The Leading Edge: Gwinnett DWR'S Approach to Infrastructure Renewal and Replacement

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ABSTRACT

Utilities continue to be under economic pressures related to implement robust renewal and replacement programs for their aging infrastructure due to increasing uncertainty and risk. Most of the common approaches to addressing this issue rely on deterministic approaches with finite, best approximation inputs. Unfortunately these deterministic approaches yield results that greatly overestimate, or in many cases greatly underestimate, uncertainty and risk. In the scramble for capital improvement funding, these outdated methods often result in costly operations and maintenance activities that may not improve the reliability of the utility's system.

Probabilistic approaches are the best way to address uncertainty and risk. These approaches are more common in some industries where risk and rewards have been much higher than in traditional water and wastewater utilities. However with aging infrastructure and funding gaps that continue to widen, probabilistic forecasting is now extremely relevant and extremely important to our industry.

This paper addresses the key differences between traditional deterministic approaches and probabilistic approaches through the Gwinnett County, Georgia, Division of Water Resources' (DWR) use of probabilistic forecasting to address uncertainty when developing 20-year renewal and replacement programs.

KEYWORDS

Probabilistic Forecasting; Monte Carlo Simulation; Reliability; Infrastructure; Renewal and Replacement; Planning

INTRODUCTION

Utilities continue to face tough financial challenges in both capital and operations & maintenance (O&M) planning for infrastructure. Financial planning using a probabilistic methodology is a proven approach in other industries and in risk management. While not as common in the general water and wastewater industry, a number of forward thinking utilities have adopted this concept to maximize their financial investments while at the same time minimizing operational and environmental risk.

All infrastructure assets deteriorate with time and use. To maintain the effectiveness and value of an asset, renewal work should be performed periodically, and when the asset has reached the end of its functional useful life, it should be replaced. At the heart of an asset management program is the effort to preserve the existing system's performance and reliability by anticipating future renewal and replacement (R&R) needs and to ensure that adequate and timely funding is planned into the capital improvement program (CIP).

Gwinnett County DWR undertook an R&R forecasting effort to develop a baseline 20-year R&R funding demand model for their water production facilities and water reclamation facilities (WRFs). The forecast model is primarily focused on mechanical and electrical equipment, as this is the most relevant to a 20-year forecast. Structural elements typically have much longer life cycles; the model allows for structural elements or other projects with longer useful lives to be added as stand-alone projects. The model developed at this point for DWR is a first generation model that provides a baseline forecast of capital and maintenance funding demands. This baseline forecast is based on current DWR practices and does not change or optimize those practices based on risk, modified levels of service, and/or maintenance strategies. DWR has plans to revise the model in the future as input data are refined to optimize the R&R forecasts.

The model is intended to serve as a risk management tool. Risk analysis is systematic use of available information to determine how often specified events may occur and the magnitude of their consequences. According to the International Organization for Standardization (ISO, 2009, 2014), risk is defined as the effect of uncertainty on objectives (the effect can be either positive or negative). The International Infrastructure Management Manual (IIMM, 2011) similarly describes risk as the effect of uncertainty on objectives; risk events are events which may compromise the delivery of an organization's key strategic objectives. There is a basis for this technical definition dating back the Frank Knight's classic book from the early 1900s, Risk, Uncertainty, and Profit, related to financial management (Knight 1921). It is also supported in a different sector, modern reliability thinking.

The treatment of risk as both a positive and negative has been roundly debated as being confused with variation or variability, and close inspection of Knight's original treatise leading a reader to the opinion that Knight equated loss with the negative effects of both risk and uncertainty (distinguishing "risk" from "uncertainty" was more of the issue). From a practical perspective, the practitioner typically associates risks with negative events and normally risks are thought of in terms of a potential loss of value.

According to the Project Management Institute (PMI, 2004), risk analysis can be performed on several different levels. These are: risk planning; risk identification, including the use of subject matter experts and creating a risk register; qualitative analysis for prioritization, including the classic likelihood and consequences matrix; quantitative analysis, that includes specific details related to probabilities, uncertainty, and reliability data; risk response planning, including options to avoid, transfer, and mitigate risks; and continual risk monitoring and control. Probabilistic analysis is one of the highest forms of quantitative risk analysis. For Gwinnett County DWR R&R forecasting effort, risk and uncertainty were quantified using a probabilistic analysis.

METHODOLOGY

The R&R forecasting methodology typically begins with a formal problem statement that is validated with all participants including the project owners. The second step includes the collection and review of available data, including an evaluation of issues related to uncertainties associated with the quality of historical data as well as the uncertainties associated with projecting historical data trends into the future.

A third key step, which should not be overlooked, is a technical evaluation of which type of probabilistic tools are most applicable for the analysis, and whether such tools need to be modified or used in combination to address overarching goals for addressing risk and reliability. These tools generally include but are not limited to probability trees, Markov analysis, and Monte Carlo analysis. Additional supporting tools may commonly include linear algebra, genetic algorithms, and neural meshes. In the way of an example, Palisade's *Decision Tools Suite* offer a number of possible tools, including @Risk (Monte Carlo analysis), Precision Tree (probability trees), Evolver and @Risk Optimizer (optimization), Stat Tools (basic statistical analysis) and Neural Tools that can be utilized in conjunction with base models. Solomon and Sharpe (2013) have documented the potential range of uses of these tools for a specific wastewater treatment and conveyance project.

In the event a Monte Carlo analysis is selected, a deterministic model should be developed and validated in Microsoft Excel®. According to O'Connor and Kleyner (2012), the steps to performing a Monte Carlo simulation may vary based on the scope of the problem. However, some basic steps should be included in any analysis. These include: define the problem and the overall objectives of the study; define the system and create a parametric model, $y = f(x_1, x_2, \ldots, x_q)$; design the simulation, including such things as data collection, probability distributions, manner of use of output data; generate a random set of inputs; run the deterministic system model with the set of random inputs; run the probabilistic system model (continue to run random sets of inputs); and analyze the result statistics.

Best practices related to the development of the model should include, but not be limited to: use of different sheets for inputs, calculations, and outputs; the use of named inputs rather than spreadsheet "battleship language"; color coding of variables and fixed input parameters; and a multi-tiered process for checking and validating the model. The use of sensitivity analysis is also recommended as another manner to validate the deterministic model (Stanford, 2009).

A commercially available software package is recommended for the probabilistic analysis. The authors prefer Palisade Corporations' @Risk program but some users may prefer Oracle's Crystal Ball or the simulations that are available for statistical packages such as Mathworks' MATLAB. Commercially available software is well developed, is continually being improved, and is user friendly. The use of commercially available software allows the analysis to focus on the model characteristics and outputs, and avoid the unnecessary steps of development and validation of the software code.

Another important step that is needed between the deterministic and probabilistic models is the development and/or confirmation of input parameter distributions. Generic probability distributions are available for different asset classes; consultants such as CH2M Hill also have compiled distributions from previous projects and testing. However, it is critically important that the distributions be confirmed based with the system owner based on actual experience and the specific operating environment. Review of reliability performance data, interviews with staff, and the use of statistical tools to validate the shape of modified or new distributions should be performed as best practices. A more detailed discussion follows in a later section of this paper.

Following the completion of the running of a Monte Carlo simulation, a statistical analysis of the outputs should be performed. The types and degree of analysis will vary depending on the type of analysis being performed. However, at a minimum this should include basics such as output data set mean, median, mode, probability density function plots, cumulative density plots, and comparative analysis with sensitivity analysis that was performed with the deterministic model.

METHODS DISCUSSION

Deterministic and Probabilistic Models Defined

A quantitative risk analysis can be performed in several different ways. Determinism theory holds that there is one correct set of inputs that will lead to a desired output. This is the traditional approach and relies on uses single-point estimates for each variable. In addition, this approach may incorporate scenario analysis whereby different discrete values are assigned to represent different situations and the outcomes are evaluated. The results provide a sensitivity analysis of three common situations: worst case, best case, and most likely case.

There are several problems with this approach, including: only a few discrete outcomes are considered, ignoring hundreds or thousands of possible outcomes; there is no attempt made to assess the likelihood of each outcome; and interdependence between inputs and other nuances are oversimplified reducing the accuracy or applicability of the results.

A better way to perform quantitative risk analysis is by using a probabilistic approach. Probabilistic approaches include probability (decision) trees or Monte Carlo analysis. The use of probability trees is rooted in Bayesian theory from the 1700's and took root as an analytical technique in various forms in the early 1900's. In 1962, the US Military first used Fault Tree Analysis (FTA) which is a top down approach with roots is probability theory. In 1964, Stanford University's Ron Howard first coined the term "decision analysis" and utilized probability trees as a dominant form of the analysis. Monte Carlo analysis dates to the 1940's and 1950's as part of the Manhattan project. With the increased robustness of Microsoft Excel® and the increased cost effectiveness of computers over the past three decades, Monte Carlo analysis has become the preferred tool in performing probabilistic analysis.

In Monte Carlo analysis, uncertain inputs in a model are represented using ranges of possible values known as probability distributions. Variables can have different probabilities of different outcomes occurring based on their probability distributions. Common probability distributions include: normal, or bell curve; lognormal; exponential; Weibull; triangular; and uniform.

During a Monte Carlo analysis, values are sampled at random from the input probability distributions. Each set of samples is called an iteration, and the resulting outcome from that sample is recorded. This process is repeated tens of thousands of times and results in a probability distribution of possible outcomes based on the various combination of input parameters.

Repairable and Non-Repairable Items

A repairable item is defined by MIL-STD-721C (1981), *Definition of Terms for Reliability and Maintainability,* as an item that can be restored to perform all of its required functions by corrective action. Similarly, Ascher and Feingold (1984) define a repairable system as one that after failing to perform at least one of its required functions, can be restored to performing all of its required functions satisfactorily by some method other than the replacement of the entire system.

Ascher and Feingold define a non-repairable system as a system that is completely replaced and discarded once it stops performing satisfactorily. A system is defined as a collection of two or more sockets and their associated parts, connected to perform some function(s). Sockets are described as a position in a circuit or in a unit of equipment that must hold a particular type of part in order to function and a part is described as an item not subject to disassembly or repair that is discarded once it fails.

In terms of terminology, the word "item" is used to refer generically to components, systems, subsystems, or assets, since models for repair and non-repair can be applied equally well to either. Repairable items are also of great interest since there are many more repairable items than non-repairable items produced in industry (Leemis, 1995).

According to O'Connor (2005), reliability prediction can rarely be made with high accuracy or confidence. Nevertheless even a tentative estimate can provide a basis for forecasting dependent factors such as life cycle costs. Reliability prediction can be a valuable part of the study of design processes, for evaluating options, and for highlighting critical reliability features.

As a best practice, the reliability prediction should begin at the overall system level. As the system becomes more closely defined it can be extended to more detailed levels such a sub-systems and individual components. In principle, eventually it is necessary to extend the analysis to individual parts; however, at the lower levels of analysis there is greater uncertainty inherent in predicting the reliability of the whole system. In practice, it is important to remember that many system failures are not caused by the failure of parts and that not all part failures cause system failures. (O'Connor, 2005, 2012)

Underlying Maintenance Approaches

Repairable systems receive repair/maintenance actions that restore system components when they fail. It is also important that a repair of a repairable system may not mean replacing any part; repair may be simply lubrication, cleaning, adjusting settings, or re-calibrating the system or subsystem (referenced herein as an item). These actions change the overall makeup of the system and affect the system behavior differently due to different repair approaches.

In evaluating reliability and forecasting financial needs, five basic underlying repair approaches fundamentally shape the analysis.

<u>"As good as new"</u> – The time between failures can be treated as an ordinary renewal process (ORP) or general renewal process (RP). The time between failures is treated as an independent

and identically distributed (IID) random variable (Kaminskiy and Krivtsov, 2010). As such, a homogeneous Poisson process (HPP) can be used to model the repair of repairable items. HPP is also used to evaluate non-repairable systems

For HPP, two fundamental properties are identical independent increments and stationarity. Independent increments describe the number of failures to be mutually exclusive. Stationarity describes the distribution of the number of failures within any time increment, depending only on the time interval itself; with stationarity, failures are no more or no less likely to occur at any one time than another, which means the assumption is restrictive since an item can either deteriorate or improve (Leemis, 1995).

Leemis (1995) describes the Poisson process as well known and popular, but for repairable systems notes that it applies to only limited situations that include replacement models with exponential standby items and repairable items with exponential times to failure and negligible repair times. In a renewal process the exponential assumption between the mean times to failure is relaxed, and in a non-homogeneous Poisson process the stationary assumption is relaxed (Leemis, 1995).

In layman's terms, an ORP or RP typically takes the form of a socket model where identical items are reinstalled as part of the general repair process. This could range from simple items such as light bulbs and electronics to a new membrane filter, and the nature of the performance behavior in the model is dependent on how the system or subsystem is evaluated.

<u>"Same as old"</u>- In this case, the repair cannot restore the item to its original condition. The time between failures is not treated as either independent or identically distributed. This means that the use of the non-homogeneous Poisson process (NHPP) is applicable. This is likely to be the case associated with complex systems that have many different types of components, many different types of failure modes, and many different types of repairable actions.

Four reasons for the use of NHPP include: the homogeneous Poisson process is a special case of an NHPP; the probabilistic model for an NHPP is mathematically tractable; the mathematical methods for an NHPP are mathematically tractable; and unlike the HPP or associated "as good as new" repair model, an NHPP is capable of modeling improving or deteriorating systems. The times between failures do not necessarily follow any of the common distributions like exponential or Weibull, and therefore parameter estimation is relatively simple and attractive.

Two significant issues can impact the use of NHPP in more detailed evaluations of system reliability. The first is that the first failure distribution is usually different than the remaining one, and as such there are complexities related to how system performance data is interpreted relative to failure modes as well potential system reliability improvement/stabilization. The second is the assumption in both the NHPP, and NPP models, that the time to repair is negligible. This second aspect will be discussed in more detail in a subsequent paper.

<u>"Not as good as new, but not as bad as old"</u> – In reality, an item is likely to find itself in this state after repair. Brown and Proschan (1982) described one of the earlier approaches to model different repair models within the same distribution using probabilities. Kijima and Sumita (1986) have established perhaps the most common approaches with the G-1 models. These approaches and others are especially important in evaluating reliability of repairable models. At

the same time, the level of required detail and assumptions are not especially relevant at a practical level for first- or second- generation renewal and replacement models.

One aspect of the G-1 models is that they introduce the concept of virtual age. Virtual age treats the repair model as scalable between the two extremes. In cases where historical data is poor and either the installation date or remaining useful life of an item is uncertain, this hybrid approach can be used to help justifying the model starting point.

"Better than new" – This approach is described by Kaminskiy and Krivtsov (2010), and others, to address the situations when an item is improved by the repair process. This can often be the situation when new and improved parts are installed into sockets within a system. However, whether the actual system performance or life distribution is truly better than new depends on the interaction with new parts with older ones as well as the manner in which the system is modeled.

"Worse than old" – Rostum (1992) proposed an approach of modifying the NHPP model by using failure rank and Doyen (1993) proposed an approach based on capturing the effect based on a particular failure-intensity model. In practice, "worse than old" is not uncommon but is also more the exception than the rule. For first- and second- generation renewal and replacement models, some use of "worse than old" may be justified but the nature of existing data and required assumptions does not justify the wholesale use of this approach. However, a more detailed analysis of maintenance strategies and maintenance performance may justify the use of the approach in more advanced analysis or in the validation process.

Selection of Probabilistic Distributions

Selecting the most appropriate probability distributions, to represent model input variables, is critically important. It is both a science and an art. These distributions may be either continuous (such as full ranges of measurement to finer and finer decimals, such as temperature measurements) or discrete (whole variables, such as "pass or fail"). Continuous distributions apply to the majority of the analysis covered by the examples presented in this paper. The major ones will be discussed briefly.

The first is the normal distribution. It is critically important that you realize that its use in the wrong applications will greatly under-predict the uncertainty of the future. It is popular because it is "quick and easy" but is also "usually wrong" as the old saying goes. Its applicability should be limited to things with strong central tendencies, strongly follow Newtonian physics, or some forms of manufacturing, at least in concept. It is most applicable where one occurrence is independent from another. Normal distributions are generally not recommended for developing renewal and replacement forecasts; however, they do have relevance when considering the time to repair in more complex models.

The exponential distribution is another commonly used distribution in reliability engineering. It is used to model constant failure rates. In the realm of physical assets, this is normally associated with electrical components and in some cases with mechanical components. Leemis (1995) calls the use of the exponential function as overly simplistic in reliability models, and is most appropriate to model electrical systems and when a used component that has not failed is as good as a new component. It is also relevant in the case of small sample sizes where a more specific and relevant distribution cannot be determined with certainty.

The Weibull distribution is one of the most commonly used distributions in reliability engineering. Its basic formula provides great flexibility through its parameter for scale, shape, and location. In turn, this allows for creating distributions similar to the lifecycle "bathtub curve", or the demonstration of the infant mortality, constant failure, and wearout phases in a single distribution. When the shape factor is between 3 and 4, the Weibull distribution approximates the normal distribution. If the shape factor is 1, then the Weibull distribution approximates the exponential distribution. In application, it requires careful consideration since one of its core underlying aspects is the memory-less exponential distribution.

The gamma distribution is somewhat similar to the Weibull distribution is that it is also a form of the exponential function. In practice the gamma distribution is more complex to use than the Weibull distribution due to its treatment of the hazard function.

The lognormal distribution is another common distribution, and has a heavy right skew. By transforming the data by taking a logarithm, the data set can then be approximately normally distributed. This is normally performed with a natural logarithm but any base logarithm can be used. The hazard function of the lognormal distribution has unique behavior in that it increases initially, then decreases, and eventually approaches zero; in lifecycle terms, this means that items with this distribution have a higher chance of failing as they age for some period of time, but then the probability of failure decreases as time increases.

Two probability distributions provided in the @Risk software that will be discussed briefly are the triangular and PERT distributions. The Triangular distribution is used when the user does not know the entire distribution but can define the minimum, most likely, and maximum values. Variables that could be described by a triangular distribution could include potential sales price variation or inventory levels. The PERT function generates a distribution that is similar to the triangular distribution but is curved. Like the triangular distribution, the PERT density increases from a minimum value to a peak at the most likely value and then decreases to a maximum value. This distribution is often used in project scheduling to describe the time to perform a task. The name PERT is the acronym for Project Evaluation and Review Technique, which has been associated with project scheduling for decades. Both PERT and triangular distributions are common in the cost estimating arena.

Lifetime Data Analysis

According the O'Connor (2005), the concept of deriving mathematical models which could be used to predict reliability is intuitively appealing and has attracted much attention. Failure rate models have been derived for a number of components, including electrical components based on parameters such as operating temperature and other stresses, non-electronic components, and even computer software. Many of these are relative simple point estimates based at the component or part level; however, many more are complex such as those that deal with electronic components or with larger subsystems and systems with many different items. Therefore predictions in reliability typically have a high degree of uncertainty (O'Connor and Kleyner, 2012).

According to Moubray (1992), "a surprising number of people" believe that extensive historical information can be used to predict useful life predictions that can be in turn used with confidence in reliability and maintenance programs. These thoughts, in his opinion, are “fraught with practical difficulties, conundrums, and contractions.” He cites complexity, sample size and evolution, reporting failure, and the ultimate contradiction that if we are able to collect meaningful data about real-world failures then we are essentially not preventing them. Moubray would agree with O’Connor, for slightly different reasons, that utilizing vast amounts of historical data does not necessarily improve the certainty of future predictions.

The literature is filled with numerous examples of lifetime data analysis. A number of good references exist as starting points to establish a default mean life expectancy and mean time between failures (MTBF) for repairable items. However, such data should be modified for actual operating environments and maintenance strategies as well as careful allowances for system design, system complexity, fault tolerance, the definition of failure, and hidden failure modes.

Data Limitations

Guo, Ascher, and Love (2001) noted that too much time has been devoted to the development of new reliability models, many of which are too simplistic and too little time spent on their applicability and associated underlying data. Guo, Ascher, and Love (2000) also noted that models should be appropriate to reflect the actual process information and data, but that such models should not be overly simplistic. Sufficient data is needed for tackling real engineering and reliability problems.

Moubray (1992) is much more limiting in his perspective. He argues that: in large industrial processes there only one or two large assets of any given type; that sample sizes for many of these larger and more critical items tend to be too small for statistical processes that carry much conviction; and the sample sizes are always too small for new assets that embody a high degree level of new technology. For large systems, he further argues that we seldom run such systems to failure and hence do not have the life data that we need in the specific operating conditions. At the individual and smaller item levels, comprehensive analysis (such as root cause analysis) is often complex and the result of many failures and failure modes rather than just one. Finally, Moubray states that analyzing failure data is even further complicated between organizations with the same equipment, largely due to reporting issues and the confusion between function and potential failures from one organization to another.

The simple fact is that many industrial operations, including water and wastewater utilities, simply do not make enough effort to collect, store and maintain their data. One example is shown in the 2012 McGraw Hill Smart Market Report for the Water Industry where only 55% of the utilities surveyed had a formal computerized maintenance management system (CMMS). Practical experience also indicated that a very small minority have formal maintenance strategies, including predictive maintenance programs, and even fewer are doing some form of formal or written root cause analysis (RCA).

There are a number of standard resources for generic data to be used in renewal and replacement models. However, none of the resources are appropriate without an accurate assessment of operating conditions in a given operating environment. A number of appropriately detailed data approaches and not overly simplistic models are well known in the field of reliability engineering. These should be utilized for more accurate predictions, and at the same time a recognition on collecting and maintaining appropriate data quality is needed.

Confidence Intervals, Bootstrapping, and Quantile-Parameterized Distributions

Howard (1966) noted the importance of probability distributions in the early development days of what he would coin as “decision analysis”. Kahneman and Tversky (1974) documented the various human biases that they encountered in the decision-making experiments under uncertainty, and particularly observed the poor ability of humans to judge probability. In the same time period, Spetzler and Stael von Holstein (1975) developed a process and tool for assisting decision-makers to estimate probability better, and in turn provided decision analysts with a methodology for developing a cumulative distribution function (CDF) that has stood the test of time. This methodology has been successfully utilized for developing useful life parameters and CDFs for renewal and replacement items in the absence of more quantitative information.

A complimentary, but also exclusive, process is referred to as bootstrapping. Efron and Tibshirani (1993) are credited with the bootstrap methodology. In simplistic terms, bootstrapping can be summarized as a technique to determine how well a data set fits with an assumed data set characteristic. Most commonly standard errors or confidence intervals are used for the analysis. The method is computer intensive but can be successfully run on Excel, MATLAB, and most commercially available statistical software. The bootstrap methodology is typically recommended in the following situations: when the theoretical distribution of a statistic of interest is complicated or unknown; when the sample size is insufficient for straightforward statistical inference; and when a small pilot sample is available that can be used to develop more extensive computations (Ader, 2008). Moreover, Pratt, Raiffa and Schlaifer (1995) used this process with good results in statistical decision making.

For renewal and replacement items, bootstrapping can be a powerful tool for developing CDFs based on limited data and a relatively well-formed idea of applicable standard probability distribution shapes by the analyst. Notwithstanding this limitation, other limitations include that the data must be independent and a classic statistical method, such as mean least sum of squares (MLSS), among others, are utilized to determine the best fit.

A third alternative that is referenced here, and that has been successfully used since the model of reference in this paper, is the use of quantile function techniques to develop a form of CDF. Quantile-parameterized distributions (QPDs) ignore assumed distributions and essentially use linear combinations of basic mathematical functions applied to a data set to develop the QPD. A particular family of QPDs corresponds to a particular set of basic functions; like normal, exponential, and logistic, but their mathematical flexibility speaks to the manner they can represent these basic shapes including their supports and tail behavior. A pre-determined classic probability distribution is not required and the models determine the shape based on the available data.

The quantile function specifies, for a given probability in the probability distribution of a random variable, the value at which the probability of the random variable will be less than or equal to that probability. It is also called the percent point function or inverse cumulative distribution function. The quantile function is one way of prescribing a probability distribution, and it is an alternative to the probability density function (PDF) or probability mass function, the CDF and the characteristic function. The derivative of the quantile function, namely the quantile density function, is yet another way of prescribing a PDF. It is the reciprocal of the pdf composed with the quantile function. (Keelin and Powley, 2011 and Powley 2013).

Participants need to know key percentage points of a given distribution such as the median and 25% and 75% quartiles or 5%, 95%, 2.5%, 97.5% levels for assessing the statistical significance of an observation whose distribution is known. This method has proven especially beneficial for facilitating team based decisions related to the probabilities associated with different life behavior for systems, subsystems, and components.

The use of QFDs has been implemented on other projects subsequently to the use of them on this one. The use of QFDs will be discussed in a future paper.

Asset Replacement Values

Asset replacement values are critically important to the development of a meaningful R&R model. Also known as replacement asset value (RAV), it is also a key component of benchmarking of best practices by such organizations as the Society for Maintenance and Reliability Professionals (SMRP). Gulati (2012) cites inconsistencies related to RAV across different organizations as a primary detriment in performing meaningful benchmarking. The same can be said as it relates to R&R forecasting. These inconsistencies are also significant within many organizations where financial, engineering, and O&M divisions calculate and track asset values in very different ways and in different databases.

For developing well defined and accurate asset replacement values, a meaning amount of cross-functional time should be allocated. In most cases, internal data will not be either complete or robust enough, and outside sources will need to be used to complete the dataset. The approaches and methods associated with developing asset replacement values will not be covered in additional detail in this paper.

RESULTS

Renewal & Replacement Forecasting for Gwinnett County Division of Water Resources

The model forecasts capital and maintenance funding needs on a yearly basis for a 20 year planning period, 2013-2032. Funding demand projections were grouped into 5-year increments to be consistent with DWR capital planning intervals. Annual forecasts for R&R are theoretically correct; however, such annual forecasts are not sufficient for decision-making since the asset performance and the exact yearly timing for replacement cannot be predicted with a high degree of certainty, especially in a first- or second-generation models.

In a first generation model, the model output should be used as an initial estimate of funding needs and to generate a list of potential capital projects. These projects should be further evaluated to confirm the needs and refine the funding estimates. The confidence and reliability of the forecasts will increase over time as input data are further refined.

Approximately $41M of capital funding was projected to be needed in the first 5-year period, for DWR five water and wastewater treatment facilities. Funding needs were anticipated to decrease over the following 15 years and to the end of the 20-year forecasting period.

The model indicated a spike in capital funding need for the first 5-year period for assets at the Shoal Creek Filter Plant (SCFP), the Lanier Filter Plant (LFP), and the Crooked Creek Water Reclamation Facility (CCWRF). This is primarily due to the first year within the 5-year period and is not uncommon in first-generation models and is normally the result of existing data (Maximo and/or nameplate) indicating that the equipment is beyond its useful life and in need of replacement Subsequent data reviews and condition assessments are typically needed to help to clarify where within the 5-year period this need is likely to occur.

The model predicted increased capital funding demands over the next 5 years in comparison to future years at CCWRF and the F. Wayne Hill Water Resources Center (FWHWRC). The CCWRF has a large number of assets at the end of their useful life. At FWHWRC, some assets identified in the model for replacement in the first few years are already programmed to be replaced in 2013. The age and useful life of assets at this facility also was causing this increase. Resolution of data uncertainties following the first-generation modeling efforts and prior to the completion of the second iteration changed the funding trends for FWHWRC.

The model predicted limited capital funding demands at YRWRF over the next 5 years, which is reasonable considering that most mechanical and electrical assets have a 15- to 20-year useful life and the plant was put into operation in 2009.

The historical annual average capital expenditures for DWR were $11.4M from 2008 through 2011 for R&R. The water production and water reclamation facilities accounted for 16 percent, or $1.9M, and 84 percent, or $9.5M, respectively, of the historical average capital expenditures. The R&R model forecasted significantly higher funding needs for next 5 years than the historical average and may be indicative of deferred R&R, aging infrastructure, shift in focus from growth to extending asset useful life, and improved asset condition information. Additionally, these planning level estimates need further evaluation and refinement.

The maintenance funding forecasts for SCFP, LFP, and CCWRF remained relatively stable over the 20-year period. The maintenance funding forecast for the YRWRF increased from the first 5-year period and remains relatively stable in the last 15-year period due to the age of the assets in the facility. The maintenance funding forecast for the FWHWRC was highest in the first 5-year period and remains relatively stable in the last 15-year period. At FWHWRC, this appeared to be primarily due to the large number of unclassified valves and actuators in the input asset data set and is expected to be reduced as data is improved.

The trend in maintenance funding tracked the overall plant asset replacement trends. As replacements occur, corrective maintenance (CM) is reduced with new assets coming online. As assets age, CM cost increases as their remaining useful life is decreased.

Over the most recent 4 years (2008–2011), DWR maintenance expenditures for existing assets were approximately $8 million per year (all plants combined), or in the average range of $1.3M to $1.9M per year per plant. The model forecast for maintenance at FWHWRC indicated an increase by a factor of 2 when compared to recent trends; based on examination of the data, the forecast was inflated by the large number of unclassified valves and actuators in the input asset data set. The LFP forecasts are consistent with the 2012 budget and historical actual expenditures.

A list of sub-processes where the model predicted a significant (at least $1 million) funding demand in the next 5 years was provided. Due to the age of the plant and the relatively low R&R funding demand in the first 5-year period, a threshold of $250,000 was used for the YRWRF. These thresholds provided at least a “top 5 priority ranking” at each plant. This list identified sub-processes requiring further evaluation related to CIP planning. The evaluation first verified that the asset was indeed in need of renewal or replacement, and second, proceed to the steps necessary to define the project and refine the capital cost estimates to place it on the CIP prioritization list.

Preliminary steps to define the project included: review the R&R model to identify the specific assets scheduled for renewal or replacement; review existing field condition assessment data or conduct a condition assessment if one had not been completed; confirmation that the current condition supports the need identified in the R&R model; develop project scope and budgetary cost estimate; and, add project to the CIP prioritization list. Ideally, all assets scheduled for renewal or replacement should be further evaluated; however, focusing efforts on the items that represent a higher percentage of the total 5-year R&R funding demand was considered by DWR to be the most cost-effective approach at that point in time.

CONCLUSIONS

The probabilistic analysis concluded that over the next 5 years combined capital improvement needs for R&R would be at lower levels than the previous 5-year average. Maintenance funding would need to be on the order of 18 percent higher than the recent 5-year rolling average, assuming maintenance strategies and levels of service remained the same.

Another important conclusion from the quantitative analysis was the relative contribution of a few sub-processes at each plant to the overall projected funding demands. This in turn was used to better direct additional reliability analysis, O&M practice review, and collection of additional data. Data collection and refinement issues were more intense and focused in certain key areas, while the amount of condition assessment work in other areas was delayed. In terms of comparison with the qualitative analysis that was performed in an earlier phase to prioritize the work approach and data collection, the quantitative analysis was able to significantly refine the initial prioritization and reduce the amount of field condition assessment that was needed in a second phase.

In terms of system understanding, mid- to long-term planning and operational improvements, insights from first- and second-generation models are often as important as the results they produce. This was indeed the case for DWR.

In specific terms, one key insight related to data management was that the R&R forecasts were in part being driven by numerous asset classes that contained a large number of assets. This was an aspect that had been inadvertently built into the data repository (Maximo) structure and had not been fully appreciated. The development of more detailed information on some of these assets types was targeted to provide additional clarity on the asset data that will in turn help to reduce the effect of this data uncertainty within the forecast model. Specifically, size identification for four key asset types related to size (diameter, horsepower, etc.) was not tracked comprehensively in Maximo. Additionally, electrical equipment and instrumentation was frequently being collected in predominately unclassified bundles in Maximo with limited regard to function, cost, or attribute grouping.

Some key specific insights gained in financial planning and analysis related to the forecast model and the meaning of the probabilistic analysis results included the effective use of probabilities and ranges when describing uncertainties, the use of sensitivity analysis in the form of a tornado diagram, and the use of box and whisker diagrams when evaluating the results from the probabilistic analysis. These insights were useful for effective interpretation of the results of the decision process related to future financial planning/budget setting activities.

The following were provided as a near-term path forward for DWR staff: completion of a second round of condition assessment of targeted important asset identified from the R&R forecast; updating and improvement of CMMS user-defined fields; recommendation that additional SOPs relative to data entry and data maintenance should be implemented; and ongoing updates to classification of “critical” assets.

Intermediate-term asset management activities that were indicated through this process included: development of a formal condition monitoring program; development of a trend analysis and reliability program; completion of the development of formal maintenance strategies; future R&R model updates, beginning in 12 months and every 3 to 5 years thereafter; and tracking and measurement of actual performance against the forecasted demand of the R&R model.

In summary, the evaluation using probabilistic forecasts provided a more common understanding of R&R and maintenance related needs, and answered the central questions of “how do we stay on top” and “where should we direct future efforts”. Benefits not discussed heretofore included the ability to look at the combined facilities under a single lens and to provide a well-defined justification and transparent plan in economically challenging, uncertain times.

Probabilistic analyses are a highly effective tool for structuring problems and gaining insights about key inputs. When done properly, they improve a decision maker’s understanding of risks, business value drivers, and the sensitivities of key decisions. They also provide an understanding of relevant importance and interdependencies of key variables, and in turn the value of both acquiring additional information and the potential areas for business process improvements.

The more frequent use of probabilistic analysis is long overdue in the water and wastewater industry. Gone are the days of Federal grants for the construction of new and replacement infrastructure. Gone are the days where protection of the natural environment is the only key measure of success for a utility. And gone are the days of “build it and they will come.”

In an uncertain world, probabilistic analysis is a practical and affordable way to plan, construct, operate, and maintain hundreds of millions of dollars of assets that are under the management of the average utility. They are essential in the support of reliability and making risk-informed decisions. You may be making good decisions without probabilistic analyses, and that may be up for debate; however, if you are not using probabilistic analyses to inform your decision making, then it is nearly certain that you are leaving value on the table.

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