CHAPTER 2

LITERATURE REVIEWS

2.1 Corrosion under Insulation

Corrosion under insulation (CUI) is a common problem not only in chemical process plants but also in utility and power plants. Kletz (1995) stated that in 1960s and 1970s, many plant designers were not concerned with the potential problems of CUI. The consequence of the under design is many cases of pitting or rusting of carbon steel, stress corrosion cracking of austenitic stainless steel and other hidden metal loss found under the insulation. A study done by Exxon Mobil Chemical that was presented to the European Federation of Corrosion in September 2003 indicated that the highest incidence of leaks in the refining and chemical industries was due to CUI and not to process corrosion (Corrosion under insulation, n.d.).

CUI contributes about 40% to 60% of piping maintenance costs (Corrosion under insulation, n.d.). The followings are some statistics found in the literature about CUI:

- One plant reported that much of its piping had to be removed and replaced after a major expansion where the insulation had been covering the piping for over 20 years (Kletz, 1995). Some 8-inch piping with 0.95 cm wall thickness had external pitting so deep that a mechanic could push his finger through the pipe wall. Also, 6-inch pipe with 0.95 cm wall thickness had external pitting with 0.41 cm in depth which was about 43% of the wall thickness.
- Fitzgerald and Winnik (2001) reported several cases of CUI found as follows:
    - After 4½ years in service, a 30-inch, light hydrocarbon line operating at 82°C was found to have very thin areas in the bottom center of the pipe as a result of CUI.

- A 6-inch hydrocarbon vapor line was found to have severe CUI and wall thinning at each insulation section joint after 12 years in service.
- After 20 years in service, a 3-inch propane line was found to have very thin areas as a result of CUI.

In refineries and process plants, piping systems are enormous and much more complex than other types of equipment (Chang et al., 2005). Thus, in general, compared with other types of equipment in these industries, more difficulty in piping inspection planning is encountered. Unfortunately, regulatory requirements on piping safety and inspection interval is lacking when compared to pressure vessels where the inspection interval requirement is clearly documented (Chang et al., 2005). Lack of regulatory requirements may cause under-inspection or over-inspection.

Piping system inspection strategy, including strategy for CUI inspection, typically is established based on the guideline by American Petroleum Institute, API 570, or based on risk-based inspection (RBI) methodology. API 570 provides a guideline on establishing piping system inspection interval based on fluid content in piping or the half remaining life (API, 2001). Alternatively, piping inspection intervals can be established by using a risk-based RBI assessment conducted in accordance with API 581 where this method is based on risk assessment.

2.2 Risk-Based Inspection

Over the past few decades, the strategies in inspection and maintenance evolved from the breakdown maintenance to the more sophisticated strategies such as condition monitoring and reliability centered maintenance. The paradigm shift was motivated by the need to implement new maintenance strategies which would increase the effectiveness and profitability of the business. Another link to the evolution is the introduction of risk-based approach to inspection and maintenance as shown in Figure 2.1.

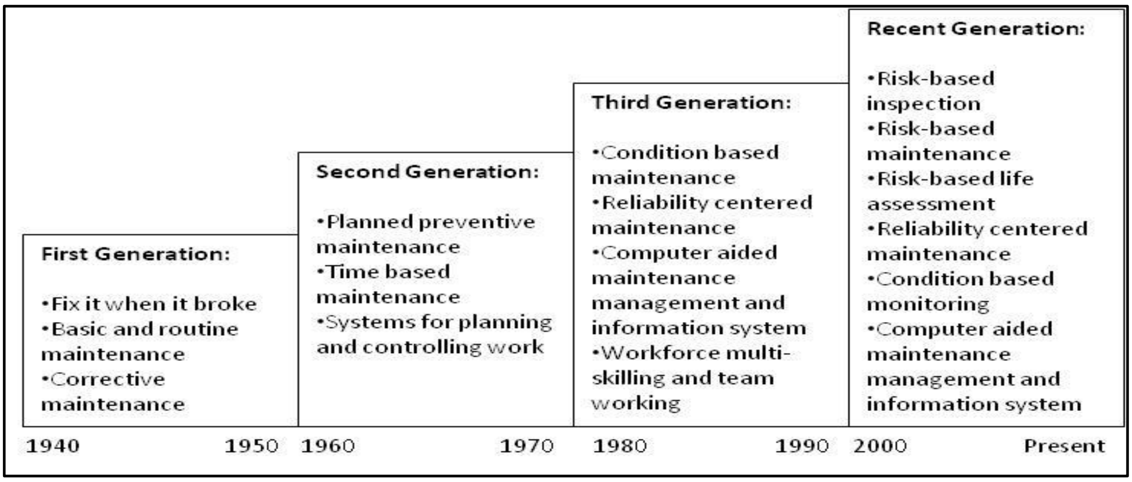

Figure 2.1: Development of maintenance philosophy (Arunraj & Maiti, 2006)

The first initiatives for the developments of risk based approaches to the inspection and maintenance planning were directed towards the inspection planning for welded connections subject to fatigue in fixed steel offshore structures (Skjong, 1985; Madsen et al., 1989; Fujita et al., 1989). Later, the same methodology was applied to other structures such as ships and tankers (Soares & Garbatov, 1996; Paik et al., 2004, Vanem & Skjong, 2008), floating, production, storage and off-loading facilities (Lotsberg et al., 1999; Goyet et al., 2002), semi-submersibles, pipelines (Willcocks & Bai, 2000; Desjardins, 2002; Dey & Gupta, 2001), process plants (Geary, 2002; Montgomery & Serratella, 2002; Kallen, 2002; Kallen & Noortwijk, 2006; Khan et al., 2006), bridges (Frangopol et al., 2004), and breakwaters (Noortwijk & Phajm, 1996) to name a few.

Risk-based inspection (RBI) has been an industry standard for prioritizing inspection of static equipment, such as pressure vessels, tanks, heat exchanger, piping systems, relief valves and control valves (Dey, 2001; Khan & Haddara 2003; Dey, Ogunlana & Naksuksakul, 2004; Krishnasamy et al., 2005; Khan et al., 2006). Although, the application of RBI is more on static equipment, it has also been applied to rotating equipment (Fujiyama et al., 2004). The concept of risk is used to target inspection and maintenance resources at areas of the plant where they can have the greatest effect in reducing risk, the occurrence and consequence of unplanned failures. In theory, risk is defined as the product of the probability of failure and its likely consequences.

According to Giribone and Valette (2004), the main driver for scheduling inspection interval is the probability of failure. The probability of failure is defined as the mean frequency or rate with which the specified failure event would be expected to occur in a given period of operation, normally one year. Therefore, estimating the probability of failure is an important input to RBI analysis.

Different methodologies were suggested to assess the probability and the consequence of failure. These methodologies range from fully qualitative to fully quantitative. In qualitative failure probability assessment, the probability of failure is primarily based on engineering judgments made by experts. The failure probability is described using terms such as very unlikely, unlikely, possible, probable or highly probable where subjective scores are assigned to different factors which are thought to influence the probability of failure. To ensure that this term will be used consistently, criteria for the descriptive categories should be defined. Several studies have been found using the qualitative assessment to generate the failure probability (Muhlbauer, 1992; Cagno et al., 2000; Dey, 2001; Dey & Gupta, 2001; Dey, 2004; Dey et al., 2004). The knowledge and input from experts is valuable in assessing the probability of failure. However, this method is highly subjective and involves a lot of randomness and uncertainty.

In semi-quantitative failure probability assessment, the probability of failure should generally be more numerically based and detailed than the qualitative approach, but still contain a large element of engineering judgments. The common method is based on the guidelines by American Petroleum Institute, API 581 Risk-based Inspection Base Resource Document (API, 2000). Several papers have been found in the literature in applying the semi-quantitative approach in failure probability assessment (Khan & Haddara, 2003a; Khan & Haddara, 2003b; Willcocks & Bai, 2000; Khan & Haddara, 2004; Khan et al., 2004; Noori & Price, 2005; Krishnasamy et al., 2005; Noori et al., 2005). Since this approach relies on the database which is built using records from all plants within a company or from various plants within an industry, from literature sources, past reports, and commercial data bases in general, the values represent may not reflect the true failure frequencies for a specific plant and equipment.

In fully quantitative failure probability assessment, the approach is to statistically estimate the failure probability based on actual data collected such as historical failure data and/or inspection data (Khan et al., 2003; Vinod, 2003; Fujiyama et al., 2004; Fleming, 2004; Khan et al., 2004; Khan et al., 2006; Podofillini et al., 2006; Yuan et al., 2008). Using this analytical approach, the numerical data are then analyzed using suitable models such as mathematical models, logic flow diagram and others. The major limitation in estimating the probability of failure using this approach is that the failure probability are estimated based on the historical failure data where those failure data is typically very limited because of the rarity of the failures. For example, in this case, the pipe failure due to CUI is sparse and, if there is any, the amount of data available is not enough to analyze the data statistically.

2.3 Failure Probability Assessment for Piping Systems

In any RBI methodology, suitable methods are needed to assess the probability of a pipe failure with an adequate accuracy. Based on literature, the probability of a pipe failure can be estimated quantitatively using statistical estimation from large databases or existing plant data and using structural reliability analysis methodology.

The primary limitation of a statistical analysis approach is that one attempts to subdivide the data based on various damage mechanisms causing smaller set of data for each damage mechanism. Another factor of concern is the level of verification and validation the database records. As in Fleming & Lydell (2004), a lack of verification and validation can drastically influence the quality of the qualitative and quantitative information generated by any given database application. In addition, Fleming & Lydell (2004) also discussed that historical failure data usually reflect the influence of previous piping inspection programs, and, if changes to these programs are proposed, such changes may render the previous failure rate estimates no longer relevant.

2.3.1 Statistical Estimation based on Failure/Inspection Data

The most straightforward approach is to obtain statistical estimates of pipe failure rates based on data collected from piping system service experience. In this context, the pipe failure is defined as leak or rupture; thus, the data collected are leak and rupture data collected from all plants within a company or from various plants within an industry, from literature sources, past reports, and commercial data bases.

Standardized leak frequencies have been developed for different types of process equipment based on recent data from onshore process plants in order to ensure that consistent frequencies are available for any equipment type and hole size which can be seen in Ref (API, 2000; Simola et al. 2004; Fleming & Lydell, 2004; Cronvall & Männistö, 2009; Berg et al., 2010). The last 10 years (1994–2003) have seen major progress in piping reliability database development and application where the data were piping failures in nuclear power plants. The failures were due to crack, pinhole leak, leak or rupture. Several databases were SKI 96:20, PIPExp, EPRI'97, SKI-PIPE and Barsebäck (Fleming & Lydell, 2004; Simola et al., 2004).

Another method found in the literature to assess the probability of failure is degradation analysis. In a situation where failure data are scarce, degradation analysis is useful for the analysis of failure time distributions in reliability studies (Bae et al., 2007). Meeker and Escobar (1998) offered a comprehensive guide to degradation analysis and show that degradation analysis has great potential to improve upon reliability analysis. Degradation analysis requires a collection of degradation data and using this data, an appropriate degradation model is identified. By assuming a stochastic model for the degradation, the lifetime distribution is automatically implied. Thus, the key to the analysis is the perceived link between the degradation model and the failure time.

Degradation models vary markedly across the fields of reliability modeling (Bae et al., 2007). Many practical problems can be modeled with a linear rate of degradation. Bogdanoff and Kozin (1985) employed both linear and more complex nonlinear models to characterize crack growth in materials testing. Noor et al. (2007) employed a linear model to characterize corrosion pits in vessel's seawater ballast tanks. Yahaya et al. (2009) used a linear model to estimate corrosion rate at a future time for submarine pipelines subject to CO_2 corrosion (i.e. internal corrosion defects).

For systems that are susceptible to wall thinning degradation mechanism, the wall thickness measurements are usually collected. For piping systems, pipe wall thickness data are being recorded in large quantities over long periods of time in chemical plants and refineries Barringer (1997). Barringer (1997) applied Weibull analysis using the pipe wall thickness taken during inspection time to assess the pipe failure probability in order to set inspection intervals. Yuan et al. (2008) presented a probabilistic model of wall thinning in feeder pipes due to flow-accelerated corrosion. The proposed model derives the feeder pipe lifetime distribution, which is useful in developing optimum strategies for life-cycle management of the feeder system.

2.3.2 Structural Reliability Analysis

Another method to assess the probability of failure of piping systems is using the structural reliability analysis methodology. The traditional, deterministic structural reliability analysis methodology is evaluated by comparing the current operating conditions with a design-limit state beyond which the component cannot operate safely (i.e. load-resistance method). For example, Ahammed, M. (1997) developed a deterministic model to evaluate the remaining strength of corroded steel pipeline over time and the maximum allowable failure pressure of corroded pipelines.

Traditional load-resistance methods have the disadvantage that they often yield somewhat conservative results, leading to potentially unnecessary repairs and inspections that result in an overall increase in maintenance costs (Khan et al., 2006). Use of deterministic methods does not provide information about potential risk that result in the unrealistic maintenance planning for process plants (Desjardins, 2002). Moreover, each parameter in the load-resistance analysis contains a degree of uncertainty.

As such, the probabilistic approach to the load-resistance methodology has gained considerable notice recently. The probabilistic approach is capable of identifying the sources of variables affecting the strength of the structure. According to Tong (2001), it has also been proven that the probabilistic method can be extended to provide very useful information to help managers in making decisions to optimize the inspection time.

There has been an increased focus on failure probability assessment for piping systems using the probabilistic fracture mechanics (PFM) framework. PFM is considered as an appropriate methodology in reasonable evaluation and risk-based decision making since it can deal with various uncertainties quantitatively (Fleming, 2004).

To date, several PFM programs have been developed as means of integrity evaluation tools to resolve industrial issues. Cizelj and Mavko (1994) proposed a method to establish steam generator plugging strategy using Monte Carlo simulation in case of axial stress corrosion cracking at tube expansion transition zone. Dillstr¨om (2000) developed a computer program to calculate failure probabilities when a defect size is either given by non-destructive testing (NDT)/non-destructive examination (NDE). Harris and Dedhia (You & Wu, 2002) developed a computer code named PRAISE (Piping Reliability Analysis Including Seismic Events) for the estimation of pipe leakage and LOCA (Loss of Coolant Accident) probabilities. The inter-granular stress corrosion cracking (IGSCC) growth data of stainless steel under various temperature conditions were used as the database for the Monte Carlo simulation. Rahman et al. (You & Wu, 2002) developed another computer code named PSQUIRT (Probabilistic Seepage Quantification of Upsets in Reactor Tubes) which considered crack morphology parameters as normal and lognormal probability density functions in order to find the leakage-rate probability of piping made of stainless steel and carbon steel subjected to IGSCC and corrosion fatigue. In Japan, Yagawa and Yoshimura (1997) carried out a series of PFM analyses of piping. Khaleel and Simonen (2000) proposed PFM model for the prediction of pressure vessels and piping failure probabilities caused by fatigue crack growth. Cioclov (2007) developed a methodology for integrating PFM with quantitative NDT for the purpose of failure risk assessment in load-carrying elements of aircraft structures subject to fatigue.

PFM has the advantage of providing data that is free from the effects of any existing inspection activities (Cronvall & Männistö, 2009). However, according to Fleming (2004), this approach was found to be not effective at developing results that are reproducible and consistent with estimates derived from service experience. Moreover, the quantity and quality of information needed to perform the necessary computations is time consuming and the associated costs tend to limit the number of piping components that can be separately analyzed within the finite budget of a risk informed project. When PFM is applied to a piping component with no obvious failure mechanism susceptibility, the failure rate predictions tend to be so low as to be suspect. Even in cases where PFM approaches are appropriate, it is highly desirable to be able to benchmark such analyses with some form of service data.

Another probabilistic engineering approach is structural reliability analysis, meant for the structural integrity analysis of structures and components under service loads. The mathematical basis for structural reliability analysis was established in the late 1960s and early 1970s (Tong, 2001). However, its theory and methods have been developed significantly in the last few years and they are in fact a useful means for evaluating the safety of complex structures or structures with unusual designs as well as simple structure (Cardoso et al., 2008). Structural reliability theory has been applied to a number of studies for structures subject to corrosion in assessing the failure probability.

Ahammed and Melchers (1995) presented a methodology to describe the assessment of the service life of liquid carrying metallic pipelines subjected to pitting corrosion. The estimate of pipeline service life is based on the loss of liquid through pit holes during transportation. The growth of corrosion pits is modeled by a two-parameter exponential function having time dependency and a decreasing rate of pit growth. Parameters which are related to corrosion, pipeline dimension and liquid flow are treated as random variables. Failure is defined in terms of a maximum allowable degree of loss or ingress of fluid. The first-order reliability method (FORM) is used to estimate the probability of failure and the relative contribution of the various uncertain parameters to it. The results showed that the probability of failure increases nonlinearly with time and that the contribution of pit hole size and pitting corrosion parameters are very significant for long service life.

Ahammed and Melchers (1996) provided a reliability approach to study the pressurized piping subjected to the localized corrosion defects. With the reliability methodology, the assumed limit state function was established and simulated according to the variation of the material, environmental condition and operating pressure. It also provided the estimated failure probability of the piping versus the time in order to prevent the catastrophic accidents occurred. The obtained results in the paper also showed that both the defect depth and the fluid pressure have significant influences on piping reliability.

Ahammed (1998) presented a methodology for the assessment of the remaining life of a pressurized pipeline containing active corrosion defects. A probabilistic approach was adapted to this methodology and the associated variables are represented by normal and or non-normal probabilistic distributions. A failure pressure model based on fracture mechanics is adopted for the assessment of pipeline failure pressure and linear idealization of the long-term corrosion growth rate is carried out. Because of the presence of nonlinearity in the limit state function and also of the presence of non-normal variables, the Level II advanced first order second moment iterative method is employed for carrying out reliability analyses. The methodology was applied to an example pipeline and the remaining useful life of this pipeline was assessed.

Priya et al. (2005) developed a probabilistic failure analysis for nuclear pipelines subject to stress corrosion cracking. The failure probabilities were computed using Monte Carlo simulation technique. Lee et al. (2006) developed and applied a probabilistic assessment program using reliability index and simulation techniques to evaluate failure probabilities of wall-thinned nuclear piping system subjected to erosion/corrosion.

Santosh et al. (2006) presented a reliability analysis of pipelines containing corrosion defects due to hydrogen sulphide in establishing RBI program for heavy water plants. The pipeline carrying hydrogen sulphide is more susceptible to the internal corrosion thus reducing the pipeline’s load carrying capacity. The reliability assessment of pipelines involves the estimation of failure pressure and evaluating the limit state function. Several failure pressure models were studied for this purpose and it was found that the modified B31G failure pressure model is the most suitable for the pipeline failure pressure modeling.

Teixeira et al. (2008) assessed the reliability of pipelines with corrosion defects subjected to internal pressure using the first-order reliability method (FORM). The limit-state function is defined based on the results of a series of small-scale experiments and three-dimensional non-linear finite element analysis of the burst pressure of intact and corroded pipelines. A sensitivity analysis was performed for different levels of corrosion damage to identify the influence of the various parameters in the probability of burst collapse of corroded and intact pipes. The Monte Carlo simulation method was used to assess the uncertainty of the estimates of the burst pressure of corroded pipelines. The results of the reliability, sensitivity and uncertainty analysis were compared with results obtained from codes currently used in practice.

2.3.3 Markov Model

The models that were discussed earlier only considered the system pipes being at two states, either fully functional or fail, whereas, in actual condition, the pipe may deteriorate into several states before a failure occurs. Moreover, the models did not include any inspection and/or repair that may change the failure probability value since intuitively, inspection and/or repair may improve the system (Fleming, 2004). When repair can be performed on such system, the system is known as a repairable system. An established reliability modeling technique for a repairable system is known as Markov modeling which can also be employed to model deterioration with inspection/repair.

A review of the literatures revealed that Markov models have been employed widely for developing deterioration models for infrastructures such as bridges with the objective to optimize maintenance and rehabilitation strategies. The application of Markov models is quite common for bridge and pavement systems (Madanat et al., 1995; Morcous et al., 2002; Cesare et al., 1992; Madanat & Wan Ibrahim, 1995).

Markov models also have been applied extensively for developing deterioration models for pipes in the wastewater systems as discussed by Wirahadikusumah et al. (2001) who modeled the deterioration of American combined sewer pipes. Another Markov chain-based deterioration model for water and wastewater systems, in this case involving water transmission pipes and trunk sewers, was proposed by Kleiner (2001). Micevski et al. (2002), on the other hand, applied a multistate Markov model to simulate the structural deterioration of storm water pipes. Adey et al. (n.d.) modeled the deteriorating underground reinforced concrete pipes in water distribution networks using a five discrete-state, discrete-time Markov model. These pipes deteriorated with time due to environmental conditions, such as chloride-induced corrosion and differential soil movement. Baik et al. (2006) also developed Markov chain-based deterioration model for water and wastewater systems.

The use of Markov process in RBI for piping system was first presented by Fleming & Gosselin (1997) and has been refined later by Fleming (2004). Fleming (2004) presented a general continuous Markov process for a piping reliability assessment. The objective of this approach is to explicitly model the interactions between failure mechanisms that produce failures, and the inspection, detection and repair strategies that can reduce the probability of failure, or that cracks or leaks will progress to ruptures before being detected and repaired. He concluded that the Markov model has demonstrated to be a useful tool to study the impact of alternative strategies for RBI. Together with appropriate estimation of its input parameters, the model is capable of making reasonable predictions of time dependent piping system reliability.

Vinod et al. (2003) came up with an idea to utilize Markov modeling technique for a piping reliability assessment in nuclear power plant. Their study developed four-state Markov model aimed to find the realistic failure frequency of piping system in pressurized heavy water reactors subject to erosion-corrosion and how the results can be employed in RBI analysis. The structural reliability analysis was used to estimate the transition rates for the continuous-time Markov process. They concluded that instead of applying directly the probabilities obtained from limit state function using structural reliability analysis, it is recommended to find the state probabilities using Markov model, since it incorporates the effect of repair and inspection works in the pipe failure frequency. Markov model also allows formulating a proper inspection program and period depending on the operating condition of the plant at any given time.

Cronvall & Männistö (2009) utilizes a discrete-time Markov model to assess the failure probability of piping systems in Finnish nuclear power plants. The analyzed degradation mechanisms were stress corrosion cracking and thermal fatigue induced cracking. The results from the probabilistic fracture mechanics analysis for crack growth were used to construct transition matrices used in a discrete-time Markov process.

One of the crucial processes in the development of a Markov model is the estimation of the transition probabilities, which provide information about the probabilities of condition changes and can be used to predict the time of condition changes in a system. For discrete-time Markov model, several methods to estimate the transition probabilities were used such as logistic regression (Wirahadikusumah et al. (2001), Poisson regression (Madanat et al., 1995), ordered probit model (Baik, et al., 2006), non-linear optimization-based approach (Baik et. al, 2006, ; Mokhtar & Ismail, 2009) and Bayesian approach (Micevki et al., 2002). For continuous-time Markov model, first-order reliability method was used to estimate the transition rate (Vinod et al., 2003). Fleming (2004) used inspection data and service data to directly estimate the transition rate and this method is applicable if data is available.

2.3.4 Logistic Regression Model

Typically, statistical analysis of wall thickness data collected during inspection period is used to assess the probability of failure due to corrosion. However, the wall thickness data are not always sufficiently available for statistical analysis. What is usually available in CUI inspection reports is the result from inspection after insulation removal which is either corrosion was found and treated, or corrosion was not seen. These types of data are classified as binary responses which can be used to predict the probability of CUI occurrence using logistic regression model (Hosmer & Lemeshow, 1989).

Logistic regression models are extensively used in medical field (Todd et al., 1995; Ottenbacher et al., 2001; Camdeviren et al., 2007; Austin et al., 2010). For instance, Todd et al. (1995) used logistic regression model to investigate the relationship between antioxidant vitamin intake and coronary heart disease in men and women. In social sciences, this model is broadly employed. Fuks & Salazar (2008) applied logistic regression model to analyze the household electricity consumption classes. Paul (2009) developed a logistic regression model to identify the various factors responsible for work related injuries in mines and to estimate the risk of work injury to mine workers. Other studies can be found in Ref. (Can et al., 2005; Sin & Kim, 2008).

Logistic regression also is widely used in business and marketing studies. For example, Sohn and Kim (2007) provided a logistic regression model to predict the default of funded SMEs based on both financial and nonfinancial factors. Using a logistic regression model, Larivière & den Poel (2007) studied the advantages for financial service providers in investing in youth marketing. Also, Cerpa et al. (2010) developed a logistic regression analysis to predict the success rate of software development projects.

A review of the literature reveals the application of logistic regression model in analyzing the dichotomous data as providing the basis for assessing systems subject to corrosion failure mode is limited. Spezzaferro (1996) developed a logistic regression model to demonstrate the possibility of identifying statistical relationships between maintenance inspection interval lengths and corrosion observed percentages. The model provided a means for conducting tradeoffs between inspection interval length and observed corrosion percentages in maintenance data, when measurable data are not available. Ariaratnam et al. (2001) proposed a logistic regression model for predicting the likelihood that a particular infrastructure system is in a deficient state. Variables of age, diameter, material, waste type, and average depth of cover are modeled, using historical data, as factors contributing to deterioration of the sewer network. The outcome of this model provides decision makers with a means of evaluating sewer sections for the planning of future scheduled inspection, based on the deficiency probability.

2.4 Concluding remarks

The review of literature indicates that there is a trend to use risk in planning for inspection interval. There is also a trend to employ a fully quantitative approach to assess the probability of failure in order to optimize risk analysis. However, currently, no unique method is used to perform the failure probability analysis for piping systems subject to CUI because of the unavailability of failure data where most of the quantitative models used in RBI are based on the field failure data. In the absence of failure data, the degradation data can also be used for predicting future failure. Several models which are potential to be used to estimate the probability of failure in RBI analysis are logistic regression model, degradation analysis, structural reliability analysis and continuous-time Markov model. Table 2.1 shows the data required for each model.

Table 2.1: Data requirement for the proposed models

Model	Data requirement
Logistic Regression Model	Internal visual inspection data (binary data)
Degradation Analysis	• Failure data, or • Degradation data to estimate the corrosion rate in order to extrapolate the mean time to failure
Structural Reliability Analysis	• Design/operating data • Degradation data to estimate the corrosion rate
Markov Model	• Design/operating data • Degradation data to estimate the corrosion rate