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A BAYESIAN INFERENCE BASED SIMULATION APPROACH FOR ESTIMATING FRACTION NONCONFORMING OF PIPE SPOOL WELDING PROCESSES

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ABSTRACT

Pipe spool fabrication is the most vital process to the successful delivery of industrial construction project. Due to the various combinations of pipe attributes in terms of Nominal Pipe Size (NPS), Pipe Schedule, and material, it is hard for practitioners to estimate the pipe welding quality performance based on the available historical data. This paper aims to develop a Bayesian Inference based simulation approach to assist making good estimates of welds fraction nonconforming for proposing a new project to clients. In this proposed approach, the pipe welding inspection process is first modeled as a Bernoulli process. Utilizing the tracked historical inspection data, Jeffreys Intervals are estimated for determining the distributions of welds fraction nonconforming. These distributions can serve as the inputs for Monte Carlo Simulation to incorporate uncertainties for fabricators' decision-making process. The simulation results demonstrate good reliability and accuracy compared to the actual project welds repair rates.

1 INTRODUCTION

ISO 9000, as a series of quality management standard, has been implemented to obtain improvements in construction quality management all over the world (Chini and Valdez 2003). In ISO 9000, quality is defined as the degree to which a set of inherent characteristics fulfill requirements (Hoyle 2001). For construction contractors, poor quality performance always leads to penalties, increased rework cost and time, and productivity loss (Battikha 2002). Consequently, poor quality performance will negatively impact the companies' reputation and competitiveness in the market (Yates and Aniftos 1997; Jaafari 2000).

Over the past few decades, the industrial construction method has been widely implemented in lieu of the conventional stick-built construction in the Alberta oil sands region. Not only can it minimize the time and cost of onsite construction in northern Alberta's harsh weather conditions, it can also improve the safety and quality performance of the project. Industrial construction has been described as a method of construction involving the large-scale use of offsite prefabrication and preassembly for industrial facilities, such as petroleum refineries, petrochemical plants, nuclear power plants, and oil/gas production facilities (Barrie and Paulson 1992). Pipe spool fabrication is an early process of industrial construction projects and is vital to the success of entire project delivery (Wang et al. 2009). Pipe spools are typically built in a fabrication shop through cutting, fitting, welding, quality inspection, and other processes according to the engineering designs (Song et al. 2006). Welding, as the main operation within pipe spool fabrication, needs to be sampled and inspected to fulfill the quality requirements. Nondestructive examination (NDE) is a basic requirement in fabrication quality control process and is commonly used to detect discontinuities in welds without causing any damage to the pipe (ASME 2005).

Many of computer-based quality management systems have been developed for quality management purposes. For example, Battikha (2002) proposed a general construction quality management decision system named QUALICON derived from the ISO 9001 standard. In practice, industrial fabricators sometimes implement customized quality management systems to track inspection results, such as AcuTrack (AbouRizk 2006). With the help of those systems, the companies using them have collected huge amounts of weld inspection data during the fabrication process over the past few years. However, practitioners have not made good use of the collected data to extract useful information for understanding and forecasting their welding quality performance.

Construction simulation is defined as "the science of developing and experimenting with computer-based representations of construction systems to understand their underlying behavior" (AbouRizk 2010). As the processes of construction projects are complex and uncertain, it is important to have physically accurate inputs from actual operation processes. The data tracked by the quality management system provides an opportunity to perform better simulation in terms of reliability and accuracy. The overall purpose of this research is to develop a data-driven simulation method to help fabricators better understand and estimate pipe welding quality performance, quantitatively. The detailed objectives are 1) to establish an analytical model for modeling the weld inspection process and inferring fraction nonconforming for a specified type of weld; 2) to develop a data-driven simulation model for estimating the fraction nonconforming (i.e., repair rate) based on a given number of welds, and welds attributes (e.g., NPS, Pipe Schedule, and material); and 3) to create sound simulation results in format of visualized statistical summary to reduce the interpretation load on practitioners.

The remainder of the paper is organized as follows. In the next section, a three-step Bayesian Inference based simulation model is developed to illustrate the inspection process, infer the historical fraction nonconforming, and simulate the fraction nonconforming. In the subsequent section, a case study is presented in a detailed manner to demonstrate and validate the outcomes from the proposed Bayesian Inference based simulation approach. Finally, benefits and challenges of the proposed approach are discussed.

2 METHODOLOGY

To achieve the research objective, a hybrid model is needed to incorporate 1) inspection process modeling; 2) Bayesian Inference for fraction nonconforming; and 3) fraction nonconforming estimate. Figure 1 illustrates the hybrid Bayesian Inference based simulation model, in which three steps are included. The modeling steps, inputs, and outputs are shown in Figure 1. Detailed introduction of each step is discussed as follows.

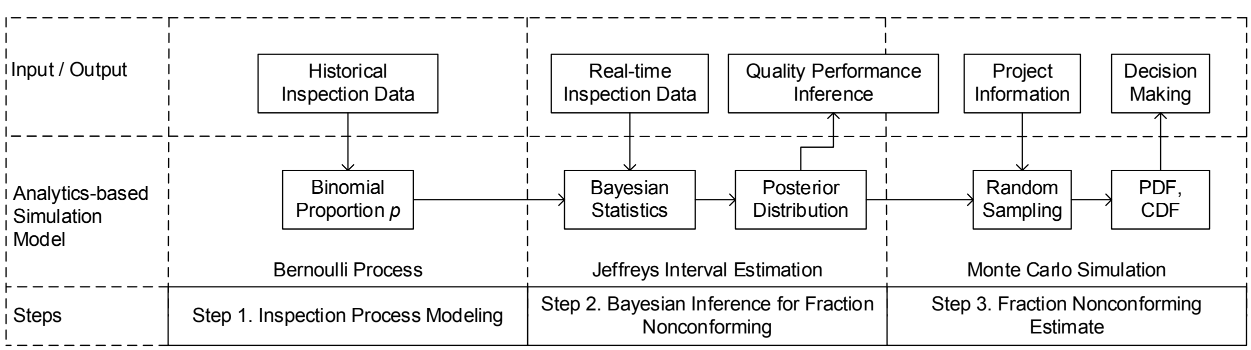


Figure 1: Workflow of the Bayesian Inference based simulation model.

2.1 Inspection Process Modeling

In the pipe welds inspection process, the desired outcome is usually called "success," and the other outcome is often called "failure." When one weld fails the inspection, it needs to be repaired and inspected until passing the inspection. The inspection outcome X can be treated as a Bernoulli random variable with probability function.

$$P(X) = \begin{cases} p & x = 1 \\ (1-p) = q & x = 0 \end{cases} \tag{1}$$

Variable X takes on the value 1 with probability p and the value 0 with probability $(1-p) = q$. A realization of this random variable is called a Bernoulli trial. The sequence of Bernoulli trials is a Bernoulli process. The number of failed inspections D has a binomial distribution $B(n,\ p)$.

The fraction nonconforming of pipe welds is defined as the ratio of the number D of nonconforming welds in the sample to the sample size n as shown in Eq. (2).

$$\hat{p} = \frac{D}{n} \tag{2}$$

$\hat{p}$ is an estimate of the true, unknown value of the binomial variable p, which represents the fraction nonconforming of the sampled pipe welds. The probability distribution of $\hat{p}$ is obtained from the binomial distribution.

$$P\{\hat{p} \le a\} = P\left\{\frac{D}{n} \le a\right\} = P\{D \le an\} = \sum_{k=0}^{\lfloor an \rfloor} \binom{n}{k} p^k (1-p)^{n-k} \tag{3}$$

Furthermore, the mean and variance of $\hat{p}$ can be calculated as Eq. (4) and Eq. (5).

$$\mu_{\hat{p}} = p \tag{4}$$

$$\sigma_{\hat{p}}^2 = \frac{p(1-p)}{n} \tag{5}$$

2.2 Bayesian Inference for Fraction Nonconforming

For inferring the fraction nonconforming, it is necessary to obtain a range of values that covers the true fraction nonconforming (Nicholson 1985). Confidence intervals are the most common options to estimate the margin of sampling error. The Wald's interval, Wilson interval, and Agresti-Coull Interval are the classical methods for setting confidence interval of Binomial distribution (Brown et al. 2001). However, the authors claim that credible interval is superior to the conventional confidence interval. The detailed comparison is discussed as follows.

2.2.1 Confidence Interval versus Credible Interval

In statistics, both confidence and credible intervals can be defined for a variable X as $P\{l \le X \le u\} = 100(1-\alpha)\%$. Where l is the lower interval limit, and u is the upper interval limit. However, the interpretation for confidence interval and credible interval is conceptually different. A confidence interval is a range of values designed to include the true value of the variable with the tolerance probability of $100(1-\alpha)\%$.

Bayesian approaches define the problem in a different way. A Bayesian method assumes the variable's value is fixed but has been chosen from some probability distribution, known as the prior probability distribution. It starts with a prior distribution of the variable, which represents the estimator's belief about the variable before any observation, and the posterior distribution is the updated belief about the variable after observation.

The Bayesian inference is simpler and straightforward. Data are collected and then utilized to calculate the probability of different values of the variable given the data. This new probability distribution is called the posterior probability. Bayesian approaches can summarize their uncertainty by giving a range of values on the posterior probability distribution that includes $100(1-\alpha)\%$ of the probability. This is called a $100(1-\alpha)\%$ credible interval. Credible interval serves a summary of posterior information. It has more meaningful interpretation than the confidence interval. Also, once the posterior sample has been generated, it has advantages to derive all other statistics such as mean, median, variance and all quantiles, which can be used as the inputs of Monte Carlo Simulation. The Bayesian posterior could be used to answer decision makers' questions more directly and intuitively.

2.2.2 Bayesian Inference

Bayesian Inference is a systematic way of updating information as more observations become available (Gelman et al. 2003). Bayesian Inference derives the posterior probability as a consequence of two antecedents, a prior probability and a likelihood function (Gelman et al. 2003). In this research, the parameter of interest is the fraction nonconformance p. The prior distribution of p is $P(p)$ and summaries what is known about p before the experiment is carried out. The likelihood function $L(p)$ provides the distribution of the data x given the fraction nonconformance p. The posterior distribution $P(p|x)$ indicates the information in the data x together with the information in the prior distribution. $P(x)$ is the marginal distribution of the data x. Based on Bayes' Theorem, the posterior distribution $P(p|x)$ can be expressed as Eq. (6).

$$P(p|x) = \frac{L(p)\ \times P(p)}{P(x)} \tag{6}$$

2.2.3 Jeffreys Interval

Jeffreys Interval is a Bayesian credible interval obtained when using the non-informative Jeffreys prior for the binomial proportion p. It is common to use beta distributions as the standard conjugate priors for inferring parameter p in binomial distribution (Berger 1985).

Suppose the number of nonconforming welds $D \sim B(n,\ p)$ and suppose fraction nonconforming p has a prior distribution $Beta(a,\ b)$. Then the posterior distribution of p is $Beta(D+a, n-D+\ b)$ (Berger 1985).

Therefore, a $100(1-\alpha)\%$ eqial-tailed Bayesian interval is given by Eq. (7).

$$[l,u] = [Beta(\alpha/2\,; D+a, n-D+b), Beta(1-\alpha/2\,; D+a, n-D+b)] \tag{7}$$

Where $Beta(\alpha; a,\ b\ )$ denotes the α quantile of a $Beta(a,\ b)$ distribution.

In this problem, the Jeffreys prior is $Beta(1/2\,,1/2\,)$ (Brown et al. 2001). After observing D nonconforming welds in n inspections, the posterior distribution for p is a Beta distribution $Beta(D+1/2\,, n-D+\ 1/2)$. The $100(1-\alpha)\%$ equal-tailed Jeffreys interval is defined as Eq.(8).

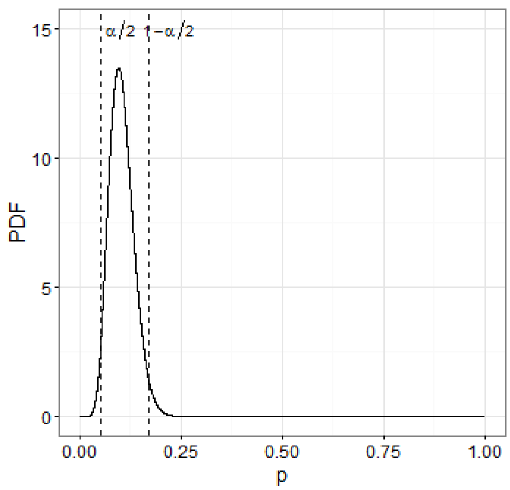
$$[l, u] = [Beta(\alpha/2\,; D + 1/2\,, n - D + 1/2), Beta(1 - \alpha/2\,; D + 1/2\,, n - D + 1/2)] \tag{8}$$

This interval leaves $\alpha/2$ posterior probability in each omitted tail.

Figure 2 shows the probability density function (PDF) and cumulative density function (CDF) of the posterior distribution of Jefferys Interval ($\alpha = 5\%$) for $D \sim B(100,\ 0.1)$. Therefore, $\mathrm{D} = 0.1 \times 100 = 10$. The lower and upper limits are calculated as Eq. (9).

$$\begin{aligned}[l, u] &= [Beta(0.05/2; 10 + 0.5, 100 - 10 + 0.5), Beta(1 - 0.05/2; 10 + 0.5, 100 - 10 \\ &\quad + 0.5)] = [Beta(0.025; 10.5, 90.5), Beta(0.975; 10.5, 90.5)] \\ &= [0.053, 0.170]\end{aligned} \tag{9}$$

The result means for 10 nonconformers out of 100, a 95% credible interval is $[0.053, 0.170]$. The sample fraction nonconforming is 10/100 = 0.1. The fraction nonconforming is theoretically distributed as $Beta(10.5, 90.5)$.



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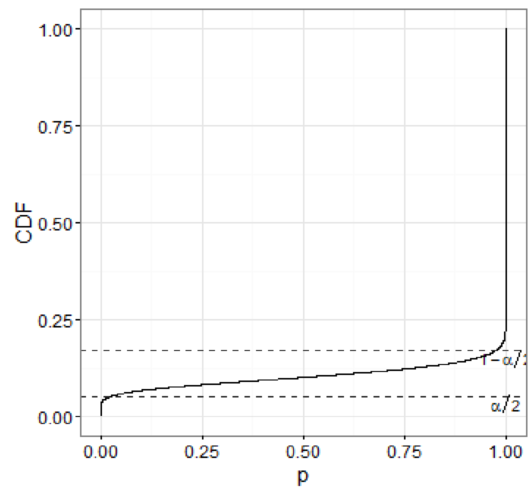

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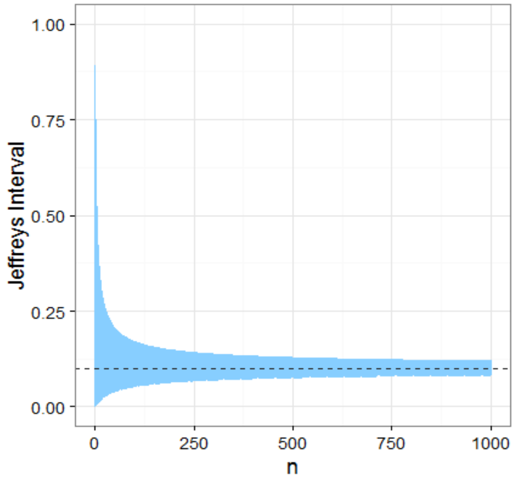
Figure 2: Posterior distribution of Jeffreys Interval ($\alpha = 5\%$) of $\mathrm{D} \sim \mathrm{B}(100,\ 0.1)$: (a) probability density function (PDF); (b) cumulative density function (CDF).

According to Eq. (6), the range of Jeffreys Interval depends on two variables. The first variable is the sample size n, the other variable is the fraction nonconforming p. Figure 3 (a) depicts the relationship of the estimated Jeffreys Interval and sample size n when fraction nonconforming p is fixed as 0.1. The Jeffreys Interval shrinks to 0.1 when n gets larger. Figure 3 (b) depicts the relationship of Jeffreys Interval and fraction nonconforming p when n is fixed as 100. The Jeffreys Interval shrinks when fraction nonconforming p gets close to 0 or 1. When fraction nonconforming $p = 0.5$, Jeferys Interval has the maximum range.



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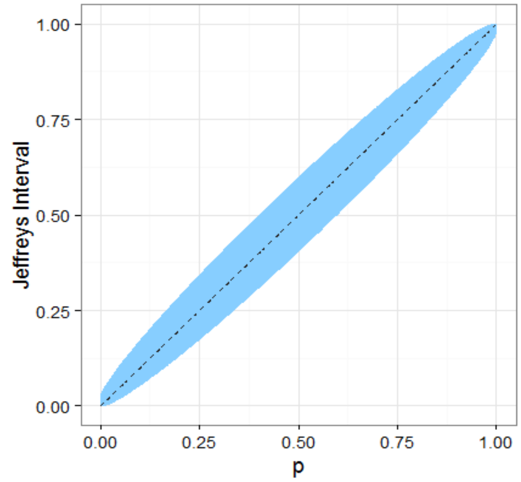


(b)

Figure 3: Relationship between Jeffreys Interval and variables: (a) Jeffreys Interval of $D \sim B(n,\ 0.1)$; (b) Jeffreys Interval of $D \sim B(100,\ p)$.

2.3 Fraction Nonconforming Estimate

In the realm of risk management, Monte Carlo method has been widely implemented to estimate uncertainties for decision making. The main steps of Monte Carlo Simulation are: 1) generating the static model; 2) identifying inputs distribution; 3) sampling random variables with multiple runs; and 4) analyzing results for decision making (Raychaudhuri 2008).

For each type of welds, a posterior distribution can be derived by implementing the first two steps of the hybrid model and incorporating real-time updated inspection data. For estimating the project fraction nonconforming, Monte Carlo Simulation is performed to find a set of fraction nonconforming for a project. The static model can be described as Eq. (10).

$$\rho = \sum_{i=0}^{N} n_i \times r_i \times p_i \tag{10}$$

Where,

ρ is the estimated fraction nonconforming of the given project.

n_i is the number of welds for weld type i.

r_i is the required sampling rate of for weld type i.

p_i is the randomly sampled fraction nonconforming p from the posterior distribution by Monte Carlo Simulation.

N is the number of pipe welds types.

After multiple runs, the Monte Carlo Simulation results are fitted into Beta distribution via the method of Maximum Likelihood. A QQ-plot and PP-plot are utilized to visually judge the goodness of fit.

The main reasons for choosing Beta Distribution are 1) the forecasted repair rate should be bounded within the range of 0 to 1; 2) beta distribution has the flexibility to provide accurate and representative output for analysis; and 3) the parameters of beta distribution are intuitively and physically meaningful and easy to estimate from the simulation output.

3 CASE STUDY

In this section, a fabricator's pipe welding quality management system, called AcuTrack, is investigated to demonstrate the proposed methodology step by step. This system has tracked the pipe welds inspection records of 35 pipe spool fabrication projects during the past 10 years. In this paper, the authors will utilize the records of Radiographic Tests (RT) of all butt welds for illustration purposes. Figure 4 shows the main procedures for implementing the proposed approach for the case study. R, a free software environment for statistical computing and graphics, is utilized to conduct all the procedures. Firstly, ODBC package is used to extract raw data from the SQL server. Then, the raw data is processed to the desired format via dplyr/tidyr package. All the graphs are generated using the ggplot2 package. Finally, mcsm package is used to perform Monte Carlo Simulation.

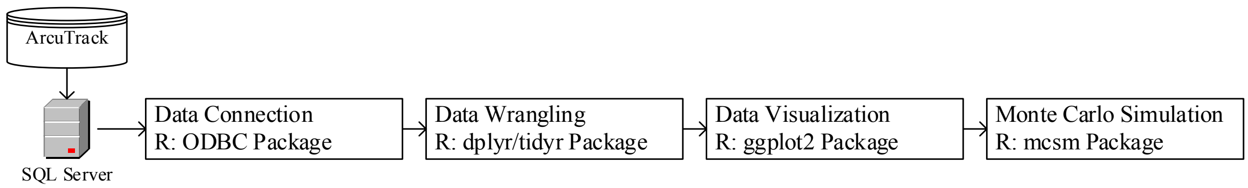


Figure 4: Procedures and tools for the proposed Bayesian Inference based simulation approach.

3.1 Data Description

In practice, a pipe is generally specified by an NPS that defines constant outside diameter and a Pipe Schedule that defines the wall thickness. Materials are categorized into Material A – Plain Carbon Steel, Material B – Alloy Steel, Material C – Stainless Steel, and Material D – Others. RT inspection results are tracked in three statuses for each butt weld, they are: 0 – no inspection performed; 1– inspected and passed; and 2 – inspected and failed. In total, 224,298 records for RT inspection of butt welds are included in the AcuTrack system. A data sample for RT inspection of Butt welds is listed in Table 1. Each weld is a combination of NPS, Pipe Schedule, and material.

Table 1: A data sample for RT inspection of butt welds.

Weld ID	Pipe Schedule	Nominal Pipe Size (NPS)	Material	Inspection Result
1	STD	4	A	1
2	STD	12	A	1
3	40S	10	B	1
4	40	2	C	0
5	XS	6	D	2
…	…	…	…	…

3.2 Data Processing and Analysis

For inferring the repair rate of each type of pipe welds, all data processing work is conducted using R. The main steps are listed as follows:

1. Connect to SQL Server via R (RODBC Package).
2. Group pipe welds based on pipe attributes, e.g., NPS, Pipe Schedule, and material.
3. Summarize the total welds, inspected welds, and repaired welds for each type of pipe welding.
4. Summarize the work proportion, inspection rate, and repair rate for each type of pipe welding.
5. Calculate the lower and upper Jeffreys Interval ($\alpha = 5\%$) limits of repair rate.
6. Document the posterior distributions for Monte Carlo Simulation use.

All 224,298 welds are grouped into 631 types of pipe welding. Based on the cumulative frequency graph shown in Figure 5, the top 35 types of pipe welds take more than 80% of all historical welds. For illustration purpose, only those 35 types of welding are shown in the following graphs. Detailed information about the top 35 types of pipe welds is listed in Appendix 1.

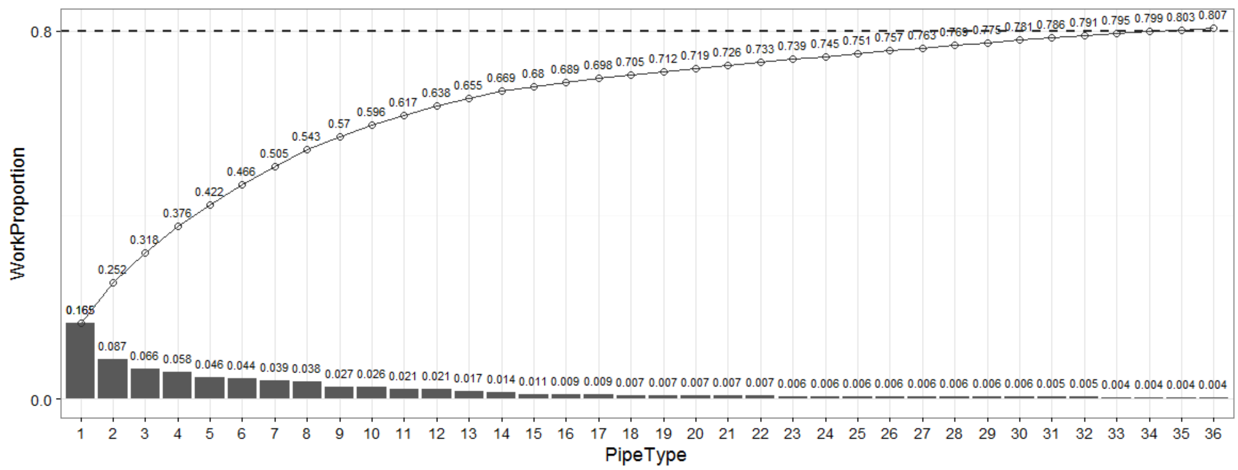


Figure 5: Cumulative work proportion of types of pipe welds.

Since the sampled welds do not include all welds from the population, an interval for repair rate needs to be estimated to allow for sampling error. As discussed, Jeffreys Interval can be used for inferring the repair rate of pipe welds. Figure 6 demonstrates the Jeffreys Intervals of the top 35 types of pipe welds. The darkness of the estimated repair rate represents the proportion that type of welds makes up. The posterior distributions derived from Jeffreys Intervals are used as the inputs of the Monte Carlo Simulation.

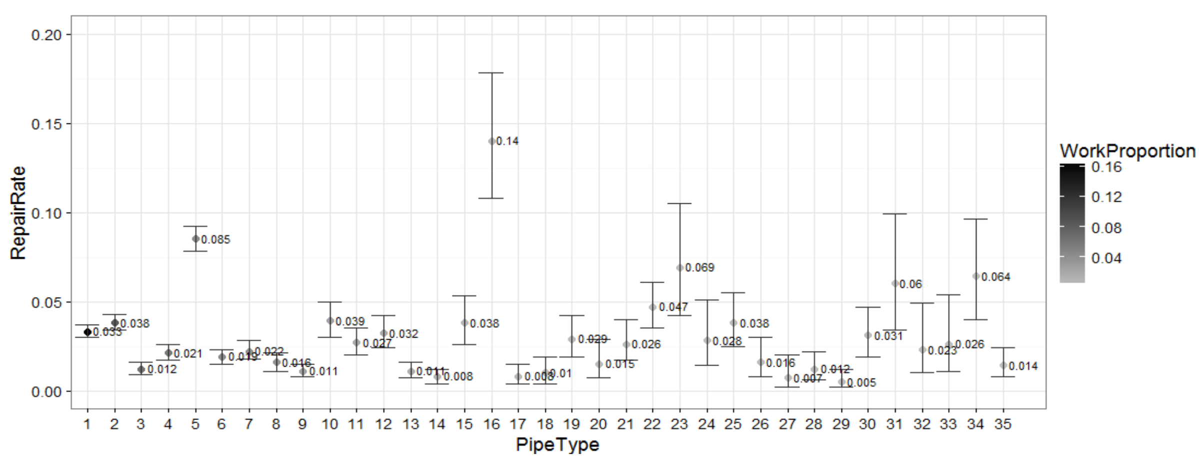


Figure 6: Jeffreys Intervals for different types of pipe welds ($\alpha = 5\%$).

3.3 Results of Simulation

To estimate the repair rate, pipe weld information (e.g., NPS, Pipe Schedule, and material) from 35 historical projects was used as the inputs for the Monte Carlo Simulation. The simulation model was run 100 times for each project to generate the graphs of 1) histogram and fitted theoretical density function

(Beta Distribution); 2) empirical and theoretical cumulative density functions; 3) Q-Q plot; and 4) P-P plot. Figure 7 shows the simulation output of one historical project.

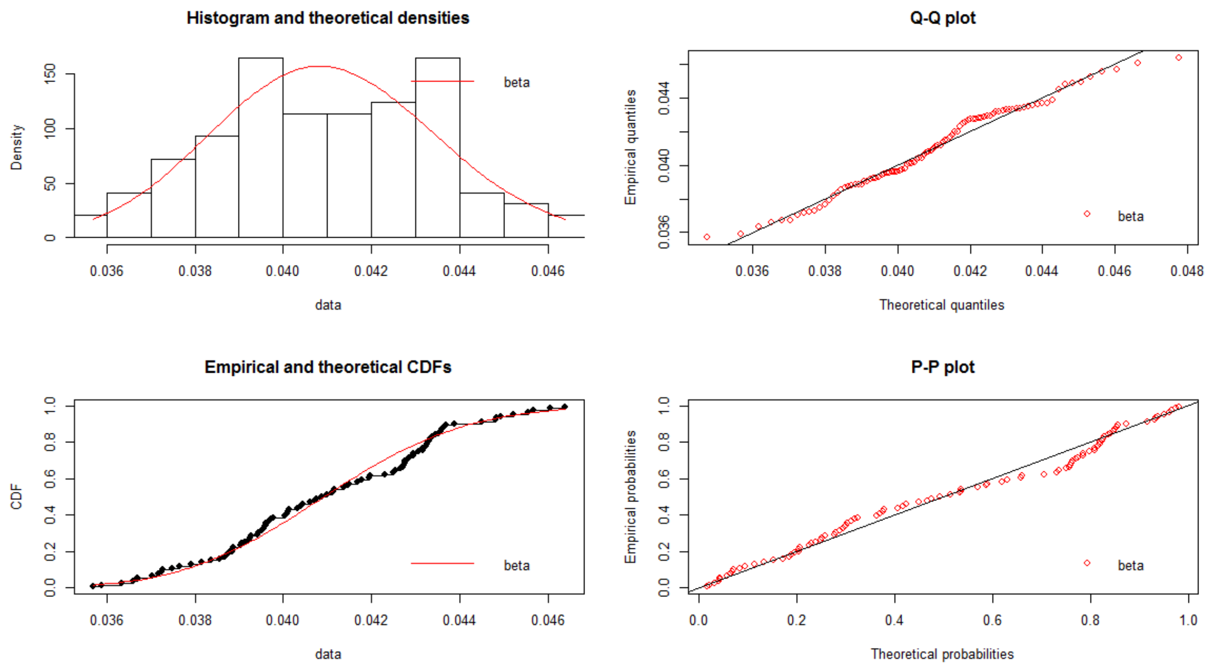


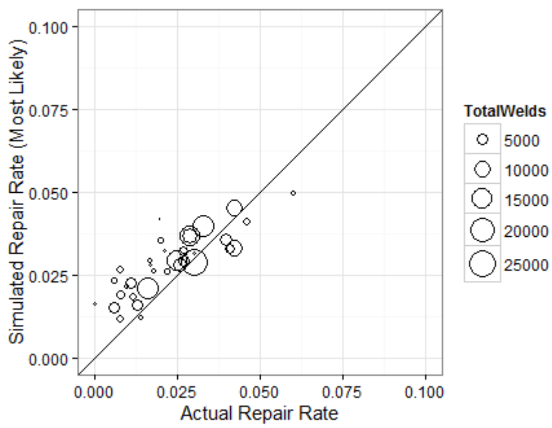
Figure 7: An example of simulation results of one historical project.

Based on the fabricators' risk attitude to a new project, an acceptable possibility for estimating the repair rate can be decided accordingly. Then, the estimated project repair rate can be found in the simulated CDFs given an acceptable quantile. For example, the 10% quantile represents an aggressive risk attitude; the 50% quantile represents a neutral risk attitude; and the 90% quantile represents a conservative risk attitude. Estimated repair rates for each type of risk attitude are listed in Table 2.

Table 2: Simulation Results for Different Risk Attitudes

Risk Attitude	Quantile	Estimated Repair Rate
Risk Seeking	10%	0.038
Neutral	50%	0.041
Risk Averse	90%	0.044

To evaluate the reliability and accuracy of the proposed Bayesian Inference based simulation model, a comparison between actual repair rate and simulated repair rate is conducted for all 35 historical projects. As shown in Figure 8, the x-axis represents the actual repair rate, and the y-axis represents the simulated repair rate with 50% (most likely) and 90% quantile value. Each circle represents a project, and the circle size indicates the amounts of welds completed in that project. If the circle is located on the left-upper side of the line y=x, it means the simulated repair rate can cover the actual repair rate, and vice versa. Apparently, the simulated repair rate can cover the actual repair rate for most projects, 30 out of 35 projects for 90% quantile, and 28 out of 35 projects for 50% quantile. The other five projects are not too far away from the line as well. Therefore, the conclusion can be drawn that the proposed data-driven simulation model can serve the purpose for estimating a safe repair rate. Practitioners can utilize the simulation tool to make better decisions for proposing new projects to clients.



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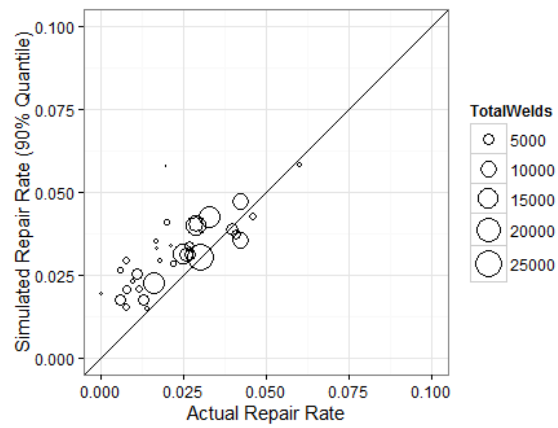

(b)

Figure 8: Comparisons of simulated repair rate and actual repair rate: (a) 50% Quantile (Most Likely); (b) 90% Quantile.

4 CONCLUSIONS

This research proposed a Bayesian Inference based simulation approach for estimating welds fraction nonconforming based on historical welds' quality inspection data. The Bernoulli Process is introduced to model the welds inspection process. Jeffreys Interval is utilized for estimating the distribution of the fraction nonconforming. The estimated distribution can be used as the input of Monte Carlo Simulation to improve the accuracy of simulation models. A real case of pipe fabrication is studied to demonstrate the proposed novel approach step by step.

The academic contributions of this research are 1) providing an analytical model for modeling the binomial quality inspection process; 2) proving the advantages of implementing Bayesian Inference in fraction nonconforming inference; and 3) developing a data-driven simulation model for estimating fraction nonconforming of the pipe welding process. For practitioners, the proposed model can be used to: 1) understand the welds quality performance based on historical data; 2) estimate project fraction nonconforming for proposing a new project to clients; and 3) perform what-if scenario analysis based on the simulation results.

In future work, the tracked inspection data will be further studied to understand how pipe attributes impact the quality performance of pipe the welding process, so practitioners can modify their welding procedures to improve performance quality.

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APPENDICES

Top 35 Types of Pipe Welds:

PipeType	Schedule	PipeSize	Material
1	XS	2	Material A
2	STD	3	Material A
3	STD	6	Material A
4	STD	4	Material A
5	STD	2	Material A
6	XS	6	Material A
7	STD	8	Material A
8	XS	4	Material A
9	160	2	Material A
10	80	2	Material A
11	STD	10	Material A
12	STD	12	Material A
13	XS	3	Material A
14	XS	8	Material A
15	40S	2	Material C
16	40	2	Material A
17	80	4	Material A
18	160	3	Material A
19	40	4	Material A
20	40	6	Material A
21	XS	10	Material A
22	XS	12	Material A
23	10S	2	Material C
24	40	3	Material A
25	40	8	Material A
26	40S	3	Material C
27	40S	4	Material C
28	80	3	Material A
29	80	6	Material A
30	STD	16	Material A
31	10S	3	Material C
32	40S	6	Material C
33	10S	6	Material C
34	10S	8	Material C
35	80	16	Material A

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