STATE OF NEW JERSEY
OFFICE OF ADMINISTRATIVE LAW
BEFORE THE HONORABLE JACOB S. GERTSMAN

IN THE MATTER OF THE PETITION	)	
OF NEW JERSEY-AMERICAN WATER	)	
COMPANY, INC. FOR APPROVAL OF	)	
INCREASED TARIFF RATES AND	)	BPU DOCKET No. WR17090985
CHARGES FOR WATER AND	)	OAL DOCKET No. PUC 14251-2017S
WASTEWATER SERVICE; CHANGE	)	
IN DEPREICATION RATES AND	)	
OTHER TARIFF MODFICATIONS	)	

DIRECT TESTIMONY OF JAMES GARREN
ON BEHALF OF THE DIVISION OF RATE COUNSEL

STEFANIE A. BRAND
DIRECTOR, DIVISION OF RATE COUNSEL

DIVISION OF RATE COUNSEL
140 East Front Street, 4th Floor
P. O. Box 003
Trenton, New Jersey 08625
Phone: 609-984-1460
Email: njratepayer@rpa.nj.gov

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INTRODUCTION

Q. PLEASE STATE YOUR NAME, POSITION AND BUSINESS ADDRESS.

A. My name is James S. Garren. I am an analyst with the economic consulting firm of Snavely King Majoros & Associates, Inc. ("Snavely King").

Q. HAVE YOU PREPARED A SUMMARY OF YOUR QUALIFICATIONS AND EXPERIENCE?

A. Yes. Attachment A is a summary of my qualifications and experience.

Q. Q. PLEASE DESCRIBE YOUR BACKGROUND IN UTILITY DEPRECIATION.

A. Since my employment at Snavely King in 2010, I have participated as an analyst in approximately 30 separate depreciation studies of electric, gas and water utilities on behalf of the firm's clients, most of which are state commissions or state-funded consumer advocate agencies. In that role, I have worked closely with the firm's principals in performing life and net salvage analyses, calculation of depreciation rates, and preparation of testimony. Additionally, I am familiar with the firm's proprietary depreciation software, the Snavely Comprehensive Investment Analysis System

("**SCIAS**"). I am also recognized as a Certified Depreciation Professional by the Society of Depreciation Professionals.[1]

Q. FOR WHOM ARE YOU APPEARING IN THIS PROCEEDING?

A. I am appearing on behalf of the New Jersey of Division of Rate Counsel ("DRC")

Q. WHAT IS THE OBJECTIVE OF YOUR TESTIMONY?

A. New Jersey American Water ("NJAW" or "the Company") has filed an Application to change its rates to the Board of Public Utilities of New Jersey ("BPU" or "the Board"). In its Application, the Company included a Depreciation Study with accompanying Direct testimony. The objective of my testimony is to detail my analysis of the Company's Depreciation Study with regard to average service lives and net salvage.

SUMMARY

Q. WHAT INFORMATION HAVE YOU REVIEWED IN PREPARATION FOR THIS TESTIMONY?

A. I have reviewed the written direct testimony and exhibits of Mr. John Spanos of Gannett Fleming, who presents testimony on the Company's Depreciation Study. Upon

[1] [1] "The Society of Depreciation Professionals was organized in 1987 to recognize the professional field of depreciation analysis and individuals contributing to this field; to promote the professional development and professional ethics of practitioners in the field of depreciation analysis; to collect and exchange information about depreciation analysis; and to provide a national forum of programs and publications concerning depreciation." http://www.depr.org/?page=AboutUs . For certification, an applicant must have at least 5 years of full time professional depreciation experience, at least 2 years of which must be in the area of depreciation administration. Among other requirements, the applicant must pass a two part (Technical and Ethics) closed book examination which includes questions about, *inter alia*, Plant and Reserve Accounting, Life Analysis Concepts, Life Analysis Using Actuarial Models, Life Analysis Using Simulation Models, Salvage and Cost of Retiring Analysis, Technology Forecasting and Depreciation Calculations." http://www.depr.org/?page=Certification

examination of this testimony and the Study, I prepared numerous data requests which were propounded to NJAW by DRC at my request. I have now had the opportunity to review NJAW's responses to these data requests as well as the documents attached to NJAW's filing. In response to some of the data requests, DRC has been provided the depreciation data used by Mr. Spanos to perform his studies. Utilizing this data, and my own analysis, I have proposed adjustments to the depreciation rates and accruals utilized for plant depreciation.

Q. WOULD YOU PLEASE SUMMARIZE THE TOTAL IMPACT OF THE NET SALVAGE ADJUSTMENTS YOU HAVE MADE?

Yes. Please refer to the table below for comparison of the depreciation rates and expenses:

Table RC-1

Summary of Depreciation Rates and Expenses
($) in millions
Based on December 31, 2016 Plant Balances

	NJAW Rate	NJAW Expense	DRC Rate	DRC Expense	Adjustment
Water	2.84%	123,511,599	2.18%	95,381,628	28,129,971[2]
Wastewater	1..99%	5,159,459	1.67%	4,344,955	814,504

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2 Exhibit JSG-1.

Q. IN BRIEF, WHAT IS THE PRIMARY FACTOR, OR FACTORS, AS TO WHY YOUR PROPOSED DEPRECIATION RATES ARE LOWER THAN THE RATES PROPOSED BY COMPANY WITNESS SPANOS?

A. The two drivers of my depreciation rate adjustment are changes to the service lives of six water accounts and one wastewater account, and the re-inclusion of gross salvage amounts to the net salvage normalization calculation.

Q. ARE YOU SPONSORING ANY EXHIBITS IN CONJUNCTION WITH THIS TESTIMONY?

A. Yes. I have prepared Exhibit JSG-1, which shows the calculation of my proposed depreciation rates for service lives and net salvage. Exhibit JSG-2 shows the calculation of the net salvage amounts used to calculate rates based on a three-year average of net salvage for water only. The net salvage amounts for wastewater have been accepted as calculated by the Company. Exhibit JSG-3 contains the service life analysis for the accounts which I am proposing to adjust.

<u>DISCUSSION OF SERVICE LIVES</u>

Q. WOULD YOU PLEASE EXPLAIN YOUR ADJUSTMENT TO SERVICE LIVES?

A. I have identified seven accounts where I believe Mr. Spanos' proposed average service lives vary significantly from the historical indications for seven accounts. These accounts are 307.00 – Wells and Springs, 309.00 – Supply Mains, 310.00 – Power

Generation Equipment, 330.00 Distribution Reservoirs and Standpipes, 334.00 – Meter Installations and Vaults, 334.10 Meters, and 361.10 Collection Sewers, Gravity Mains.

I have reviewed Mr. Spanos' testimony, workpapers and responses to data requests in an attempt to understand Mr. Spanos' rationales for this deviation, but Mr. Spanos has not explained his departure from the statistical indications. Below, I discuss my life analysis methodology and considerations in reaching my proposed average service lives. I also discuss two primary issues that result in Mr. Spanos underestimating average service lives for each account. Finally, I discuss specific considerations in reaching proposed average service lives for individual accounts.

Q. PLEASE DEFINE "AVERAGE SERVICE LIFE" AS IT IS USED IN UTILITY DEPRECIATION CALCULATIONS?

A. The "average service life" for a given account is a projection of the number years that a new unit of plant can be expected to remain used and useful on average. Many units in a given account will be retired at earlier ages, and thus have a shorter than average life, and many units will retire at later ages, and thus have a longer than average life. Average service life is used to calculate the average remaining life, which, in turn, is the denominator in the calculation of depreciation expense. Therefore, all else being equal, a longer average service life directly results in a lower depreciation expense.

Q. PLEASE DESCRIBE THE PROPER WAY TO DETERMINE THE AVERAGE SERVICE LIFE COMPONENT OF DEPRECIATION RATES.

A. I have analyzed NJAW's transmission accounts using an actuarial life analysis process called the Retirement Rate method. Actuarial methodologies were developed initially in the 17th and 18th centuries, primarily by life insurance companies that needed mathematical means of estimating the mortality risk of individuals over a long period of time. This resulted in the development of "life tables," which show the mortality risk of a group of individuals with similar risk factors at each age.

The Retirement Rate method is an actuarial technique used to study plant lives, much like the actuarial techniques used in the insurance industry to study human lives. It requires a record of the dates of placement (birth) and retirement (death) for each asset unit studied. Retirement data that contains this date of placement and retirement is referred to as "aged data" because it tells the analyst the age of the plant at the time it was retired. The Retirement Rate method is the most sophisticated of the statistical life analysis methods because it relies on the most refined level of data.

In the Retirement Rate method, aged retirements and total plant in service at a given age (referred to collectively as "exposures") from a company's records are used to construct an observed or original life table. I discuss the composition of an observed life table in detail below, but the details are important because they result in data points showing the percentage of a given unit of plant that is expected to survive at a given age. The actuarial analysis smooths and extends the observed life table by fitting it to a family of 31 standardized survivor curves ("Iowa curves"). The curve-fitting uses the least squared differences approach to find a best fit life for each curve. The "sum of least squared difference" is a common means of fitting curves (in this case the Iowa curves) to a set of data (in this case the observed life table data). The difference between each point of data and a point on a line is squared, and the square of all of those differences is summed to provide the total difference between the set of data and the line. The line that produces the least difference from the set of data is considered the "best fit." The purpose of squaring the difference is to ensure that negative differences contribute to the overall difference rather than canceling out positive differences.

Numerous iterative calculations are required for a Retirement Rate analysis. In the end, the analysis produces a life and Iowa curve best fit for a single average vintage. My understanding is that this is the same type of life analysis that NJAW performed for its depreciation study.

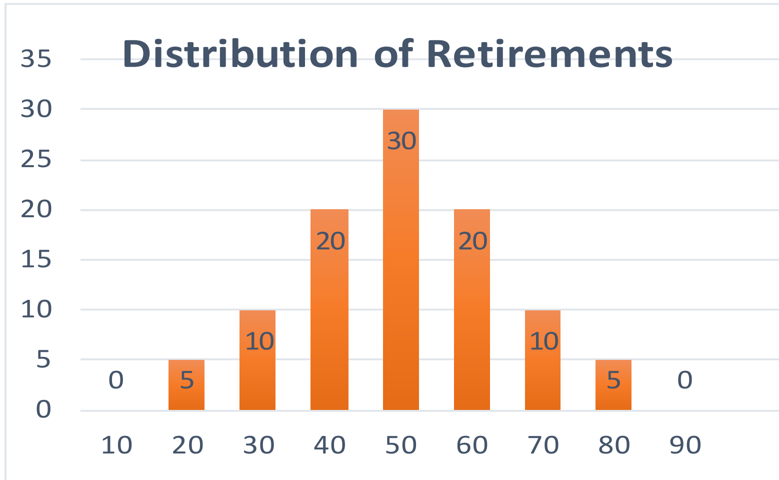
Q. WHAT ARE IOWA CURVES?

A. An Iowa curve is a surrogate or standardized observed life table based on a specific pattern of retirements around an average service life. The Iowa curves were devised over 60 years ago at Iowa State University. The curves provide a set of standard patterns of retirement dispersion. Retirement dispersion merely recognizes that accounts are comprised of individual assets or units having different lives.

For example, imagine an account that begins with a new addition of one hundred units. These units are unlikely to all retire at the same time. Rather, different units within the group will retire at different times. Represented graphically, the result might appear as follows:

Graph RC-1

Age:	Units Retired
10	0
20	5
30	10
40	20
50	30
60	20
70	10
80	5
90	0

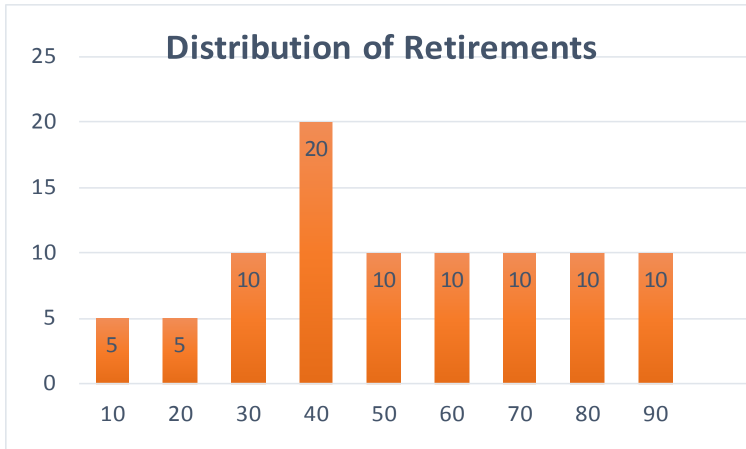


In this example, the average service life would be fifty, and the retirement dispersion curve would tell us how the retirements are arranged around the average service life. In this example, the distribution of retirements around the average service life is symmetrical, with the "mode," or the age with the highest number of retirements, being at the average service life. In this data, the retirements are also relatively tightly grouped around the average service life.

Iowa curves describe many different patterns of dispersions. Returning to our example, imagine a different pattern of retirements as follows:

Graph RC-2

Age:	Units Retired
10	5
20	5
30	10
40	20
50	10
60	10
70	10
80	10
90	10



In this example, the average service life is still fifty but the dispersion characteristics are very different. The mode is at age 40, which is an earlier age than the average, and overall the distribution of retirements is more spread out than in the previous example. By using different types of Iowa curves, I can capture these different characteristics that can be seen in retirement data.

One way that Iowa curves illustrate these different patterns is by their orientation as left-skewed, symmetrical or right-skewed curves, which are known, respectively, as "L curves," "S curves," and "R curves." The letters describe the location of the "mode," as discussed above, relative to the average service life. Hence, in the first example, which is symmetrical, I would use an "S curve," whereas in the second example, in which the mode was at a younger age than the average service life, I would use an "L curve." If the mode falls after the average service life, then I would use an "R curve." In addition to L, S and R curves, there is a set of Origin Modal, or "O curves," which are so called because the mode for these curves is at age one, or the "origin." Generally speaking, O-shaped Iowa curves are not appropriate for utility plant.

In addition to the letter that describes the location of the mode, Iowa curves are numbered one through six, which identifies the spread of the retirement dispersion. Lower numbers represent a wider retirement dispersion. Referring back to the first example above, in which the retirements were more tightly grouped around the average service life, a higher number would be used, whereas in the second example, in which the retirements were more diffuse, a lower number would be used.

To combine these two concepts, an appropriate Iowa curve for the first example might be an S5, whereas an appropriate Iowa curve for the second example might be a L2. This combination of one letter and one number defines a dispersion pattern. Adding an average service life to an Iowa curve (*e.g.*, 5-S0) provides a survivor curve intended to depict a reasonable expectation of how a group of assets will survive, or conversely be retired, over the expected average service life.

Table RC-0005-2 below compares curves with the same shape (S0) but different average service lives (5- and 10-years) to illustrate different iterations with the same curve. The percent surviving represents the amount of plant surviving at each age interval shown in the first column. The 5S0 life and curve sums to the five-year average service life, while the 10S0 life and curve sums to a ten-year average service life.

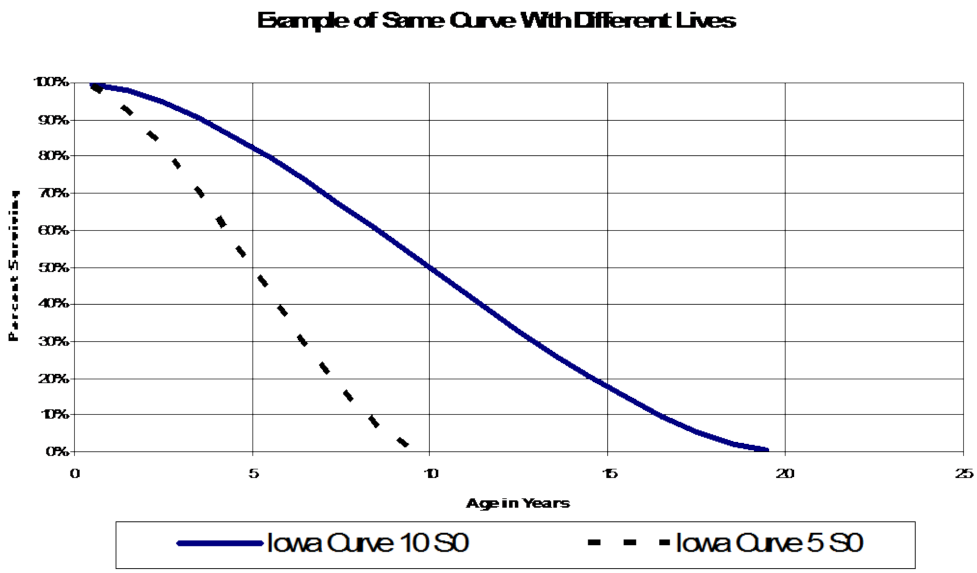
Table RC-2

Sample Survivor Curves

Age	**5 S0 Curve Percent Surviving**	**10 S0 Curve Percent Surviving**
0.5	0.99	1.00
1.5	0.92	0.98
2.5	0.83	0.94
3.5	0.70	0.90
4.5	0.57	0.85
5.5	0.43	0.80
6.5	0.30	0.74
7.5	0.17	0.67
8.5	0.08	0.60
9.5	0.01	0.53
10.5		0.47
11.5		0.40
12.5		0.33
13.5		0.26
14.5		0.20
15.5		0.15
16.5		0.10
17.5		0.06
18.5		0.02
19.5		0.00
Total	**5.00**	**10.00**

These are called "curves" because, when plotted on charts with the x-axis representing "age" and the y-axis representing "percent surviving," they appear as shown below in Graph 3:

Graph RC-3



Q. HOW DO YOU USE THE IOWA CURVES IN YOUR SERVICE LIFE ANALYSIS?

A. The purpose of Iowa curves is to enable the calculation of an average remaining life. Remaining life calculations take the current age of each vintage within an account and then use the retirement rate projected by the appropriate Iowa curve to project the remaining life of each of these vintages of plant. Ultimately, depreciation accruals for plant investment are calculated from remaining lives, so it is important to select the correct average service life and the correct Iowa curve.

Q. IS IT NECESSARY TO FIT ALL OF THE AVAILABLE DATA POINTS TAKEN FROM THE OBSERVED LIFE TABLE?

A. No. In some cases, it is appropriate to disregard some or even many of the oldest aged data. This is because actuarial data that the company keeps often is tied to long-lived assets that represent so small a percentage of the total plant as to not be statistically significant or represent accounting anomalies, such as retirements that were never recorded. This process, which is represented in the graphs below, is called a "T-cut." While there is no hard and fast rule for where a T-cut is appropriate, it is generally appropriate to make a T-cut where the remaining retirement data diverges materially from the established pattern of retirements seen to that point.

As will be discussed in detail below, the decision to make a T-cut, and at what point in the data set to make the cut, is one of the most important, yet subjective, elements to an actuarial analysis. In most cases, making a "larger" T-cut (that is, one that results in fitting the curve to less of the actuarial data) will result in a shorter estimated average service life, because the data eliminated is for the longest lived assets in the set of data.

Additionally, an inconclusive analysis may occur if data points are eliminated from an observed life table with a limited data set (that is, an account that has reliably few recorded retentions). Typically, the portion of an Iowa curve between 85% surviving and 15% surviving most distinguishes one curve from another. With the exception of O curves, Iowa curves follow a parabolic distribution of retirements. That is, as we discussed above, they tend to have limited retirements at the beginnings and ends of their life. Thus, the portion between 85% and 15% surviving is the most indicative because that is when the bulk of retirements in a given account happen, and where variation in the pattern of retirements tends to occur. If a T-cut eliminates too much of the observed life table data, the matching of that data to an Iowa curve will be more likely to produce ambiguous and misleading results. I believe that the full set of aged data should be used in the service life analysis unless specific circumstances warrant exclusion of the data.

Q. DO YOU HAVE ANY CONCERNS WITH THE SERVICE LIVES COMPONENT OF MR. SPANOS'S DEPRECIATION STUDY FOR NJAW?

A. I have two broad concerns with Mr. Spanos's service life recommendations. First, Mr. Spanos inappropriately truncates (that is, makes a larger T-cut) the historical data used in his survivor curves to exclude older aged data without adequate justification. Mr. Spanos' depreciation studies for water and wastewater purport to present the service life statistical analysis of historical depreciation data. However, the information is incomplete and, as a result, Mr. Spanos's depreciation study does not adequately justify adoption of his service life recommendations. Through discovery I obtained the Company's full set of historical depreciation data, which I recommend be used in establishing the service life rate for the Company's depreciation accounts. Second, Mr. Spanos employs a curve fitting technique that favors visually matching the truncated retirement data to Iowa curves and largely disregards the mathematical fitting approach that I favor. Below, I show how these two concerns work in tandem to result in Mr. Spanos's adoption of Iowa curves with artificially low average service life; that is, the visual fit approach preferred by Mr. Spanos produces artificially shorter service lives because it relies on inappropriately truncated aged data.

Q. PLEASE DESCRIBE YOUR CONCERNS REGARDING MR. SPANOS'S INAPPROPRIATE TRUNCATION OF THE HISTORICAL DATA.

A. The Depreciation Study provides, for each account Mr. Spanos studied, a graph comparing his proposed average service life and curve superimposed on a subset of points corresponding to the percent surviving for each age, as shown in the original life table which follows the graph for each account. Referring to account 330.00 – Distribution Reservoirs and Standpipes, we can see that Mr. Spanos' graph, at page VII-102 of his Water depreciation study, stops displaying data points at approximately age 75. However, the original life table continues well past age 75 with the final retirement for this account taking place at age 113,[3] leaving approximately 38 years of data uncharted on Mr. Spanos's graph. This goes back to my concern that a T-cut that fails to use the portion of data between 15% and 85% will produce misleading results. There is simply no reason to exclude approximately 35 years of data that form a smooth pattern of retirements with the data that precede them. Moreover, the exclusion of these data from the graph makes it much more difficult to evaluate the appropriateness of Mr. Spanos's proposed average service life and Iowa curve visually, which as I demonstrate below, creates further concerns with his service life analysis.

Q. WHAT IS THE NET EFFECT OF THIS TRUNCATION ON MR. SPANOS' ANALYSIS?

A. The truncation of the data at the highest available ages of the depreciation data has the effect of biasing Mr. Spanos' analysis towards shorter lives. Below, I provide graphs for each account like the one referenced above, showing the truncated data. These graphs are also available in Exhibit JSG-3. These graphs clearly show a pattern of excluding

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[3] *New Jerser American Water 2016 Depreciation Study – Water* at VII-105.

data for long-lived assets, which has the result of biasing anyone reviewing these graphs in the direction of shorter lives.

Q. CAN YOU WALK THROUGH THE ANALYSIS OF A PARTICULAR ACCOUNT AS AN EXAMPLE?

A. Yes. Understanding how a life table functions is crucial to understanding life analyses. Therefore, let us take 330.00 – Distribution Reservoirs and Standpipes, as an example. Below, I have reproduced ages 0 to 4.5 of the observed life table for Account 330 using an experience band of 1976-2016.

Table RC-3

Observed Life Table for Account 330

Age	Exposures	Retirements	Retirement Ratio (%)	Survivor Ratio (%)	Cumulative Survivors
BAND		**1976 - 2016**			
0	90,654,233	200,843	0.2215	99.7785	1.0000
0.5	90,438,196	19,575	0.0216	99.9784	0.9978
1.5	80,321,271	63,707	0.0793	99.9207	0.9976
2.5	79,579,061	33,804	0.0425	99.9575	0.9968
3.5	74,603,870	32,190	0.0431	99.9569	0.9964
4.5	74,419,798	75,686	0.1017	99.8983	0.9959

The first column shows the age. The observed life table groups data from all vintages together and analyzes the mortality characteristics based on the age of the plant. In the next column are exposures. This is the total plant in service exposed to retirement at a given age. Exposures decrease as age increases because the most recent vintages have not yet had time to attain higher ages. Next, we have retirements, which are total retirements on all vintages that occur at a given age. Earlier, we discussed aged retirement data, and this is where that data comes into play. To review, the age of the retirement is the year that it was taken out of service minus the age that it was put into service. The next column, retirement ratio, is simply retirements divided by exposures. Broadly, this tells you what the odds of a given unit retiring at this age should be. The survivor ratio is then 100% minus the retirement ratio, which, converse to retirement ratio, tells you what percent of the exposures should survive this age. Finally, cumulative survivors are an iterative calculation that begins at 100% and then is multiplied by the previous year's survivor ratio. This measures the chance that a unit will survive at the beginning of its life, which is 100%, and then subjects that percentage to the risk of retirement at each subsequent age.

The cumulative survivors at each age become the data points, which are then compared to the points on each Iowa curve by an algorithm to arrive at the best fit. For Account 330, the life-curve combination with the lowest sum of squared differences is an S0 curve with a 124 year average service life with a sum of squared differences of 937.498. The curve fitting results display the average service life that gives the lowest sum of squared differences for each different curve shape. Table RC-4 presents the top seven curve fits for this account:

Table RC-4

Curve Fitting Results for Account 356

Curve	**Life**	**Sum of Squared Differences**
BAND	**1976 - 2016**	
S0	124.0	937.498
R1	119.0	1,093.896

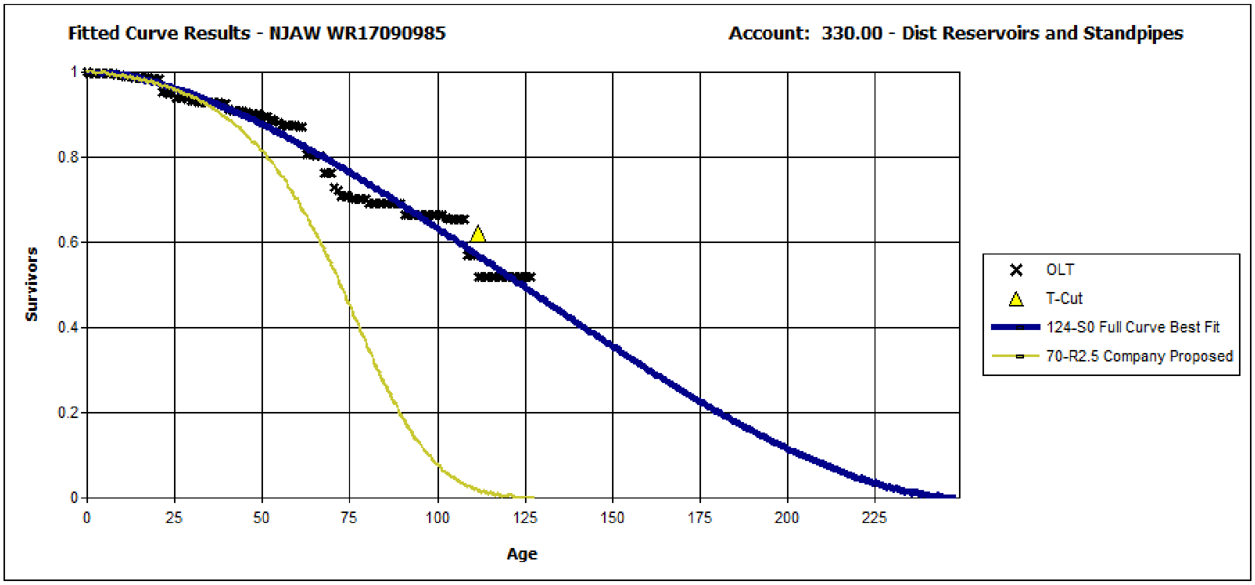
R1.5	113.0	1,288.092
S0.5	118.0	1,392.847
L1	125.0	1,412.780
S-0.5	125.0	1,520.399
R0.5	125.0	1,631.883

Reviewing this table grants a sense of the range of lives that might be appropriate given the curve shape selection. Looking further down the curve fitting results for Account 330, we can see that the best fit results for each curve shape range from as low as 113 years to as high as 125 for the top seven results. We can also see that the number components in the best fitting Iowa curves are quite low, between 0 and 1.5, which means that each of the best fit curves is consistent with a broad distribution of retirements. We can also see that the Company's proposed curve for Account 330, an R2.5 curve, is not one of the top seven curve fits for this account.

The next section of the life analysis is a graph, depicted below as Graph RC-5, which plots the cumulative survivors from the observed life table against the best fitting Iowa curve and the Iowa curve proposed by Mr. Spanos. I provide the graph for each of the Company's accounts below in my account-by-account analysis. I also include these graphs, in Excel format, in Exhibit JSG-3.

Graph RC-5

Best Curve Fit Results for Account 330



Graph RC-5 illustrates the bias that results from truncating the 38 years of data in Mr. Spanos's analysis. As you can see, between ages 0 and 35, both the Company's proposed curve (represented by the grey line) and my proposed curve (represented by the bl ack line) closely follow the historical data from the original life table (represented by the black Xs). However, right around age 50, the Company's proposed curve deviates from the historical data and dips sharply downward, whereas my proposed curve still closely follows the historical data. As a result, the Company's proposed service life of 70 years for Account 330 is significantly shorter than the data actually suggests, which is a service life of 124 years. I provide a more detailed discussion of my proposed service life for Account 330 below. The problem is exacerbated by Mr. Spanos' use of an improper curve fitting technique, as discussed further below.

Q. PLEASE DESCRIBE YOUR CONCERNS WITH MR. SPANOS'S CURVE FITTING TECHNIQUE.

A. In Mr. Spanos's response to data request RCR-DR-34, Mr. Spanos claims he considers both visual and mathematical curve fitting to arrive at his selection of the best-fitting curves for each account. But as the example on Account 330 demonstrates, I have found that Mr. Spanos largely disregards the results from the mathematical curve fitting analysis and instead relies much more heavily on a visual curve fitting. In essence, visual curve fitting is the processes of overlaying a number of different curve shapes against the data in the life table to make a determination of which curve best fits the data. I also use my informed judgment in my analysis. But in contrast to Mr. Spanos, I offer a reasoned basis for that judgment that relies more heavily on mathematical curve-fitting, as detailed above, which uses the sum of least squared difference to arrive at the curve that mathematically best fits the available data.

A mathematical curve fitting is superior to a visual curve fitting. A brief example will help illustrate this point. Selecting the best curve for a given set of data is not unlike determining the number of M&Ms in a glass jar. Someone with a great deal of experience, and aided by computer imaging may make very accurate estimates as to the number of M&Ms in a jar, and even may make a completely accurate estimate from time to time. However, to determine the number of M&Ms truly accurately, you must count the number of M&Ms in the jar individually.

This is equivalent to the function of a mathematical curve fitting, which takes each individual data point and processes it individually to arrive at the exact best fit.

Moreover, a mathematical curve fitting also tells how good of a fit one curve is relative to every other curve. Before the computer software was accessible, this type of fitting was impractical, as it requires thousands, or tens of thousands, of individual calculations. Fortunately, we can now efficiently perform these types of calculations with the aid of a computer algorithm.

Q. HAVE YOU PROVIDED THE RESULTS OF YOUR MATHEMATICAL FITTING ANALYSIS?

A. Yes, Exhibit JSG-3 includes a Schedule titled "Best Fit Curve Results" for each account studied that shows my mathematical curve fitting analysis. Except in limited cases, the "best fit" here, defined as the life-curve combination with the least sum of squared differences, has been selected as our proposed average service life and retirement dispersion curve for that account. These differ from the best fits resulting from Mr. Spanos's analysis primarily because I am using different experience bands than those used by Mr. Spanos. For most accounts, I have utilized "full band" analyses, which utilize the entire range of retirement experience, as well as a 1976-2016 band, which considers only more recent retirement experience.

Q. ARE THERE INSTANCES WHERE THE MATHEMATICAL BEST FIT LIFE AND CURVE ARE NOT APPROPRIATE?

A. Certainly. The mathematical best fit is appropriate in most cases in which the future retirement patterns can reasonably be expected to follow historical experience. However, this is not always the case. There are numerous factors that might lead a utility depreciation expert, familiar with the particular plant account for a given company for a given account, to conclude that future depreciation expectations are different than historical experience. These factors, including major replacement or maintenance projects, differing life expectations of new technologies, or economic or engineering decisions of utility management, might significantly affect the expectations for future retirement rates. Thus, informed judgment is an important component of the service life analysis, but any decision not to follow historical experience must be supported by a reasonable basis.

Q. ARE THERE ACCOUNTS THAT YOU STUDIED WHERE THE BEST FITTING CURVE IS NOT APPROPRIATE?

Yes. As I will note below in my discussion of the various accounts, the historical data for several accounts indicated substantially longer service lives than I would consider reasonable. For such accounts, I have taken into consideration the industry data provided by the Company in response to RCR-21. In these cases, my proposed average service life is the result of informed judgment, giving consideration both to this industry data, and the Company's own historical data.

Q. DO THE RESULTS OF YOUR ANALYSIS CHANGE IF YOU WERE TO ADOPT THE T-CUTS MR. SPANOS USES IN HIS VISUAL ANALYSIS?

A. The results of the mathematical curve fitting would certainly change if Mr. Spanos's proposed T-cuts were to be adopted. However, I would not expect the results to change dramatically. More to the point, I would not expect the mathematical best fit to result in average service lives nearly as short as those proposed by Mr. Spanos. Furthermore, making the T-cuts at an earlier point would make the results less reliable and therefore less consistent. This occurs because reducing the number of data points to which your analysis can match increases the range of average service lives and Iowa curves to which the data can appear to be a reasonable fit, thereby increasing the role of judgment.

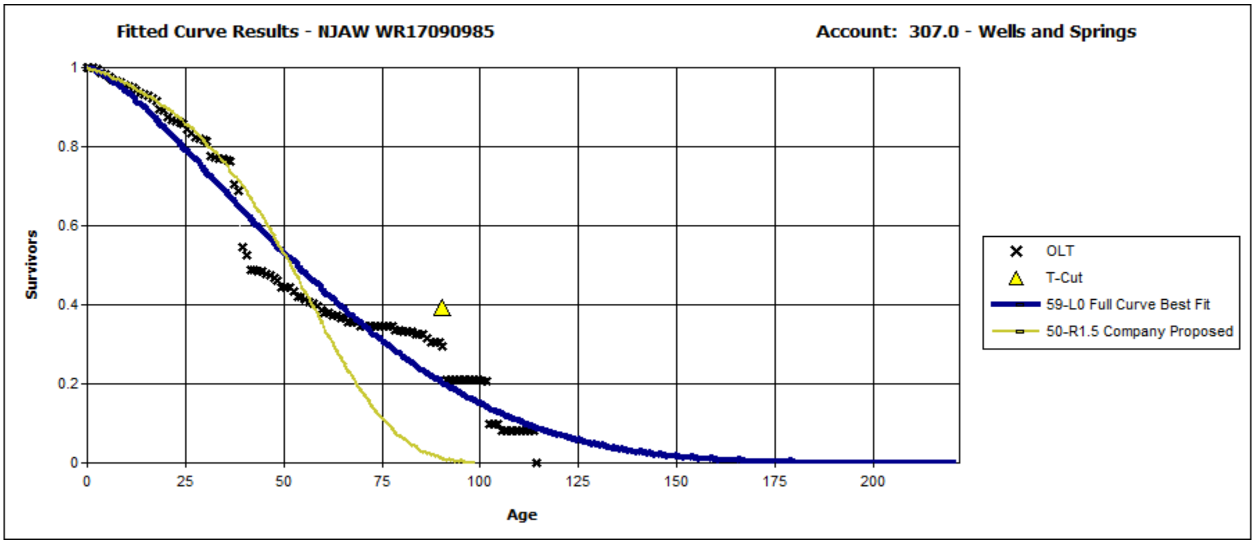
I want to underscore that Mr. Spanos's reliance on visual curve fitting and his use of significant T-cuts are two separate issues that compound one another. If Mr. Spanos had relied on visual curve fitting, but utilized all, or most, of the available data, his results would be more reliable.

Q. CAN YOU DESCRIBE THE FINDINGS FROM YOUR LIFE ANALYSIS FOR EACH ACCOUNT?

A. Yes, below is a discussion of my life analysis for each account, as well the information provided by Mr. Spanos, and how I arrived at my proposals for each account. Each account description is accompanied by a graph, showing the observed life table data (in black Xs), the best-fitting Iowa curve according to the mathematical curve-fitting (blue line), and the Iowa curve proposed by Mr. Spanos (yellow line).

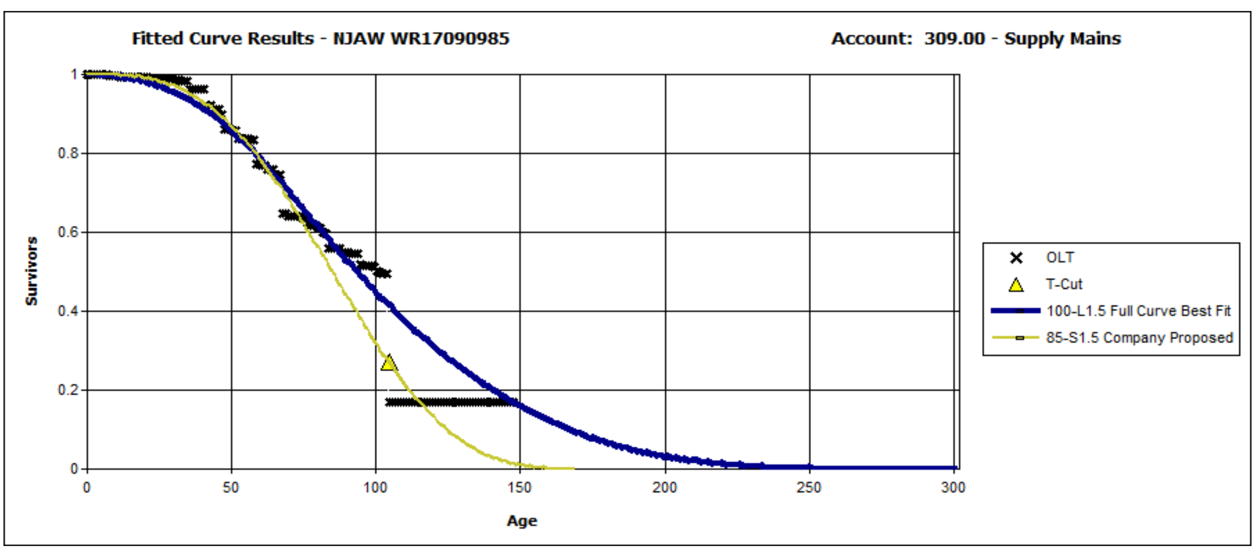
<u>Water Service Lives</u>

<u>307.00 – Wells and Springs</u>



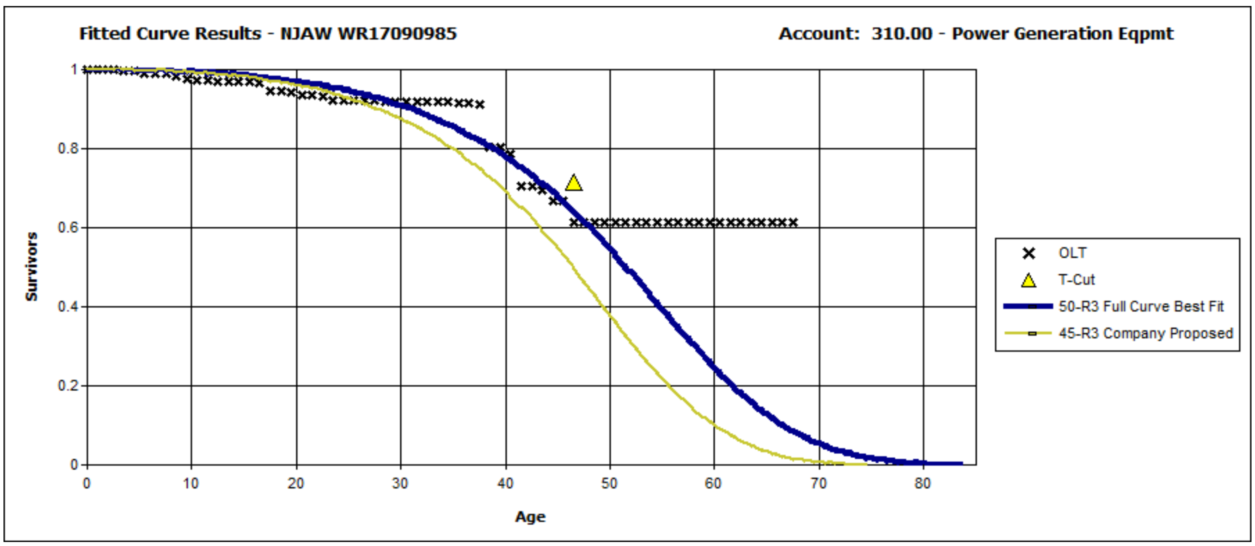
Mr. Spanos is proposing a 50-year average service life with a R1.5 retirement dispersion. However, the best mathematical fits to the historical data suggest longer lives and a left-modal curve shape. In this case I am proposing a 59-year average service life with a L0 retirement dispersion, which is the best fit to the available data.

<u>309.00 – Supply Mains</u>



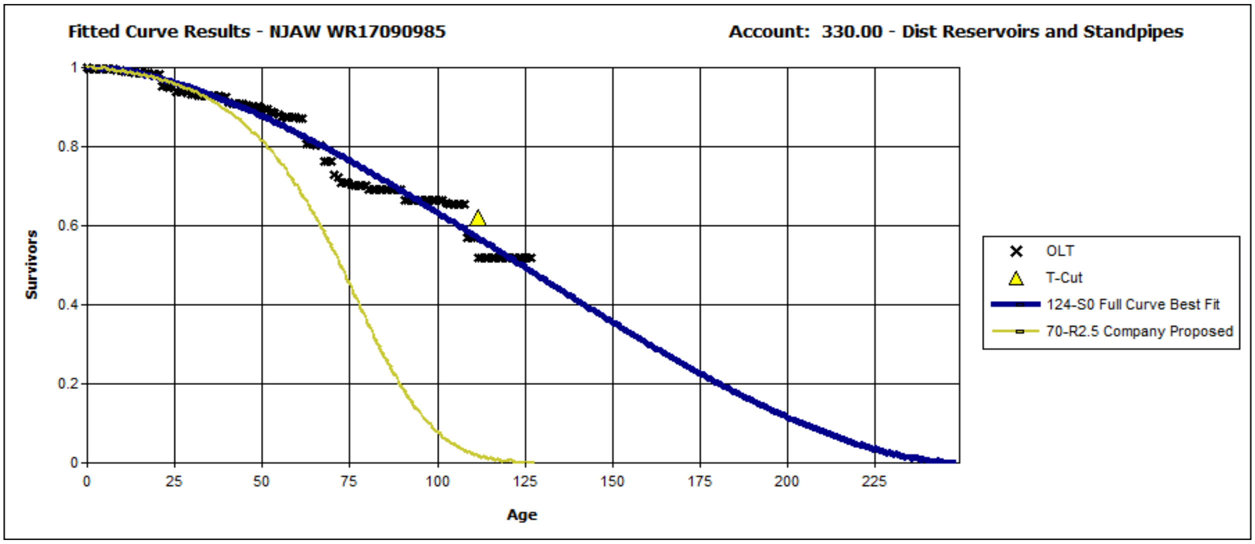
Mr. Spanos is proposing an 85-year average service life with a S1.5 retirement dispersion. However, the best mathematical fits to the historical data suggest longer lives and a low left modal or symmetrical retirement pattern. In this case I am proposing a 100-year average service life and a L1.5 retirement dispersion, which is the best fit to the available data.

310.00 – Power Generation Equipment



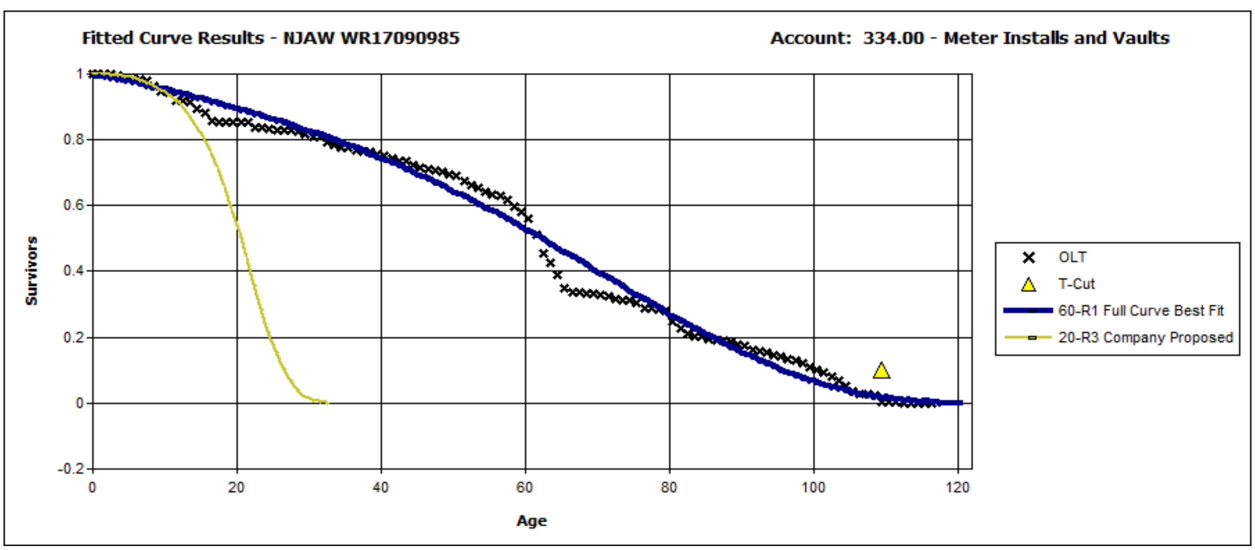
Mr. Spanos is proposing a 45-year average service life with a R3 retirement dispersion. However the best mathematical fits to the historical data suggest a slightly longer average service life. In this case, I am proposing a 50 year average service life, maintaining the R3 retirement dispersion, which is the best fit to the available data.

330.00 – Distribution Reservoirs and Standpipes



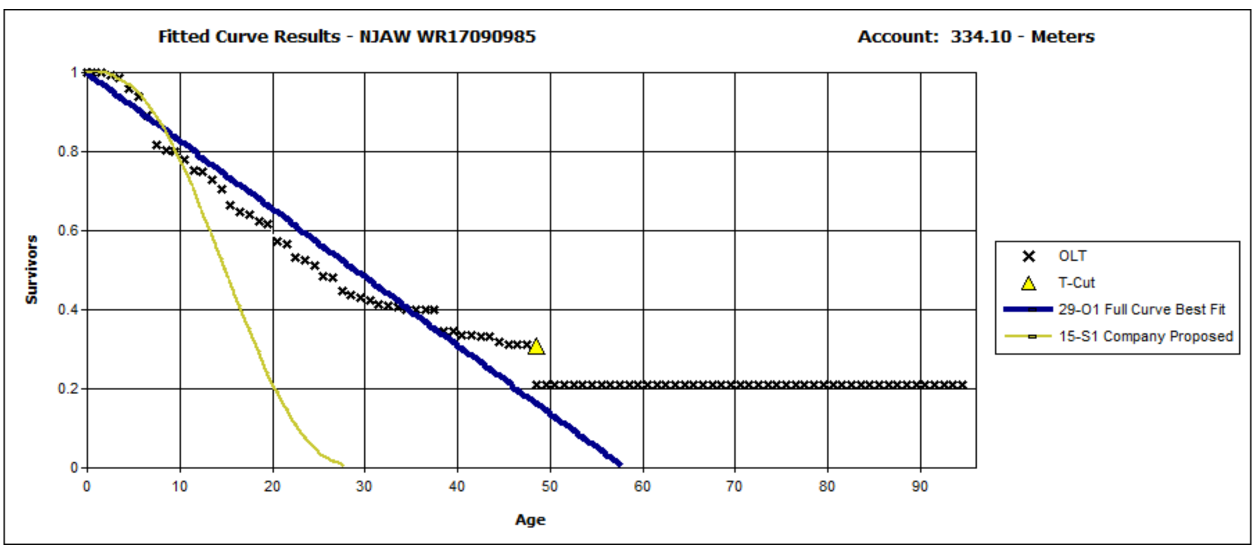
Mr. Spanos is proposing a 70-year average service life with a R2.5 retirement dispersion. However the best mathematical fits to the historical data suggest a significantly longer average service life. In this case, I am proposing a 124-year average service life with a S0 retirement dispersion, which is the best fit to the available data.

334.00 – Meter Installations and Vaults



Mr. Spanos is proposing a 20-year average service life with a R1 retirement dispersion. The best mathematical fits to the historical data suggest a significantly longer average service life. The best fitting average service life is 60 years with a R1 retirement dispersion. However, in this case, it is necessary to take several additional factors into account. First, NJAW has an active meter replacement program in place, which can be expected to lead to early retirements and shorter lives in the future. Additionally, given the technological differences between the old and new meter types, it is reasonable to be conservative regarding future life expectations. Therefore, taking into consideration both the historical data and reasonable future expectations, I am proposing an average service life of 40 years with a R3 retirement dispersion.

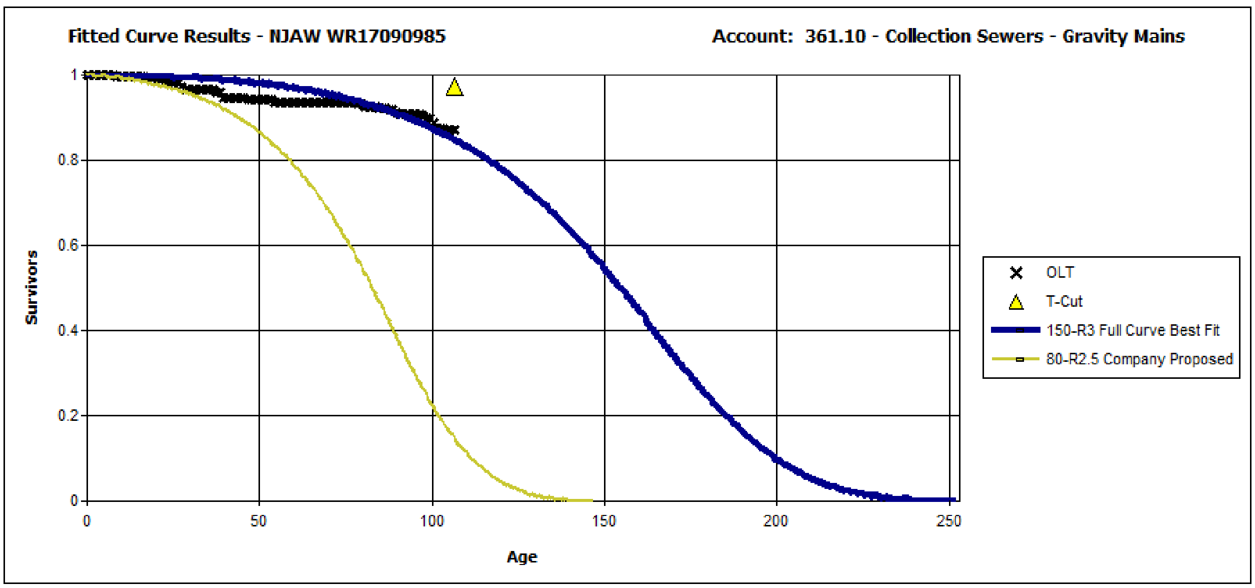
<u>334.10 – Meters</u>



Mr. Spanos is proposing a 15-year average service life with a S1 retirement dispersion. The four best-fitting service lives and dispersions are for original modal curves with much longer average service lives than that proposed by Mr. Spanos. Generally, high original modal curve shapes are not a good fit to utility plant. However, the O1 retirement dispersion pattern, which is simply a straight line of retirements is a reasonable choice. Additionally, the same considerations impact account 334.10 as discussed above with regard to 334.00 – Meter Installations. Considering the factors discussed above, and disregarding the high original modal curve shapes, I am proposing an average service life of 29 years with a O1 retirement dispersion.

<u>Wastewater Service Lives</u>

<u>361.10 – Collection Sewers, Gravity Mains</u>



Mr. Spanos is proposing an 80-year average service life with a R2.5 retirement dispersion. However the best mathematical fits to the historical data suggest a significantly longer average service lives. In fact, given the extremely long history of this account with relatively limited retirements, the best fitting average service lives to the available data are in the range of 200 to 300 years. I do not expect that that is a reasonable expectation, despite the historical data. Therefore, I am proposing an average service life of 150 years for this account, which is very conservative, given the historical data, and using a somewhat high right modal retirement dispersion of R3, which assumes that there will be an increase retirement experience in the future.

DISCUSSION OF NET SALVAGE

Q. DO YOU DISPUTE THE METHODOLOGY THAT MR. SPANOS HAS USED TO CALCULATE NET SALVAGE IN THIS CASE?

A. No. Mr. Spanos has calculated net salvage rates based on a three-year average of recent net salvage. This methodology provides the company with net salvage expense that is tied to their actual net salvage experience.

Q DO YOU HAVE ANY ISSUES WITH THE WAY THAT MR. SPANOS HAS CALCULATED THE THREE-YEAR AVERAGE OF NET SALVAGE?

A. Yes. Mr. Spanos has excluded from his net salvage normalization calculations $9.8 million of gross salvage which resulted from storm damages and insurance compensation. Mr. Spanos rationalizes this exclusion by stating that these amounts represent outliers. However, he has removed these outliers from gross salvage without attempting to assess whether there are related outlier cost of removal amounts. I note that cost of removal recorded in 2015 is substantially higher than cost of removal recorded for either 2014 or

2016. Given the ambiguity in the excluded amounts, and the significance of the impact that Mr. Spanos' exclusion has on net salvage rates overall, I can only conclude that the $9.8 million in excluded gross salvage must be re-included into the normalization calculation, distributed on a plant in service-weighted basis to each account.

Q. DOES YOUR TESTIMONY AND EXHIBITS INCORPORATE THE TESTIMOYN AND ADJUSTMENTS PROPOSED BY MICHAEL J. MAJOROS?

A. My colleague, Mr. Majoros, is submitting testimony regarding the Company's proposal to create a regulatory asset for accumulated net salvage and requesting the amortization of that asset. I have reviewed Mr. Majoros' testimony and concur with his conclusions. However, there is no need to incorporate his proposed adjustments into the depreciation rates, as they do not impact that calculation of annual depreciation rates and accruals.

Q. DOES THIS CONCLUDE YOUR TESTIMONY?

A. Yes.