Bayesian Survival Analysis Model for Girth Weld Failure Prediction

Qingshan Feng 1,2,3, Shengyi Sha 1,* and Lianshuang Dai 4

1 Pipeline Integrity Management Center, PetroChina Pipeline Company, Langfang 065000, China; qsfeng@petrochina.com.cn
2 College of Pipeline and Civil Engineering, China University of Petroleum, Qingdao 266580, China
3 The Erosion/Corrosion Research Center, The University of Tulsa, Tulsa, OK 74104, USA
4 School of Materials Science and Engineering, Tianjin University, Tianjin 300072, China; lsdai@petrochina.com.cn
* Correspondence: shashengyi@petrochina.com.cn; Tel./Fax: +86-316-2170873

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Abstract: The formation and development of a dataset for pipeline systems have affected the management and decision-making of pipeline operators. The dataset, combined with a proposed theoretical analysis method, can provide significant improvement for the safe and economic operation of pipelines. On the basis of the pipeline data and its essential impact on pipeline risk assessment, the authors propose for the first time the Staged Bayesian failure model for girth welds of a pipeline, using the “tree-type” accident theory and Bayesian survival analysis method. This model of girth welds is consistent with the distribution of Kaplan–Meier functions and can predict the influence of different factors on the survival probability of girth welds. These new research results can lay the technical foundation for the failure analysis of pipeline girth welds.

Keywords: survival analysis; pipeline; girth weld; prediction

1. Introduction

The rapid growth of population and economies requires increased oil and gas pipeline infrastructure. There were 3500 oil and gas pipelines in service worldwide until 2015, with a total length of 1.83 million kilometers [1]. Pipelines are one of the safest ways to transport oil and gas but can cause horrific damage to buildings and injury or death to nearby residents once a rupture occurs [2]. Most of the accidents have indicated that the pipeline is always at risk of different kinds of fractures at fragile points that can be known or undetected [3]. Pipeline operators continuously seek ways to operate under safe and economic conditions, and the findings from this work can aid in this important objective.

New natural gas pipelines with high-pressure, large-diameter pipes and high-grade steels have become major trends in international construction [4,5]. However, in recent years, there have been a number of ruptures and leakages of new pipeline girth welds, which have led to serious property damage, environmental pollution, and even casualties [6,7]. The failure of pipe girth welds has become a major issue that threatens the safe operation of pipelines. According to casual statistics, there were about 64 cracks and leakages that caused accidents in onshore pipelines s from 2005 to 2015 in the United States and China [8]. Thus, the issue of to how to detect and evaluate more than 160 million girth welds on pipelines around the world and prevent the cracking of girth welds has become a worldwide concern. Because of the special position of girth-weld defects, it is difficult to identify and accurately quantify a defect size through in-line inspection. Especially for high-pressure natural gas pipelines, there is no mature detection technology for girth-weld cracks. In terms of existing trenchless
technology, magnetic flux leakage (MFL) techniques are still considered to be the most cost-effective and easy-to-implement techniques among girth-weld defect-detection methods [9,10]. However, the irregular girth-weld morphology makes it difficult to accurately identify and quantify the girth-weld defects in a short detection window. At present, there are no specific precision requirements for MFL inspection for girth-weld defects. The decision for girth-weld repair plans in accordance with the standards of the Fitness for Service (FFS) and Engineering Critical Assessment (ECA) methods [11–13] based on MFL inspections alone may significantly increase the operating costs, because of the possibility of large deviations in the data. Decisions based on this type of data cannot completely eliminate the risk of girth-weld failure. Furthermore, the factors influencing the failure of girth welds are relatively complex and still difficult to quantify and analyze and include welding defects, weld geometry, and loading, which is also affected by complex external factors, such as soil displacement, earthquakes, floods.

Traditional managers are accustomed to using general knowledge, limited experience, and limited data to determine the possible risk factors and locations of leaks in pipelines. However, the limitation of this method has been to use the data collected from other pipelines to analyze the data of a specific pipeline by analogy. Additionally, insufficient data regarding the pipe and the surrounding environment lead to the incorrect evaluation of the results. After decades of development, this model has improved and become a relatively more mature technology, with quite remarkable effects [14,15]. Many experts continue to revise evaluation models and algorithms in this area, so that the accuracy of risk prediction is continuously improved under limited cognitive conditions [16,17]. However, recent pipeline accidents show that there is an urgent need for research on how to use the information to identify and evaluate the failure of girth welds and on how to convert the information into practical aspects of integrity management to improve the safety of pipeline operation. Therefore, current research has tended to focus on new prediction methods in substitution of the traditional risk-assessment model. Although the current information or data have certain problems such as accuracy, they are enough to help to improve the evaluation of the safety status of the pipeline.

Previous research focused on discussing the knowledge of Pipeline Big Data (PBD) and what will change in the risk model [18]. With the development of technology, part of the dataset of the PetroChina pipe has become systematic and comprehensive, helping to almost fully understand the risk factors of the pipeline. This has permitted to change from “black-box” identification and evaluation of the risk factors to “white-box” identification and full control of the operators. This paper is an attempt to set up a framework method of girth-weld prediction with the Bayesian survival-analysis algorithm based on data t, ”tree-type” accident-cause theory, and anti-fragile concept to avoid the method of simple data analysis or the traditional risk analysis [19,20]. This framework is aimed to improve the tools of girth-weld failure prediction to reduce accidents and prevent disasters similar to the San Bruno pipeline rupture.

2. Survival Prediction Model

2.1. Girth-Weld Failure Causes

Detailed information or dataset can identify more failure’s causes than traditional theory analyses of accident’s causes. Initial work in this field focused primarily on the “tree-type” accident analysis model to analyze accidents, and risk analysis should be based on internal data analysis [21]. Once the failure-factor data are provided, then a risk model is needed to determine the “occupation rate” between the number of unknown failure factors and that of possible known failure factors. In other words, in the whole life cycle of a pipeline, when the failure factors of an accident are already known, the higher the ratio, the higher the probability of an accident.

The difference from the traditional analysis method is that the new method can be used to determine the probability of a leak by analyzing the possibility of leaks in specific segments of a pipe or groups defects with the same features, while the traditional method evaluates the possibility of
certain types of accidents by analogy with other accidents. It is necessary to change the type of analysis of such accidents, find out the factors causing the accidents, and analyze the “occupation rate” as a data-mining rule to identify and determine the pipeline status.

According to the “tree-type” pipeline accident-cause theory and girth-weld failure data, all the elements that may lead to the failure of girth welds are set to the part of the tree as shown in Figure 1.

The root cause, direct cause, and indirect cause of pipeline girth-weld cracking or leakage can be summarized and analyzed according to the “tree-type” accident-cause model. Then, on the basis of the model, it has been found that the key factors leading to the failure of the pipe girth weld include the following:

Case 1: Girth weld with defects, such as lack of fusion, crack, data from in-line inspection (ILI) or X-ray.

Case 2: Physical problem of girth weld, for example, the fracture toughness of the girth weld does not meet the standard, according to data from lab or field test.

Case 3: Geometric problem of girth weld, for example, misaligned girth weld, wall-thickness change, presence of a dent, etc., according to data from ILI, construction record, and nondestructive testing (NDT).

Case 4: Girth weld with additional external loads, caused, for example, by lifting and ditching during construction, presence of a weld within or near a pipe bend, ground displacement during operation, accidental loads, caused, for example, by earthquakes and other environmental factors, according to data from ILI, monitoring, etc.

Case 5: Special weld, such as tie-in weld, repaired weld, according to data from construction record.

Case 6: Non-straight girth weld deviating by over 3 degrees, according to data from ILI, NDT, etc.

Figure 1. “Tree-type” accident-cause model for girth weld.
Case 7: Imprecise management records, such as one 12 m pipe recorded as a combination of three short segments, construction company management lever, construction culture or background, imprecise information of welding quality or failure recorded by the welding team, and similar parameters.

Case 7 as a cause of defect is represented at the root of the tree in the above figure; Cases 1-3, 6, causing defects during construction, are represented in the tree trunk; Case 5 is linked to Case 7, Case 4 depends on monitoring during operation management and corresponds to the leaves of the above tree. The death of a tree or the breakage of a branch indicates failure.

These conclusions can provide guidance for identifying high-rupture-risk girth welds. However, due to the limitations of existing defect detection techniques, many indicators are difficult to quantify and cannot be considered in the risk assessment or evaluation of fitness. Therefore, using the theory and quantitative model of describing the causes of a pipeline’s defects, combined with a survival analysis and other prediction methods, the Bayesian survival-analysis model of girth weld can be established and can be used to analyze the influence of different factors on the life of girth welds and predict their mean survival.

2.2 Kaplan–Meier Survival Analysis Function

The survival analysis is based on data obtained from experiments or surveys and analyzes and infer the survival time of materials and objects. This method has been used in medicine, biology, economics, statistics, and other disciplines [22,23]. In this paper, we took a closer look at the patterns of girth weld failure and leaks in 64 girth-welding accidents and created a Bayesian model that predicts the probability of a girth weld maintaining its integrity in the future. The life of a girth weld is the time from its construction to its failure, due for example to cracking; girth-weld failure represents its “death”. After determining the life of a girth weld, a non-parametric Kaplan–Meier survival-method [24] is used for analysis. The life of a girth welds is described using parameters: “d” represents the number of “deaths” of the sample at a certain time “t”, and “n” represents the number of “survivals” of the sample at a certain time. The survival function indicates the probability of surviving the time “t”, as shown in Equation (1):

$$S(t) = \prod \left( \frac{n - d}{n} \right)$$

Hazard function is another basic function in survival analysis that measures the probability of a sample’s “death”. The hazard function $h(t)$ is calculated as:

$$h(t) = \frac{d}{dt} [-\ln P(t)]$$

The survival curve example in Figure 2a shows that the probability of failure of girth welds increases sharply in the first seven years and is relatively constant between 10 and 40 years; the failure rate increases after about 40 years. This is consistent with the three stages of the Bathtub curve for pipeline accidents, namely, the early “infant mortality” failure, the “constant” failure, and the “wear-out” failure due to pipeline aging.

According to accident records, the girth-weld with the longest life failed in its 63rd year. Therefore, this article can analyze only the 63rd year using the Kaplan–Meier method. There is only one variable allowed in the Kaplan–Meier method, and it cannot predict the future development of an event.

Also, since only the cracked, failed girth-weld samples are considered in the modeling analysis, if data related to functional samples are combined with those of the failed girth weld, for example, the planar defect found by in-line inspection is defined as failure, then the failure probability and survival function of the failed girth weld will change.
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2.3. Bayesian Survival Analysis Function

The Bayesian method [25] is used to obtain the distribution of parameters based on their prior distribution and the likelihood function.

Since the 1970s, Berliner et al. [26,27] started using the Bayesian method for the analysis of survival data. Later, different theoretical models were developed. The Bayesian survival analysis method can make up for defects, such as small-sample and incomplete data, and achieve survival analysis or failure prediction. The prior distribution of girth-weld failure can be described as in Figure 2a, monotonically increasing or decreasing, satisfying the characteristics of the Weibull distribution. The probability density function of Weibull distribution is:

\[ f(x|\alpha, \lambda) = \lambda \alpha x^{\alpha - 1} \exp(-\lambda x^\alpha) \]  (3)

where \( \alpha \) is the size parameter, and \( \lambda \) is the shape parameter.
The survival function represents the probability that the analysis target survives to time \( t \), expressed as Equation (4):

\[
S(t|\alpha, \lambda) = P(T > t) = \int_{t}^{\infty} f(x|\alpha, \lambda)dx = \exp(-\lambda t^\alpha)
\]  \hspace{1cm} (4)

The sample data are related to the failure of girth welds. On the basis of the prior distribution and sample data, the posterior distribution of parameters at each stage can be obtained by the Bayesian method. However, we cannot determine the posterior distribution of parameters \( \alpha \) and \( \lambda \) before the analysis. Therefore, the Markov Chain Monte Carlo (MCMC) [28] is used to solve the problem that the parameters of the posterior distribution are unknown, and the calculation process is complex. The calculation of the posterior distribution of the two parameters is performed by the WinBUGS [29]. Consider that the average value of the two parameters was 0.7298 and 0.1118. Because the sample data were taken from the failure girth-weld data, in the 63rd year, all girth welds failed, and the corresponding survival probability was 0. Take the lower-limit value and the upper-limit value of the two parameters under the 90% confidence interval. The survival function is shown by the dotted line in Figure 3.

If the survival function conforms to the Weibull distribution, \( \ln[-\ln S(t|\alpha, \lambda)] \) is linearly distributed to \( t \).

\[
\ln[-\ln S(t|\alpha, \lambda)] = \ln(\lambda) + \alpha \ln(t)
\]  \hspace{1cm} (5)

The Kaplan–Meier survival function in Figure 3 does not exactly fit the linear relationship. Therefore, the data of girth-weld failed samples do not completely conform to the Weibull distribution. In Figure 3, the data from 10 years are in good agreement with the Weibull distribution; however, a wide range of confidence intervals and some of the data are outside the range after 10 years because of a limited sample number.

Figure 3. Survival function of girth-weld failure accident.

According to the distribution trend of the survival curve in Figure 2a, the posterior distribution can be divided into three stages. Different stages use different functional forms, which can be called Staged Bayesian. This model is a brand-new Bayesian form and is proposed in this paper for the first time. The Weibull distribution was used in the early “infant mortality” failures stage, the uniform distribution was used in the second stage, and the exponential distribution was used in the last one. The cutoff years between stages are 10 and 40, which were selected according to historical statistics and
the turning point in the survival curve in Figure 2. The Weibull distribution still uses the parameter estimates of the survival function in Figure 2. The Table 1 shows the parameters and values of Staged Bayesian. As shown in Figure 3, the Staged Bayesian distribution is consistent with the Kaplan–Meier survival function, and the fitting results are matched.

### Table 1. Survival function parameter of different stages.

| Lifetime (Year) | 0–10 | 11–40 | 41–63 |
|-----------------|------|-------|-------|
| Type            | Weibull distribution | Uniform distribution | Exponential distribution |
| Parameter       | $\alpha$ | $\lambda$ | $K$ | $C$ | $a$ | $\lambda$ |
| Value           | 0.7298 | 0.1118 | -0.005796 | 0.642026 | 13.08 | 0.09138 |

3. Survival Probability and Cases

Section 2 analyzes several key factors closely related to a girth-weld accident based on the “tree-type” accident cause theory. The prediction method is discussed in Section 2.3. It is well accepted that the rupture of a girth weld is often caused by multiple factors simultaneously. If each factor is independent of time, it will occur only under random conditions or conditions that cause fragility. It is assumed here that an undamaged pipe girth weld does not fail in service, and only a defective weld can be predicted to fail, as a consequence of the 7 factors mentioned in Section 2.1. The influence of different factors on the failure of a girth weld was analyzed by predicting the survival function factors.

It is assumed that the largest number of factors causing a certain type of pipeline accident is $m$, and the pipeline state is found to have $k$ factors. According to the occupation rate, the probability of occurrence of the accident is $k/m$. However, we should distinguish the extent to which each factor affects the failure.

The survival function uses the staged Bayesian result in Figure 3. The 14 girth-weld failures with detailed information were selected for setting up the survival probability modeling in the “infant mortality” stage. These 14 failure cases, from a total of 64 failure cases, occurred after less than 10 years of service. Table 2 shows the factors related to each case, with the top 7 factors as described in Section 3; 1 means that the corresponding factor is satisfied, 0 means that it is not satisfied, and 2 means that two elements of the same factors are satisfied.

### Table 2. Failure cases with failure factors.

| Failure Casing | Failure Lifetime | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 | Case 7 |
|----------------|------------------|-------|-------|-------|-------|-------|-------|-------|
| 1              | 0.35             | 1     | 1     | 0     | 1     | 1     | 0     | 0     |
| 2              | 0.5              | 1     | 1     | 0     | 1     | 2     | 0     | 0     |
| 3              | 0.5              | 1     | 0     | 0     | 1     | 0     | 0     | 0     |
| 4              | 0.5              | 1     | 0     | 2     | 0     | 1     | 0     | 0     |
| 5              | 1                | 1     | 0     | 1     | 0     | 2     | 0     | 0     |
| 6              | 1                | 1     | 0     | 0     | 0     | 1     | 0     | 0     |
| 7              | 1                | 1     | 0     | 1     | 1     | 0     | 0     | 0     |
| 8              | 1.5              | 1     | 1     | 0     | 0     | 1     | 0     | 0     |
| 9              | 1.5              | 1     | 1     | 1     | 0     | 1     | 0     | 0     |
| 10             | 2.1              | 1     | 0     | 1     | 1     | 1     | 0     | 0     |
| 11             | 3                | 1     | 0     | 0     | 0     | 0     | 0     | 0     |
| 12             | 3.5              | 1     | 0     | 0     | 0     | 1     | 0     | 0     |
| 13             | 4                | 0     | 0     | 2     | 0     | 0     | 1     | 1     |
| 14             | 7                | 1     | 0     | 0     | 1     | 0     | 0     | 0     |

Firstly, according to the 14 accident samples, the life curve of every single factor leading to the failure of the girth weld was calculated, and the influence of each factor on the failure probability of the new pipe girth weld was determined. Then, the life curve of the girth failure was analyzed considering
all factors and comparing the effects on girth-weld failure of various combinations of them, that is, the probability of “survival”.

According to these assumptions, to directly consider the influence of multiple factors on a girth-weld function, let $\lambda$ of staged Bayesian be:

$$\lambda = r_0 + r_1 z_{1i} + r_2 z_{2i} + r_3 z_{3i} + r_4 z_{4i} + r_5 z_{5i} + r_6 z_{6i} + r_7 z_{7i}$$  \hspace{1cm} (6)

where:

- $r_1 \sim r_7$ Indicates the influence factor of seven different cases on the failure of the girth weld,
- $r_0$ is a correlation factor between different factors,
- $z_{1i} \sim z_{7i}$ represents the values corresponding to seven different Cases (see Table 2).

The girth-weld survival function based on the failure case sample is determined by calculating $r_0$ and $r_1 \sim r_7$ in Equation (6).

Figure 4 shows the survival function of the girth weld under the influence of a single factor. As can be seen from Figure 4, the lowest probability of girth weld survival is when the physical properties of the weld do not meet the specifications, which means that it is the most critical of the seven factors; and the impact of Case1 is relatively small. Therefore, the mechanical properties of the weld should be strictly controlled by monitoring weld defects.

![Figure 4](image)

**Figure 4.** Survival function of the girth weld under the influence of a single factor.

Figure 5 shows the predicted survival function of the girth weld under the influence of several different factors, where:

- Num1 indicates that only the Case1 factor is operating,
- Num2 indicates that the Case1 and Case4 factors are operating,
- Num3 indicates that the Case3, Case4, and Case5 factors are operating,
- Num4 indicates that the Case1, Case2, Case3, and Case4 factors are operating,
- Num5 indicates that the Case1, Case2, Case3, Case4, and Case5 are operating,
- Num6 indicates that other factors than Case6 are operating,
- Num7 indicates that all factors are operating.

As the failure factor increases, the occupancy rate also increases, and the survival probability of the girth weld is significantly reduced. So, the more the factors, the more fragile the girth weld.
With this model, it is easy to determine the failure trend in time and the most critical factors and weld under the influence of a single factor and of several combinations of different factors, according to the survival function model described above, a weld with similar failure factors had a survival probability of 0.120 in 2017 and of 0.109 in 2018. If the accident in 2017 is included to the sample, and the impact factor of Equation 7 is recalculated, the survival probability of the girth weld in 2018 changes to 0.104, which is not much different from the original calculation result. Therefore, the number of samples is sufficient for effectively predicting the cracking of the girth weld.

This study also analyzed the other girth welds in this pipeline, and the statistical results showed that only two weld failures corresponded Cases 2, 4, and 5 at the same time; also, Case 4, was not represented by other weld failures. So, two girth-weld accidents occurred since the hydrotest. The pipeline operating company should take measures to prevent additional external loads from pressing on the pipe.

The failure factors of girth welds are relatively complex and difficult to quantify, and traditional risk assessment determine the possible risk factors on the basis of general knowledge and limited experience. This paper proposes a new model to improve the tools of girth-weld failure prediction. With this model, it is easy to determine the failure trend in time and the most critical factors and combination of factors for girth welds of a pipeline.

4. Conclusions

This study first proposes the Staged Bayesian survival analysis model for girth-weld failure prediction using the tree-type cause theory and survival analysis method. The results show that the Staged Bayesian model is consistent with the Kaplan–Meier model. Meanwhile, the results of the model fit the trend of the “Bathtub Curve” of a pipeline and the intrinsic characteristics of a girth weld. Further analysis based on the survival model shows the tendency of the survival probability of the girth weld under the influence of a single factor and of several combinations of different factors, according to data of previous 14 accidents that happened within 10 years of pipe life after hydro-pressure. The model and analysis method can also be used to improve the risk assessment and provide guidance for risk-mitigation measures for the company operating a pipeline.
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References

1. Song, A.; Liang, G.; Wang, G. Status Quo and Development of Worldwide Oil and Gas Pipelines. *Oil Gas Storage Transp.* 2005, 24, 1–6.
2. American Petroleum Institute. *Association of Oil Pipelines*; 2017 Performance Report; American Petroleum Institute: Washington, DC, USA, 2018.
3. Feng, Q.; Dai, L. *Revelation of Pipeline Accidents*; China Building Materials Press: Beijing, China, 2016; pp. 5–15.
4. Li, H. Some Hot Issues in the Research and Application of Natural Gas Transmission Steel Pipes. *Welded Pipe Tube* 2000, 3, 43–46.
5. Li, H. Trends and Prospects of Development of Oil and Gas Pipelines. *Welded Pipe Tube* 2004, 6, 1–19.
6. Hu, M.; Liu, Y.; Zhu, L.; Qi, L.; Yang, F. Analysis of leakage failure of girth welded joints in natural gas transmission pipelines. *Welded Pipe Tube* 2014, 2, 56–63.
7. Bruce, W.A.; Amend, W.E.; Wang, Y.; Zhou, H.M. *Guidelines to Address Pipeline Construction Quality Issues*; Pipeline Research Council International: Chantilly, VA, USA, 2013.
8. PHMSA. Pipeline Safety-Flagged Incidents [EB/OL]. 14 December 2013. Available online: http://primis.phmsa.dot.gov/comm/reports/safety/PSI.html (accessed on 12 May 2015).
9. Feng, Q.; Li, R.; Nie, B.; Liu, S.; Zhao, L.; Zhang, H. Theory and Application of In-Line Inspection Technologies for Oil and Gas Pipeline Girth Weld Defection. *Sensors* 2017, 17, 50. [CrossRef] [PubMed]
10. Wang, T.; Yang, H.; Feng, Q.; Zhou, L.; Wang, F.; Xiang, X. Current status and the prospect of inline inspection technologies for defects in girth weld of oil and gas pipeline. *Oil Gas Storage Transp.* 2007, 34, 694–697.
11. API 579-1/ASME FFS-1: *Fitness-For-Service*; American Petroleum Institute: Washington, DC, USA, 2016.
12. British Standards Institution. *BS 7910 Guide to Methods for Assessing the Acceptability of Flaws in Metallic Structures*; British Standards Institution: London, UK, 2013; pp. 25–59.
13. Amend Bill, P.E.; Columbus, D.N.V. *Vintage Girth Weld Defect Assessment Comprehensive Study*; Pipeline Research Council International: Chantilly, VA, USA, 2010; pp. 33–37.
14. Peter, T.; Nader, Y.-G.; John, B. Benchmarking Pipeline Risk Assessment Processes. In Proceedings of the 9th International Pipeline Conference, IPC 2012-90045, Calgary, AB, Canada, 24–28 September 2012.
15. Zhang, H.; Cheng, W.; Zhou, L.; Feng, Q.; Zheng, H.; Dai, L.; Xiang, X.; Cao, T.; Liu, Y. Pipeline risk assessment practice of PetroChina Pipeline Company. *Oil Gas Storage Transp.* 2012, 31, 96–98.
16. Dai, L.; Zhang, J.; Zhang, X.; Zhang, H.; Cao, T.; Feng, Q.; Zheng, H. Risk Score Pipeline Risk Assessment and Its Application. *Oil Gas Storage Transp.* 2010, 29, 818–821.
17. Mojtaba, M.; Li, C.Q. Failure assessment and safe life prediction of corroded oil and gas pipelines. *J. Pet. Sci. Eng.* 2017, 151, 434–438.
18. Feng, Q. A thought over the pipeline risk assessment methods based on Big Data. *Oil Gas Storage Transp.* 2014, 33, 457–461.
19. Feng, Q. Theoretical study on characteristics and quantification of oil and gas pipeline failure. *Oil Gas Storage Transp.* 2017, 36, 369–374.
20. Feng, Q. “Tree-type” model of accident cause theory. *Oil Gas Storage Transp.* 2014, 33, 115–128.
21. Feng, Q. New Concept Based on Big Data to Pipeline Risk Management. *Pipeline Gas J.* 2015, 242, 65–67.
22. Li, R. Based on the Bayesian Survival Test Censored Regression Model and Its Application; Hunan University: Changsha, China, 2006.
23. Philip, H. *Analysis of Multivariate Survival Data*; Springer: New York, NY, USA, 2001.
24. Kaplan, E.; Meier, P. Nonparametric estimation from incomplete observations. *J. Am. Stat. Assoc.* 1958, 53, 457–481. [CrossRef]
25. S. James Press. *Bayesian Statistics: Principles, Models, and Applications*; Wiley: New York, NY, USA, 1992.
26. Chen, W.C.; Fayos, J.V.; Hill, B.M. Bayesian-analysis of survival curves for cancer-patients following treatment. *Biometrics* **1978**, *34*, 531–541.
27. Omurlu, I.K.; Ture, M.; Ozdamar, K. Bayesian Analysis of Parametric Survival Models: A Computer Simulation Study based Informative Priors. *J. Stat. Manag. Syst.* **2015**. [CrossRef]
28. Gilks, W.R.; Richardson, S. *Markov Chain Monte Carlo in Practice*; Chapman and Hall: New York, NY, USA, 1995.
29. Lunn, D.J.; Thomas, A.; Nicky, B.; David, S. WinBUGS-A Bayesian modeling framework, concepts, structure and extensibility. *Stat. Comput.* **2000**, *10*, 325–337. [CrossRef]