm)

Initial Autocorrelation Assessment

CUSUM control chart is a valuable technique to detect a significant cost change. Before creating a CUSUM control chart, the time-series of pipe material costs must be examined if the series does not show an autocorrelation relationship. When the time-series are autocorrelated, the CUSUM control chart can provide a false signal of deviation derived from the inflation trend or seasonal patterns of a time-series. The Ljung-Box Q-test investigates whether the pipe material costs are autocorrelated. If the pipe material costs are autocorrelated according to the results of the Ljung-Box Q-test, an appropriate time-series model should be developed to model the cost time-series. Then, the residuals of the fitted time-series model should be plotted in the CUSUM control charts.

Time-Series Analysis

The characteristics of a time-series, including stationarity and seasonality, should be investigated before developing an appropriate time-series model (Kim et al. 2022). A stationary time-series has constant statistical properties over time. The stationarity of the pipe material costs can be examined using the Augmented Dickey-Fuller (ADF) test. Seasonality denotes repeating cyclical patterns in a time-series (Kim et al. 2021b). The seasonality of a time-series can be identified through decomposition.

Seasonal Autoregressive Integrated Moving Average (ARIMA)

A nonstationary and seasonal time-series can be fitted using seasonal ARIMA (Kim et al. 2020). Equation (1) represents the *SARIMA* (p, d, q)(P, D, Q) s model for modeling polyvinyl-chloride pipe costs.

$$(1 - B)^d(1 - B^S)^D PVC_t = \frac{\theta(B)\theta(B^S)}{\phi(B)\phi(B^S)} Z_t + \mu \quad (1)$$

where B is the backshift operator; d is the non-seasonal differencing order; D is the seasonal differencing order; S is the period of seasonality; μ is the mean of time-series; $\phi(B)$ is the non-seasonal autoregressive (AR) operator; $\Phi(B)$ is the seasonal AR operator; $\theta(B)$ is the non-seasonal moving average (MA) operator; $\Theta(B)$ is the seasonal MA operator; Z_t is the white noise. Parameters p, q, P , and Q of the seasonal ARIMA were selected based on the observations of ACF and PACF plots. The lowest Akaike Information Criterion (AIC) values were considered to select the most preferred combination of p, q, P , and Q for seasonal ARIMA.

Diagnostic Tests on the Residuals of the Time-Series Models

The residuals of the seasonal ARIMA model should follow a white noise process with zero mean and finite variance. A Ljung-Box test was conducted to examine whether the model residuals are white noise. The null hypothesis of the Ljung-Box test is that the residuals follow a white noise random process.

CUSUM Control Chart Creation

CUSUM control charts can accurately detect statistical out-of-control cost changes in the historical time-series. The upper and lower control limits of CUSUM control charts were calculated using the residuals of the fitted time-series models (Chen & Huang 2014). Since the post-disaster cost fluctuations in pipe materials were examined based on the standard deviation of its original time-series in the CUSUM control charts, the CUSUM control charts can provide more accurate results for diagnosing the out-of-control deviation in post-disaster pipe cost fluctuations. The pipe material cost data were monitored using the cumulative deviations from the mean of the process. The CUSUM values above and below the mean were calculated as follows:

$$CU_i = \max [0, (CU_{i-1} + R_i - k*\sigma)] \quad (2)$$

$$CL_i = \min [0, (CL_{i-1} + R_i + k*\sigma)] \quad (3)$$

where CU_i is the cumulative deviation of point i above the mean; CL_i is the cumulative deviation of point i below the mean; R_i is the residuals of seasonal ARIMA model (i.e., $R_i = \text{Actual pipe cost} - \text{Forecasted pipe cost by seasonal ARIMA model assuming no disaster}$); k is the reference value, which is considered as the allowable size of change; and σ is the estimated standard deviation. When CU_i or CL_i exceeds the decision interval h , it indicates that the process has substantially changed.

Out-of-control Point Diagnosis

The out-of-control point is the point where the process exceeds upper or lower control limits in the CUSUM control chart. A deviation point is a starting point where a process starts to deviate from the normal process toward the out-of-control point. The forward CUSUM control charts were used to diagnose deviation points in pipe material costs after the Texas winter storm in 2021. The forward CUSUM control charts monitored the CUSUM values (CU_i and CL_i) from the start point (January 2021) to the endpoint (November 2021). A recovery point is a point where a deviating process starts to return to its usual variations. The reverse CUSUM control charts were utilized to identify recovery points as a change point where the recovery begins in pipe material costs data after the Texas winter storm in 2021. The reverse CUSUM control chart diagnosed the data in reverse from the endpoint (November 2021). The recovery period for pipe material cost fluctuations after the Texas winter storm was estimated by the time difference between the deviation and recovery points.

Pipe Material Cost Change Quantification

The post-disaster recovery period for each pipe material cost after the Texas winter storm was identified using the forward and reverse CUSUM control charts. The actual pipe material costs during the recovery period were compared with the forecasted pipe material costs using the seasonal ARIMA model, assuming a normal condition of no disaster during the recovery period. The pipe material cost change after the Texas winter storm was quantified using the difference between the average actual cost and forecasted cost of a pipe material during the recovery period.

EMPIRICAL RESULTS

Initial Autocorrelation Assessment

The Ljung-Box Q-tests were conducted to examine if Dallas pipe material cost time-series are not autocorrelated. Table 2 presents the results of the Ljung-Box Q-tests for eighteen pipe material costs in Dallas. The null hypothesis of the Ljung-Box Q-test was rejected at the 1% significance level for all pipe material cost time-series. In other words, all the pipe material cost time-series have autocorrelations among their historical values. Therefore, an appropriate time-series model should be fitted to each pipe material cost. The residuals of the fitted time-series model should be plotted in a CUSUM control chart to avoid a false signal of deviation arising from the trend or seasonality of a time-series.

Table 2. Results of Ljung-Box Q-tests for Dallas Pipe Material Costs

Material	Q-statistic	Material	Q-statistic
Reinforced concrete pipe 12" (30.48cm)	151.54 ^a	Polyvinyl-chloride pipe (PVC): water 6" (15.24cm)	146.37 ^a
Reinforced concrete pipe 24" (60.96cm)	145.19 ^a	Polyvinyl-chloride pipe (PVC): water 8" (20.32cm)	132.93 ^a
Reinforced concrete pipe 36" (91.44cm)	144.87 ^a	Polyvinyl-chloride pipe (PVC): water 12" (30.48cm)	147.24 ^a
Reinforced concrete pipe 48" (121.92cm)	146.8 ^a	Polyethylene pipe (PE): underdrain 4" (10.16cm)	138.75 ^a
Corrugated steel pipe 12" (30.48cm)	150.03 ^a	Ductile-iron pipe (DIP) 6" (15.24cm)	146.34 ^a
Corrugated steel pipe 36" (91.44cm)	144.36 ^a	Ductile-iron pipe (DIP) 8" (20.32cm)	151.28 ^a
Corrugated steel pipe 60" (152.4cm)	142.21 ^a	Ductile-iron pipe (DIP) 12" (30.48cm)	151.2 ^a
Polyvinyl-chloride pipe (PVC): sewer 4" (10.16cm)	154.72 ^a	Copper water tubing: type L 1/2" (1.27cm)	153.05 ^a
Polyvinyl-chloride pipe (PVC): sewer 8" (20.32cm)	142.91 ^a	Copper water tubing: type L 1 1/2" (3.81cm)	130.3 ^a

Note: ^aRejection of the null hypothesis at the 1% significance level

Time-Series Analysis

The characteristics of a pipe material cost time-series were investigated using the ADF test and decomposition. The ADF tests were conducted to examine if the Dallas pipe material costs are stationary. The results of ADF tests in Table 3 rejected the null hypothesis of nonstationarity for all pipe material costs. The first differencing is required to make the time-series stationary. Also, all pipe material costs showed a seasonality of twelve months according to the results of decomposition.

Table 3. Results of ADF Tests for Dallas Pipe Material Costs

Material	t-statistics	Material	t-statistics
Reinforced concrete pipe 12" (30.48cm)	-0.92 (5)	△Reinforced concrete pipe 12" (30.48cm)	-4.3 ^a (5)
Reinforced concrete pipe 24" (60.96cm)	-2.16 (5)	△Reinforced concrete pipe 24" (60.96cm)	-5.6 ^a (5)
Reinforced concrete pipe 36" (91.44cm)	-2.85 (5)	△Reinforced concrete pipe 36" (91.44cm)	-5.38 ^a (5)
Reinforced concrete pipe 48" (121.92cm)	-2.36 (5)	△Reinforced concrete pipe 48" (121.92cm)	-5.64 ^a (5)
Corrugated steel pipe 12" (30.48cm)	-2.29 (5)	△Corrugated steel pipe 12" (30.48cm)	-4.36 ^a (5)
Corrugated steel pipe 36" (91.44cm)	-3.76 (5)	△Corrugated steel pipe 36" (91.44cm)	-4.64 ^a (5)
Corrugated steel pipe 60" (152.4cm)	-2.58 (5)	△Corrugated steel pipe 60" (152.4cm)	-4.27 ^a (5)
Polyvinyl-chloride pipe (PVC): sewer 4" (10.16cm)	-1.23 (5)	△Polyvinyl-chloride pipe (PVC): sewer 4" (10.16cm)	-4.97 ^a (5)
Polyvinyl-chloride pipe (PVC): sewer 8" (20.32cm)	-2.04 (5)	△Polyvinyl-chloride pipe (PVC): sewer 8" (20.32cm)	-4.83 ^a (5)
Polyvinyl-chloride pipe (PVC): water 6" (15.24cm)	-2.32 (5)	△Polyvinyl-chloride pipe (PVC): water 6" (15.24cm)	-4.16 ^a (5)
Polyvinyl-chloride pipe (PVC): water 8" (20.32cm)	-2.44 (5)	△Polyvinyl-chloride pipe (PVC): water 8" (20.32cm)	-5.19 ^a (5)
Polyvinyl-chloride pipe (PVC): water 12" (30.48cm)	-2.49 (5)	△Polyvinyl-chloride pipe (PVC): water 12" (30.48cm)	-5.15 ^a (5)
Polyethylene pipe (PE): underdrain 4" (10.16cm)	-1.51 (5)	△Polyethylene pipe (PE): underdrain 4" (10.16cm)	-5.14 ^a (5)
Ductile-iron pipe (DIP) 6" (15.24cm)	-1.59 (5)	△Ductile-iron pipe (DIP) 6" (15.24cm)	-4.44 ^a (5)
Ductile-iron pipe (DIP) 8" (20.32cm)	-1.53 (5)	△Ductile-iron pipe (DIP) 8" (20.32cm)	-5.51 ^a (5)
Ductile-iron pipe (DIP) 12" (30.48cm)	-1.59 (5)	△Ductile-iron pipe (DIP) 12" (30.48cm)	-5.89 ^a (5)
Copper water tubing: type L 1/2" (1.27cm)	-0.86 (5)	△Copper water tubing: type L 1/2" (1.27cm)	-5.56 ^a (5)
Copper water tubing: type L 1 1/2" (3.81cm)	-1.53 (5)	△Copper water tubing: type L 1 1/2" (3.81cm)	-5.23 ^a (5)

Note: Δ = the first difference operator; The numbers in parentheses denote the lag length.

^aRejection of the null hypothesis at the 1% significance level

Since all the monthly pipe material costs in Dallas have nonstationarity and seasonality, seasonal ARIMA is recommended for modeling and forecasting pipe material costs in normal conditions of no disaster (Kim et al. 2020). The pipe material costs from January 2010 to December 2020 were used to develop seasonal ARIMA models. The combinations of AR (p), MA (q), seasonal AR (P), and seasonal MA (Q) orders for seasonal ARIMA were selected based on ACF and PACF graphs. The seasonal ARIMA models developed for each pipe material cost are presented in Table 4. The residuals of the seasonal ARIMA models were diagnosed for no autocorrelation using Ljung-Box Q-tests. The results of the Ljung-Box Q-tests in Table 4 indicate that no autocorrelation was found among the model residuals because the null hypothesis of no autocorrelation was not rejected at the 5% significance level. Therefore, the developed seasonal ARIMA models passed the residual diagnostic tests.

Table 4. Seasonal ARIMA Models for Pipe Material Costs

Material	Line items	Seasonal ARIMA (p,d,q)(P,D,Q)	AIC	Ljung-Box Q-test statistic
Reinforced concrete pipe	12" (30.48cm)	(0,1,0)(0,0,1) ₁₂	-12.6	0.66 ^a

Corrugated steel pipe	24" (60.96cm)	(0,1,0)(1,1,1) ₁₂	391.07	0.06 ^a
	36" (91.44cm)	(0,1,0)(0,1,1) ₁₂	523.46	0.07 ^a
	48" (121.92cm)	(0,1,0)(1,0,1) ₁₂	669.33	0.05 ^a
	12" (30.48cm)	(0,1,0)(0,0,1) ₁₂	141.91	0.53 ^a
	36" (91.44cm)	(1,1,1)(0,0,1) ₁₂	120.89	0.38 ^a
Polyvinyl-chloride pipe (PVC): sewer	60" (152.4cm)	(0,1,0)(1,1,1) ₁₂	406.77	0.03 ^a
	4" (10.16cm)	(0,1,0)(1,0,0) ₁₂	-321.45	2.84 ^a
Polyvinyl-chloride pipe (PVC): water	8" (20.32cm)	(0,1,0)(1,0,1) ₁₂	-66.84	0.72 ^a
	6" (15.24cm)	(1,1,0)(0,0,1) ₁₂	26.03	0.00 ^a
	8" (20.32cm)	(0,1,0)(1,0,1) ₁₂	-29.61	0.04 ^a
Polyethylene pipe (PE): underdrain	12" (30.48cm)	(0,1,0)(0,0,1) ₁₂	108.65	0.06 ^a
	4" (10.16cm)	(0,1,0)(0,0,1) ₁₂	-400.34	0.00 ^a
	6" (15.24cm)	(0,1,0)(2,0,0) ₁₂	18.34	0.16 ^a
Ductile-iron pipe (DIP)	8" (20.32cm)	(0,1,0)(0,0,2) ₁₂	221.72	0.06 ^a
	12" (30.48cm)	(0,1,0)(0,0,2) ₁₂	275.85	1.87 ^a
Copper water tubing: type L	1/2" (1.27cm)	(0,1,0)(1,0,0) ₁₂	-329.37	0.05 ^a
	1 1/2" (3.81cm)	(1,1,0)(0,0,1) ₁₂	-23.34	0.12 ^a

Note: ^aNo rejection of the null hypothesis at the 5% significance level

Out-of-control Point Diagnosis in CUSUM Control Charts

The CUSUM control charts were illustrated to diagnose the deviation in residuals of seasonal ARIMA for Dallas pipe costs after the Texas winter storm in February 2021. The forward CUSUM control chart monitors the deviations in the residuals of the seasonal ARIMA models from January 2021 to November 2021. The reverse CUSUM control chart identifies the deviations in the residuals from November 2021 to January 2021. While the forward CUSUM control chart was used to detect the deviation point where the process starts to deviate from its usual variations toward the out-of-control point, the reverse CUSUM control chart was utilized to diagnose the recovery point where the process starts to recover from deviations. Figure 2 describes the forward and reverse CUSUM charts for corrugated steel pipe 12" (30.48cm) costs. The deviation point of May 2021 was detected in the forward CUSUM chart, while the recovery point of October 2021 was identified in the reverse CUSUM chart. The forward CUSUM chart detected the first out-of-control point in July 2021 while the reverse CUSUM chart diagnosed the first out-of-control point in June 2021. Since the recovery period was estimated by the time difference between the deviation and recovery points, the recovery period for corrugated steel pipe 12" (30.48cm) after the Texas winter storm is from May 2021 to October 2021.

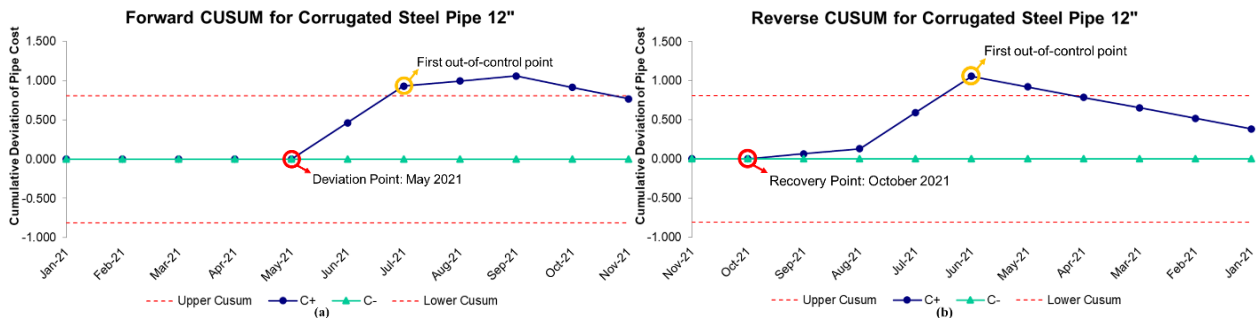


Figure 2. (a) Forward and (b) Reverse CUSUM Charts for Corrugated Steel Pipe Costs

The out-of-control point is the point where the process deviates from its usual variations over the control limits. The control limits were measured by four times the standard deviation in this research to diagnose out-of-control points over the threshold. If the cumulative deviation of a

pipe material cost exceeds the control limits, it signifies that the pipe material cost has experienced a major change. Table 5 presents the results of out-of-control point diagnoses to detect major changes in Dallas pipe material costs. Substantial cost changes after the Texas winter storm were identified in corrugated steel pipe costs, PVC sewer pipe costs, PVC water pipe 8" (20.32cm) and 12" (30.48cm) costs, Ductile-iron pipe 6" (15.24cm) and 8" (20.32cm) costs, and Copper water tubing costs.

Table 5. Results of Out-of-control Point Diagnosis for Dallas Pipe Material Costs

Material	Major change	Material	Major change
Reinforced concrete pipe 12" (30.48cm)	No major change	Polyvinyl-chloride pipe (PVC): water 6" (15.24cm)	No major change
Reinforced concrete pipe 24" (60.96cm)	No major change	Polyvinyl-chloride pipe (PVC): water 8" (20.32cm)	Major change
Reinforced concrete pipe 36" (91.44cm)	No major change	Polyvinyl-chloride pipe (PVC): water 12" (30.48cm)	Major change
Reinforced concrete pipe 48" (121.92cm)	No major change	Polyethylene pipe (PE): underdrain 4" (10.16cm)	No major change
Corrugated steel pipe 12" (30.48cm)	Major change	Ductile-iron pipe (DIP) 6" (15.24cm)	Major change
Corrugated steel pipe 36" (91.44cm)	Major change	Ductile-iron pipe (DIP) 8" (20.32cm)	Major change
Corrugated steel pipe 60" (152.4cm)	Major change	Ductile-iron pipe (DIP) 12" (30.48cm)	No major change
Polyvinyl-chloride pipe (PVC): sewer 4" (10.16cm)	Major change	Copper water tubing: type L 1/2" (1.27cm)	Major change
Polyvinyl-chloride pipe (PVC): sewer 8" (20.32cm)	Major change	Copper water tubing: type L 1 1/2" (3.81cm)	Major change

Pipe Material Cost Change Quantification

Eleven pipe materials that experienced a major cost change in Table 5 were used to estimate the recovery periods and quantify the post-disaster cost changes. Table 6 describes the quantification of recovery periods and cost changes for Dallas pipe materials that substantially changed after the Texas winter storm. Average pipe material costs were quantified using the actual observations and the forecasted values by seasonal ARIMA during the recovery periods. The actual average costs were compared with the forecasted average costs during the identified recovery periods. Pipe cost changes after the Texas winter storm were measured by the percentage of cost escalation from the forecasted average cost to the actual average cost. PVC sewer 4" (10.16cm) and Copper water tubing 1 1/2" (3.81cm) pipe costs have increased by 10% during the recovery periods.

Table 6. Quantification of Recovery Periods and Cost Changes for Dallas Pipe Materials

Material	Recovery period	Average cost (Actual, \$/ft)	Average cost (Forecasted, \$/ft)	Cost change (%)
Corrugated steel pipe 12" (30.48cm)	May 2021 - Oct 2021	14.1	13.8	2.2
Corrugated steel pipe 36" (91.44cm)	May 2021 - Nov 2021	36.2	33.6	7.5
Corrugated steel pipe 60" (152.4cm)	Jul 2021 - Nov 2021	85.4	81.6	4.7
Polyvinyl-chloride pipe (PVC): sewer 4" (10.16cm)	Aug 2021 - Nov 2021	1.9	1.7	10.0
Polyvinyl-chloride pipe (PVC): sewer 8" (20.32cm)	Jun 2021 - Nov 2021	6.3	6.0	4.2
Polyvinyl-chloride pipe (PVC): water 8" (20.32cm)	Mar 2021 - Nov 2021	10.6	9.8	7.7
Polyvinyl-chloride pipe (PVC): water 12" (30.48cm)	Mar 2021 - Nov 2021	22.3	20.3	9.5
Ductile-iron pipe (DIP) 6" (15.24cm)	Feb 2021 - Nov 2021	21.2	19.8	7.2
Ductile-iron pipe (DIP) 8" (20.32cm)	Feb 2021 - May 2021	33.65	32.6	3.1

Copper water tubing: type L 1/2" (1.27cm)	Apr 2021 – Nov 2021	2.07	1.98	4.3
Copper water tubing: type L 1 1/2" (3.81cm)	Apr 2021 - Nov 2021	6.84	6.17	10.8

CONCLUSIONS

Natural hazards have significant impacts on construction resource costs. The sudden and substantial construction cost escalation can hamper a timely post-disaster reconstruction process. Quantification of cost recovery periods and changes in construction resource costs following a disaster can assist capital planners, risk mitigation agencies, and policymakers in identifying more urgent resource demands and enhancing their reconstruction strategies. It is imperative to quantify the pipe material cost changes following a disaster because the pipeline networks must be reconstructed immediately to serve essential social services.

This research measured the recovery periods and post-disaster cost changes for Dallas pipe materials after the Texas winter storm. This research utilized the CUSUM control charts and seasonal ARIMA models to detect major changes in pipe material costs following the disaster. The empirical results provide information about recovery periods and significant changes for pipe costs. Eleven pipe material costs have experienced substantial inflation during the recovery periods. Copper water tubing: type L 1 1/2" (3.81cm) pipe costs have escalated by 10.8%, showing the greatest deviations from the normal condition of no disaster among pipe costs. Most pipe costs have substantially escalated until November 2021, which is up to three quarters after the disaster. Pipe material costs except the ductile-iron pipe costs started to increase in a month or later following the disaster. It is implied that the demand for sewer and water pipes has significantly increased in the reconstruction process following the Texas winter storm because the sewer and water pipe materials, including PVC sewer pipes, PVC water pipes, and copper water tubing pipes, have experienced substantial cost inflation.

The research findings enable policymakers and post-disaster reconstruction engineers to improve their reconstruction strategies by quantifying post-disaster cost fluctuations and recovery periods. Policymakers and reconstruction engineers can compare the impacts of a disaster on pipe costs and identify more vulnerable pipe costs following a disaster using the proposed methodology. For example, policymakers and reconstruction engineers can prioritize mitigating the inflation of copper water tubing pipe costs over the inflation of reinforced concrete pipe costs after the Texas winter storm. In future research, the cost fluctuations in other locations need to be compared to the fluctuations in Texas to investigate the Covid-19 pandemic effect on inflation.

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REFERENCES

- Ahmadi, N., & Shahandashti, M. (2020). Characterizing Construction Demand Surge Using Spatial Panel Data Models. *Natural Hazards Review*, 21(2), 04020008.
- Ahmadi, N., & Shahandashti, S. M. (2018). Role of Predisaster Construction Market Conditions in Influencing Postdisaster Demand Surge. *Natural Hazards Review*, 19(3), 04018010.
- Baek, M., & Ashuri, B. (2018). Profile monitoring for examining impact of Hurricane Katrina and Rita on highway construction cost. *Transportation research record*, 2672(51), 79-87.

- Balaei, B., Wilkinson, S., Potangaroa, R., Adamson, C., & Alavi-Shoshtari, M. (2019). Social factors affecting water supply resilience to disasters. *International Journal of Disaster Risk Reduction*, 37, 101187.
- Billings, S. B., Gallagher, E., and Ricketts, L. (2019). Let the rich be flooded: The unequal impact of hurricane Harvey on household debt. *Available at SSRN 3396611*.
- Brusentsev, V., & Vroman, W. (2017). Disasters in the United States: frequency, costs, and compensation. WE Upjohn Institute.
- Chang, S. E. (2016). Socioeconomic impacts of infrastructure disruptions. In *Oxford research encyclopedia of natural hazard science*.
- Chen, H., & Huang, C. (2014). The use of a CUSUM residual chart to monitor respiratory syndromic data. *IIE Transactions*, 46(8), 790-797.
- Esfahani, N. A., & Shahandashti, M. (2020). Post-hazard labor wage fluctuations: a comparative empirical analysis among different sub-sectors of the US construction sector. *Journal of Financial Management of Property and Construction*.
- Girgin, S., & Krausmann, E. (2016). Historical analysis of US onshore hazardous liquid pipeline accidents triggered by natural hazards. *Journal of Loss Prevention in the Process Industries*, 40, 578-590.
- Khodahemmati, N., & Shahandashti, M. (2020). Diagnosis and quantification of postdisaster construction material cost fluctuations. *Natural Hazards Review*, 21(3), 04020019.
- Kim, S., Abediniangerabi, B., & Shahandashti, M. (2020). Forecasting Pipeline Construction Costs Using Time Series Methods. In *Pipelines 2020* (pp. 198-209). Reston, VA: American Society of Civil Engineers.
- Kim, S., Abediniangerabi, B., & Shahandashti, M. (2021a). Forecasting Pipeline Construction Costs Using Recurrent Neural Networks. In *Pipelines 2021* (pp. 325-335).
- Kim, S., Abediniangerabi, B., & Shahandashti, M. (2021b). Pipeline Construction Cost Forecasting Using Multivariate Time Series Methods. *Journal of Pipeline Systems Engineering and Practice*, 12(3), 04021026.
- Kim, S., Choi, C. Y., Shahandashti, M., & Ryu, K. R. (2022). Improving Accuracy in Predicting City-Level Construction Cost Indices by Combining Linear ARIMA and Nonlinear ANNs. *Journal of Management in Engineering*, 38(2), 04021093.
- Nejat, A., Brokopp Binder, S., Greer, A., and Jamali, M. (2018). Demographics and the Dynamics of Recovery: A Latent Class Analysis of Disaster Recovery Priorities after the 2013 Moore, Oklahoma Tornado. *International Journal of Mass Emergencies and Disasters*, 36(1).
- Olsen, A. H. (2012). Demand surge following earthquakes. In *15th World conference on earthquake engineering (15WCEE)*, Lisbon, Portugal.
- Psyrras, N. K., & Sextos, A. G. (2018). Safety of buried steel natural gas pipelines under earthquake-induced ground shaking: A review. *Soil Dynamics and Earthquake Engineering*, 106, 254-277.
- Ward, P. J., Blauhut, V., Bloemendaal, N., Daniell, J. E., Ruiter, M. C. D., Duncan, M. J., ... & Winsemius, H. C. (2020). Natural hazard risk assessments at the global scale. *Natural Hazards and Earth System Sciences*, 20(4), 1069-1096.
- Zhou, Z., Gong, J., Roda, A., & Farrag, K. (2016). Multiresolution change analysis framework for postdisaster assessment of natural gas pipeline risk. *Transportation research record*, 2595(1), 29-39.