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WATER SUPPLY PEAKING FACTOR STOCHASTICS

A study into the probability of occurrence of water supply demand peaking factors

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ABSTRACT

Annual daily flow meter records were collected from six south-east Queensland water supply authorities. Persistence curves prepared from those records were found to be closely represented by a variation of the Goodrich Formula which included their Maximum Day and 30 Day peaking factors. The number of accepted data sets was reduced to 369 after the original 685 data sets had been reviewed for completeness and uniformity. The data was adjusted for in-catchment storage mitigation affects.

Stochastic peaking factors suitable for the investigation and design of water supply distribution infrastructure were prepared by arbitrarily separating the twelve month sets of daily flow meter records into average day demand bins and undertaking exceedance probability analyses of the members of each bin. The representative probability lines from each bin were combined using the 95% and 5% confidence limits as a guide to produce a series of smooth shaped curves showing the 100, 50, 20, 10, 5, 2 and 1 year recurrence interval Maximum Day, 7 Day and 30 Day peaking factors for supply areas with average day demands between 0.1 and 600 ML/d.

The outcomes from this methodology were confirmed by back-calculating the Maximum Day peaking factors using independently prepared 7 Day and 30 Day peaking factors and the representative persistence curve Goodrich Formula.

Key Words: Water supply; Peaking factor; Stochastic

INTRODUCTION

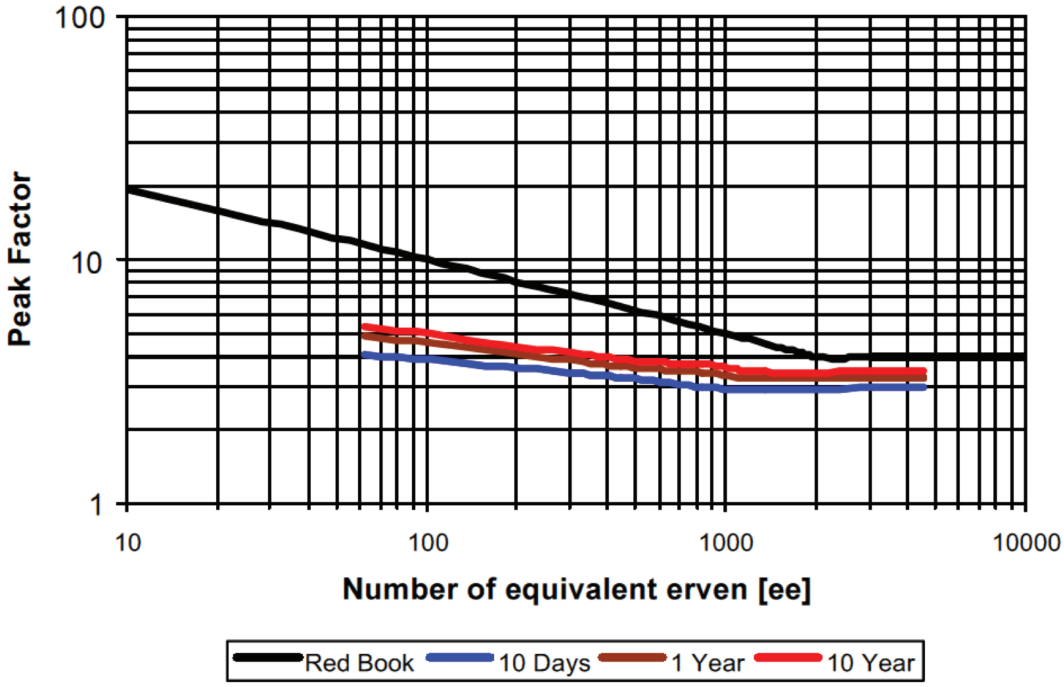
The intent of this paper is to investigate the development of stochastic peaking factor values suitable for practical application in south east Queensland (SEQ), Australia. Stochastic peaking factor curves could complement the deterministic peaking factors set out in the current *SEQ Water Supply and Sewerage Design & Construction Code* (SEQ WS&S D&C Code, 2015). Water supply codes generally do not recognise the stochastic nature of water supply demands and there is little published information about the exceedance probabilities, or return intervals of peaking factors. This is a limitation to water supply practitioners who generally can only use single value water supply peaking factors whereas the availability of stochastic based peaking factors would allow water supply infrastructure to be sized to match their levels of importance and quantitative risk assessments to be undertaken.

There have been a number of published stochastic peaking factor studies relating to urban water supplies, but most have been associated with small populations. There are no known precedents for the preparation of stochastic peaking factors on the scale of the SEQ supply area but the stochastic nature of water supply demands have been long recognised at a building reticulation scale. Hunter (1940) appreciated that building water demands were stochastic and proposed that plumbing flows be calculated as the 99th percentile of a binomial distribution. Hunter's work, while now recognised as being conservative, still forms the basis for a large percentage of the world's building water reticulation and drainage codes.

Nevertheless, there have been numerous empirical relationships given in the technical literature indicating that water supply and sewerage peaking factors reduce as the supply population increases. Zhang (2005) noted that water specific peaking factor equations of the logarithmic decay function form had been developed by organisations such as the US Bureau of Reclamation. Martinez-Solano et al (2005) in Spain and Tricarico et al (2007) in southern Italy separately also published equations of that form. Equation (1) is reproduced from Tricarico et al (2007):

$$\textbf{\textit{Peaking Factor}} = 11 \times N^{-0.2} \quad (1)$$

While these authors had recognised that there were also stochastic relationships, Booyens and Haarhoff (2002) in South Africa published the work which possibly most resembles the aim of this document. Figure 1 shows the set of demand probability curves which they prepared to complement the South African Red Book's (Red Book, 1994) deterministic guidelines. The curves in Figure 1 were produced by analysing about 5 months of flow meter data and ranking 15 minute interval components of the meter flow data as ratios of the average 15 minute flow. Ranking was carried out using the Weibull formula to obtain flow return intervals.



Note, an erven is one household.

Figure 1: Stochastic Peak Factors from Booyens and Haarhoff (2002)

It is noted that the published stochastic peaking factor work has generally been associated with demand data with durations of less than a year, and the resultant peaking factors have adopted sample time intervals commonly between 6 seconds and 30 minutes. A number of researchers including Booyens and Haarhoff (2002), Tricarico et al (2007), and Gato-Trinidad and Gan (2014) have shown that peaking factors increase as the sampled time interval is reduced.

Some researchers have commented that sampling time intervals should be adopted depending on the supply area size and the intended use of the peaking factors. Scheepers (2012) referred to Booyens (2000) who concluded that for developments with an average day demand of less than 100 kL that a 15-minute sampling time could be applied, while a 1 hour time would be acceptable for developments with an AD demand greater than 100 kL. Scheepers (2012) noted that the differences between peaking factors for varying sampling times became less as the population size increased, and suggested that the peak factor time interval is not a pertinent consideration for more than 1,000 households.

The adoption of a 15-minute sampling time by Booyens and Haarhoff (2002) has not been followed by this document. That time interval would be inappropriate for the development of peaking factors to be used for storage and risk assessments which could have critical durations extending into multiple days. Small sampling times would also not complement the existing SEQ WS&S D&C Code, 2015, which only refers to the Maximum Hour and Maximum Day. To that end this paper focuses on the development of daily stochastic peaking factors based only on the analyses of 1-day demand duration data.

DATA COLLECTION AND ACCEPTANCE

Many water supply authorities now have access to large demand data bases which potentially could be stochastically analysed to develop a better understanding of their water supply demands. In SEQ that data base is provided by regional billing flow meters and flow meters installed in demand management areas to limit leakage losses during the 2001 to 2009 drought. Most of those demand management areas utilise pressure reduction valves in conjunction with flow meters and data loggers, i.e. they also serve as de facto supply area demand recorders. Sets of twelve-month long daily flow meter data were collected from 340 SEQ metering sites within the five SEQ water authorities' supply areas (QUU, Unitywater, Redland Water, Gold Coast City Council and Logan City Council) over the period 2000 through to 2014, although the majority of the collected data was for the period 2007 to 2014. The maximum number of years of data from a single site was eight but generally sites provided only one twelve-month data record.

Seqwater is the bulk water supplier to the five water supply authorities listed above which service the SEQ supply area as an interconnected water grid. Seqwater flow meter data to the individual authorities was combined to create demand data for the whole water grid.

When the collected flow meter data was first analysed it was found that there were major inconsistencies in the Maximum Day peaking factors between the individual water authorities. It had been expected that there could be peaking factor differences between supply areas but the quantum of those differences appeared to be excessive. The raw data was therefore reviewed with an emphasis on data completeness and data uniformity. Data completeness was measured as a percentage of daily data records within a twelve-month record. Data uniformity is where the data record complied with expected patterns and was measured as a correlation of the recorded data's persistence curve against the representative persistence curve (discussed further below). Typical causes of non-uniformity were when a flow meter became "stuck" and recorded the same value regardless of the actual flow rate or the supply area had more than one metered inflow and the data source flow meter only recorded part of a supply area's demand. It was deemed that a data completeness of 99.5% and a data uniformity of 0.95, measured using the correlation coefficient, would be necessary for acceptance of an annual data record. The number of data records subsequently accepted for the peaking factor analyses was reduced to 369 from the 685 records originally collected.

PERSISTENCE CURVES

The analysis of each twelve-month data record included the preparation of a demand persistence curve. Demand persistence curve values can be calculated from any supply area's twelve-month daily demand record as the maximum 1 day of demand, the maximum 2 days of demand, the maximum 3 days of demand, etc. through to 365 days of demand. The 1 day demand persistence is called the Peak Day or Maximum Day (MD) demand and the 365 day demand persistence period is called the Average Day (AD) demand. The 30 day persistence is sometimes called the Mean Day Maximum Month but is named the 30 Day demand in this document.

Persistence curves take the form of a logarithmic decay function. Equation (2) shows the Goodrich Formula (McGhee (1991), p. 14) which is sometimes quoted in text books for estimating maximum day demand for a time t as a percentage of the annual average demand.

$$P = 180.t^{-0.10} \quad (2)$$

While the Goodrich Formula is based on a fixed one-day maximum day peaking factor of 1.8 and a maximum persistence period of 365 days, that equation can be generalised as:

$$\textit{Peaking Factor} = A \times \textit{Persistence period}^{\,b} \quad (3)$$

where *A* equals the actual one-day MD peaking factor and *b* is a negative coefficient which indicates the degree of demand persistence, and is calculated as a function of the MD and 30 day peaking factors:

$$b = \log_{10}(\textit{30 Day Peaking Factor} / \textit{MD Peaking Factor}) / \log_{10}(30) \quad (4)$$

Equation (3) in conjunction with equation (4) has been designed for this document to generally only be valid for persistence periods of less than about 35 days. Figure 2 shows a typical persistence curve prepared from a single twelve-month flow meter record overlaid with the representative curve prepared using equations (3) and (4). The figure illustrates the high correlation with actual data records which can be achieved using those equations.

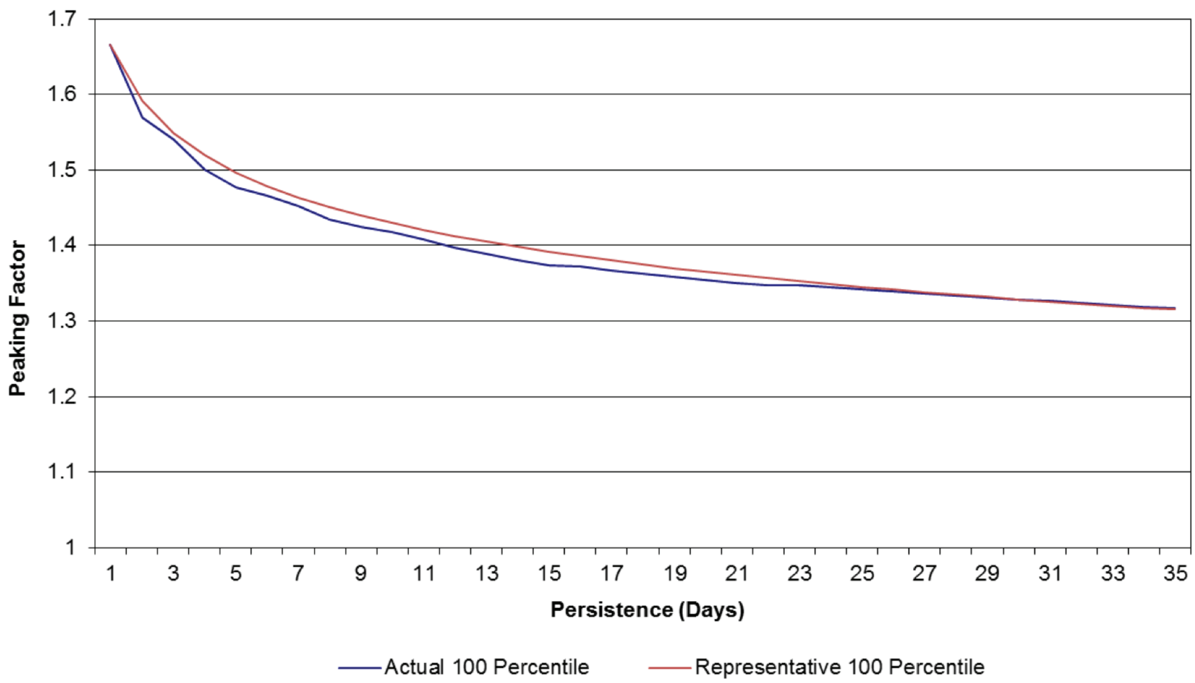


Figure 2: Example of Actual and Representative Persistence Curves

PEAKING FACTOR STORAGE ADJUSTMENT

Flow meter data records often relate to supply areas which contain storages which tend to balance out daily demands and mitigate the peaking factors extracted from the recorded data. The extent of mitigation depends on the size of the storage relative to its inflows and how the storage is operated.

An appreciation of the mitigation impacts of storages on peaking factors was obtained from an analysis historical flow metering data. During the period 2001 to 2005 records were kept of both daily outflows to the Brisbane bulk water system and corresponding daily changes in tank storage volumes. Similar data was kept for the supplies to the Caboolture, Pine Rivers and Redcliffe districts for the period 2008 to 2010. Examination of the persistence curves generated from the collected flowmeter data, and corrected flow meter data after taking into account changes in the daily measured storage volumes, showed that the adjusted demand storage curve has a greater MD peaking factor but the storage impacts were seen to cease after about seven days. It was also noted that the areas under both the storage unadjusted and adjusted persistence curves for days 1 to 7 were approximately the same.

A methodology was developed to adjust the MD peaking factor for each twelve-month data record by generating, using EXCEL *Goal Seek*, a persistence curve using equations (3) and (4) such that the areas under the generated and actual flow metered data curves for the first seven days were the same with the MD peaking factor being the only variable. The MD peaking factor calculated using the flow meter data was adopted when the persistence curve area balancing methodology gave a lower value than that obtained from the original data, which was expected in those situations where the supply area had a small storage volume or the storage was operated between close fill and draw settings. The average increase in the MD peaking factor resulting from the persistence curve area matching methodology outlined above was 2.9%. The maximum increase was 44% and the 95th percentile was 14%. Figure 3 shows an example of a flow meter data persistence curve with a storage adjusted developed persistence curve.

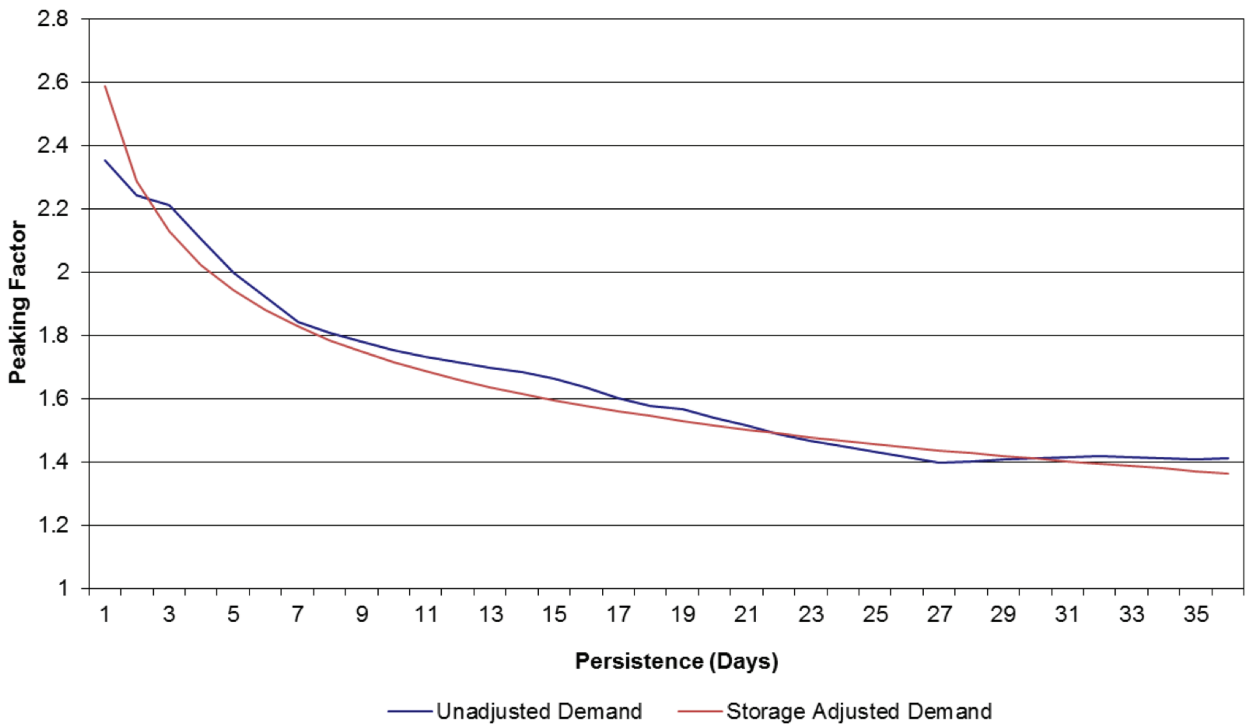


Figure 3: Example of Storage Adjustments to Flow Meter Data Persistence Curve

STOCHASTIC PEAKING FACTOR DEVELOPMENT

Maximum Day Peaking Factor Stochastics

Figure 4 shows the MD peaking factors derived from the accepted storage adjusted data plotted against their respective AD demands on log-log scales. The AD demand was chosen for the X-axis instead of population units because of variabilities in per capita demand between different supply areas.

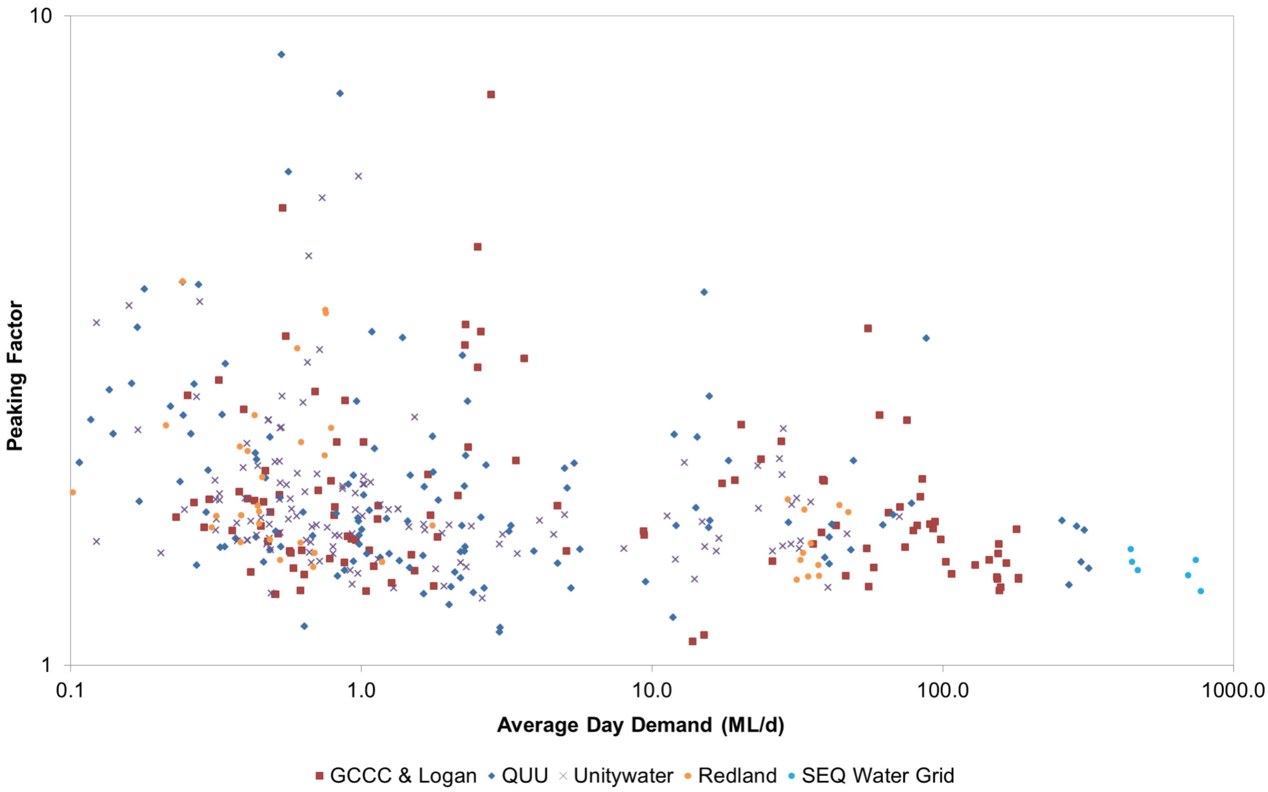


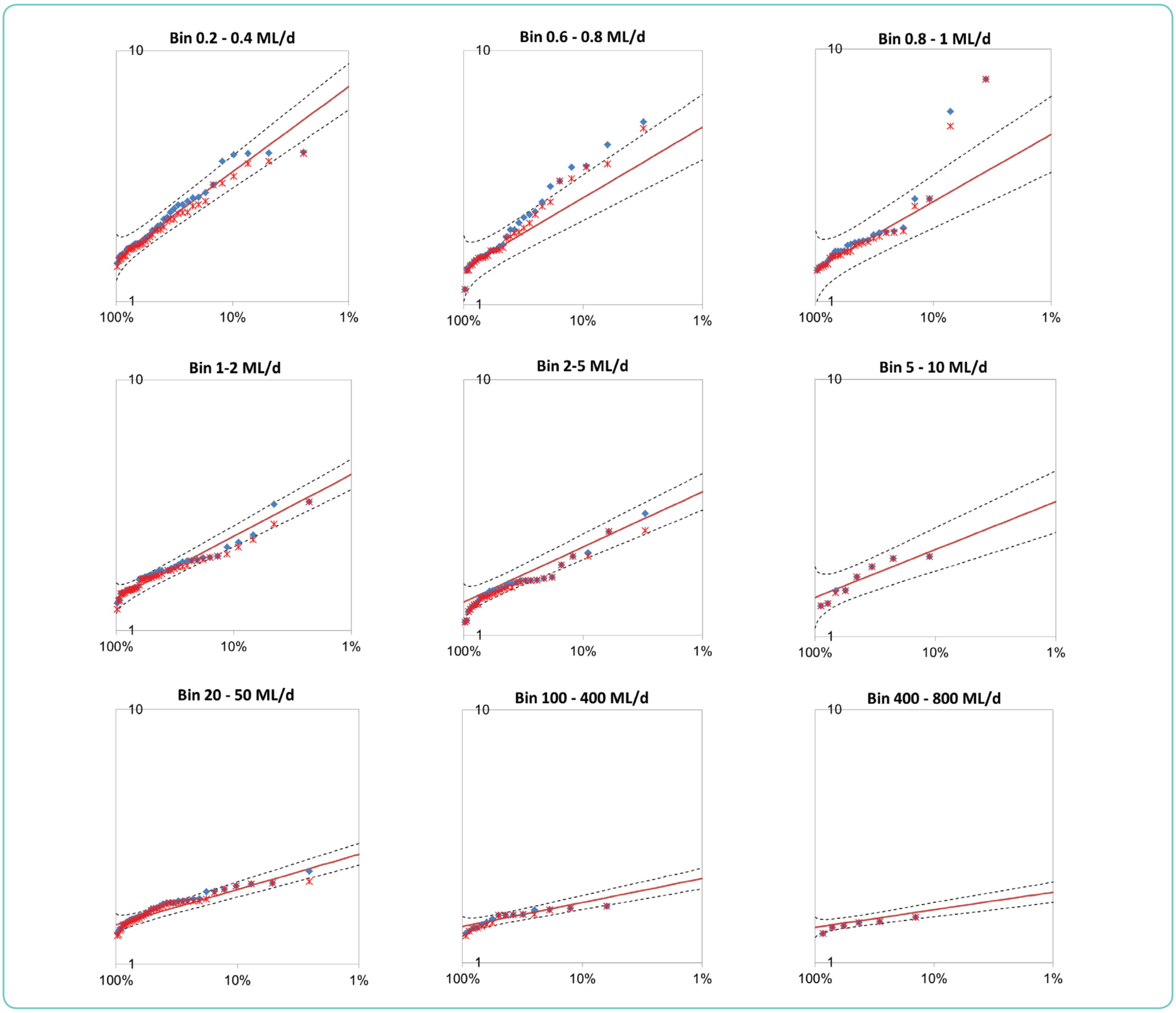
Figure 4: SEQ Maximum Day Peaking Factors

At first glance the peaking factor plot on Figures 4 did not appear to have a recognisable pattern but it was noted that some of the data points were for the same flow meter locations and it was suspected the plotted plotted data represented probabilities of occurrence. This hypothesis was tested by arbitrarily subdividing the data into AD demand bins, and carrying out a probability exceedance analysis for each bin. Thirteen AD demand bins were selected, i.e. 0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, 0.8–1.0, 1–5, 5–10, 10–20, 20–50, 50–100, 100-400 and 400–800 ML/d. Similar to the approach taken by Booyens and Haarhoff (2002), the probability analyses involved the members of each bin being ranked and given exceedance probability plotting positions using the Weibull formula:

$$\textit{Plotting Position} = {}^{m}/N + 1 \quad (5)$$

where *m* is the rank of peaking factor in bin, the largest peaking factor having a rank *m* = 1, and *N* is the number of peaking factors in the bin.

Figure 5 shows, for brevity, the probability exceedance plots of nine of the thirteen bins including both the storage adjusted (coloured blue) and unadjusted (coloured red) peaking factors with representative probability exceedance lines (solid red lines), and 5% and 95% confidence limits (broken black lines). It is noted that the differences between the storage adjusted (red coloured) and non-adjusted (blue coloured) data points do not appear to be great.



Note: Peaking factors are plotted on the Y axis (log scale) and exceedance probabilities are plotted on the X axis (log scale) for each data bin. The storage adjusted peaking factors are coloured blue and the unadjusted peaking factors are coloured red. The representative probability exceedances are shown as solid red lines and the 5% and 95% confidence limits are shown as broken black lines.

Figure 5: Maximum Day Exceedance Probability Plots

Selection of log-log scales for the X and Y axes for Figure 5 was adopted because the bin distributions were all found to be highly skewed to the left. The log-log transformation sufficiently amended that skew to the extent that near linear plots could be achieved. This need for a log-log transformation, i.e. treatment of the data as a log-normal distribution has been previously investigated by others. R. Gargano et al (2010) found for small populations (up to 1,220 persons) that peak demands are described well by both the log-normal and Gumbel distributions.

Figure 6 was formed by plotting the peaking factors from each bin's representative probability exceedance line against the bin's representative AD demand for the 1%, 2%, 5%, 10%, 20%, 50% and 100% exceedance probabilities. The representative AD demand for each bin was calculated as the average of its Average Day demand data points.

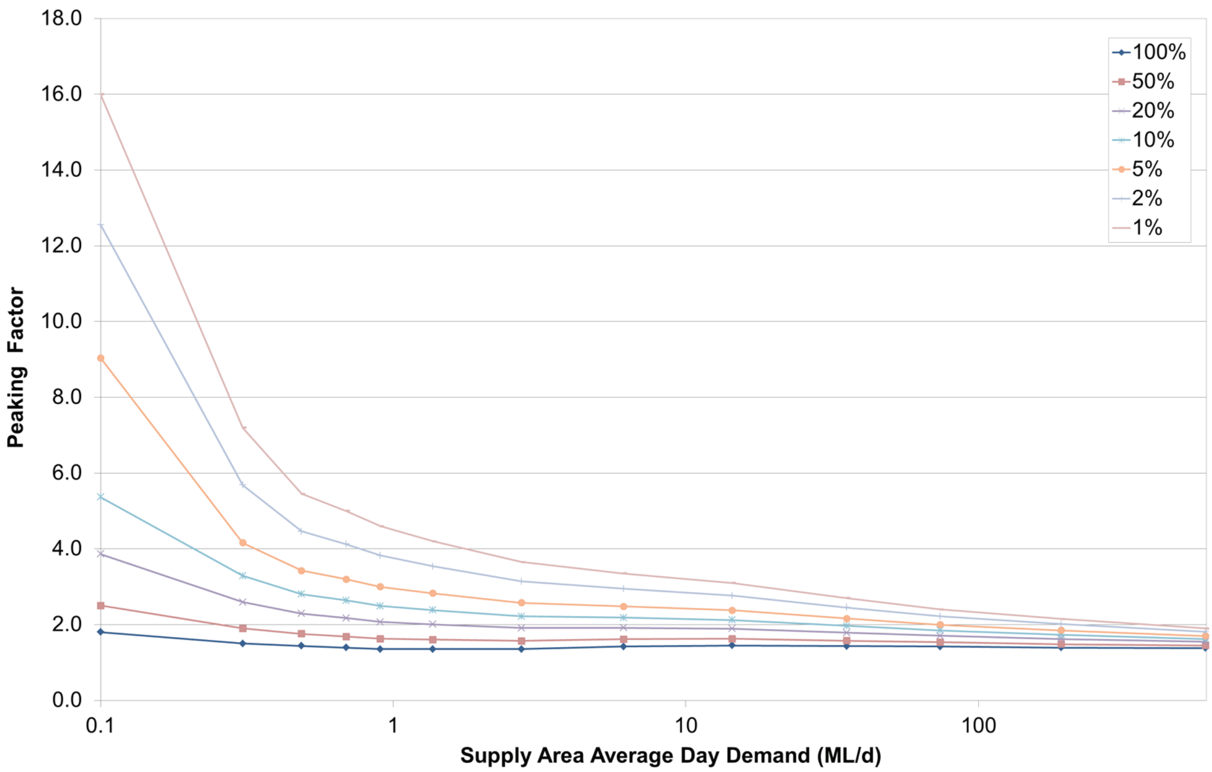


Figure 6: Maximum Day Peaking Factor Exceedance Probability Profiles

The slopes and axis intercepts of the Figure 5 representative probability lines were determined by their progressive adjustment to achieve the smooth shaped curves of Figure 6 while retaining the Figure 5 plots' data points within their respective 5% and 95% confidence limits. The confidence limits were calculated using equation (6):

Upper and lower confidence limits

$$= y_p \mp z.\frac{s_y}{\sqrt{n}}\sqrt{(1+\tfrac{1}{2}z_p^{2})} \qquad (6)$$

where y_p is the representative probability exceedance value for probability *p*, *z* is the standard normal variable for the 95% limit (= 1.96), s_y is the standard deviation of the logarithms of the sampled data, *n* is the number of data points in the sample, and z_p is the standard normal variable for probability *p*.

It is noted that an alternative method of creating the Figure 6 probability profile curves using regression analyses was found to be unworkable because the resultant profiles were irregular and did not provide the expected continuous reduction in peaking factor values for increases in the average day demand. This is illustrated by Figure 7 which is a plot of the MD peaking factor exceedance probability profiles prepared after undertaking a regression analysis on each bin's data set.

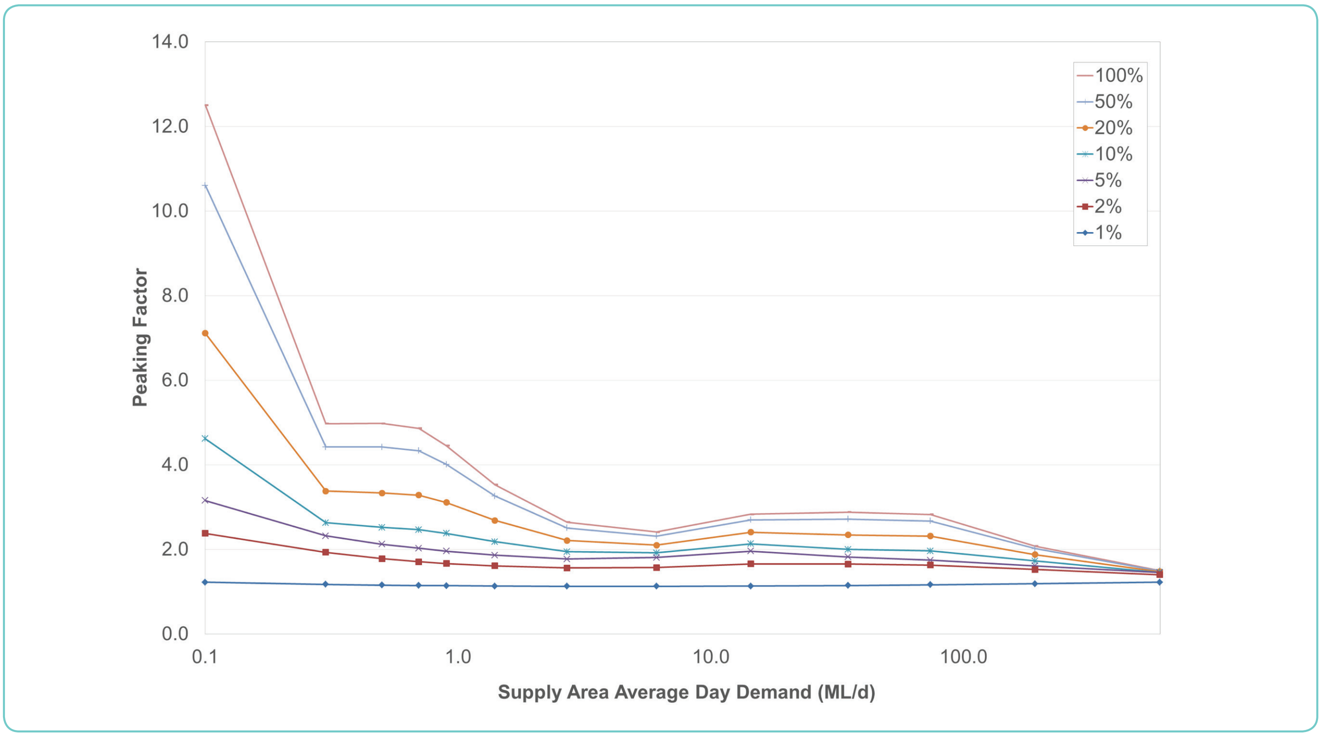


Figure 7: Maximum Day Peaking Factors Profiles by Regression Analysis

Table 1 tabulates the MD peaking factor values used for the preparation of Figure 6 with respect to the 100, 50, 20, 10, 5, 2 and 1-year recurrence intervals (RI). These RI are respectively the inverses of the 1%, 2%, 5%, 10%, 20%, 50% and 100% exceedance probabilities.

Table 1: Maximum Day Peaking Factors

RI	Supply Area Demand (*ML/d*)												
(*Year*)	0.1	0.3	0.5	0.7	0.9	1.4	2.7	6.1	14.4	35	74	192	597
1	1.80	1.50	1.44	1.39	1.35	1.35	1.35	1.42	1.45	1.43	1.42	1.39	1.38
2	2.50	1.90	1.76	1.69	1.62	1.60	1.57	1.62	1.63	1.57	1.54	1.48	1.45
5	3.86	2.60	2.29	2.17	2.07	2.01	1.91	1.92	1.89	1.79	1.71	1.62	1.54
10	5.37	3.29	2.80	2.64	2.49	2.38	2.22	2.18	2.12	1.96	1.85	1.73	1.62
20	7.46	4.16	3.42	3.20	3.00	2.82	2.58	2.48	2.38	2.16	2.00	1.85	1.70
50	11.52	5.69	4.46	4.12	3.82	3.54	3.14	2.94	2.76	2.45	2.22	2.01	1.81
100	16.00	7.20	5.45	5.00	4.60	4.20	3.65	3.35	3.10	2.70	2.40	2.15	1.90

7 and 30 Day Exceedance Probabilities

Plots of the 7 and 30 Day exceedance probabilities were independently prepared in the same manner as outlined above for the MD exceedance probability plots. For brevity only the 30 Day exceedance probability profiles and table of probability values is presented in this document. Figure 8 shows the peaking factor curves formed by plotting the peaking factors from the 30 Day bin's representative probability exceedance curves against their representative AD demands. This figure, when compared to the MD's Figure 6, demonstrates the close similarity between the different persistence period exceedance probability profiles.

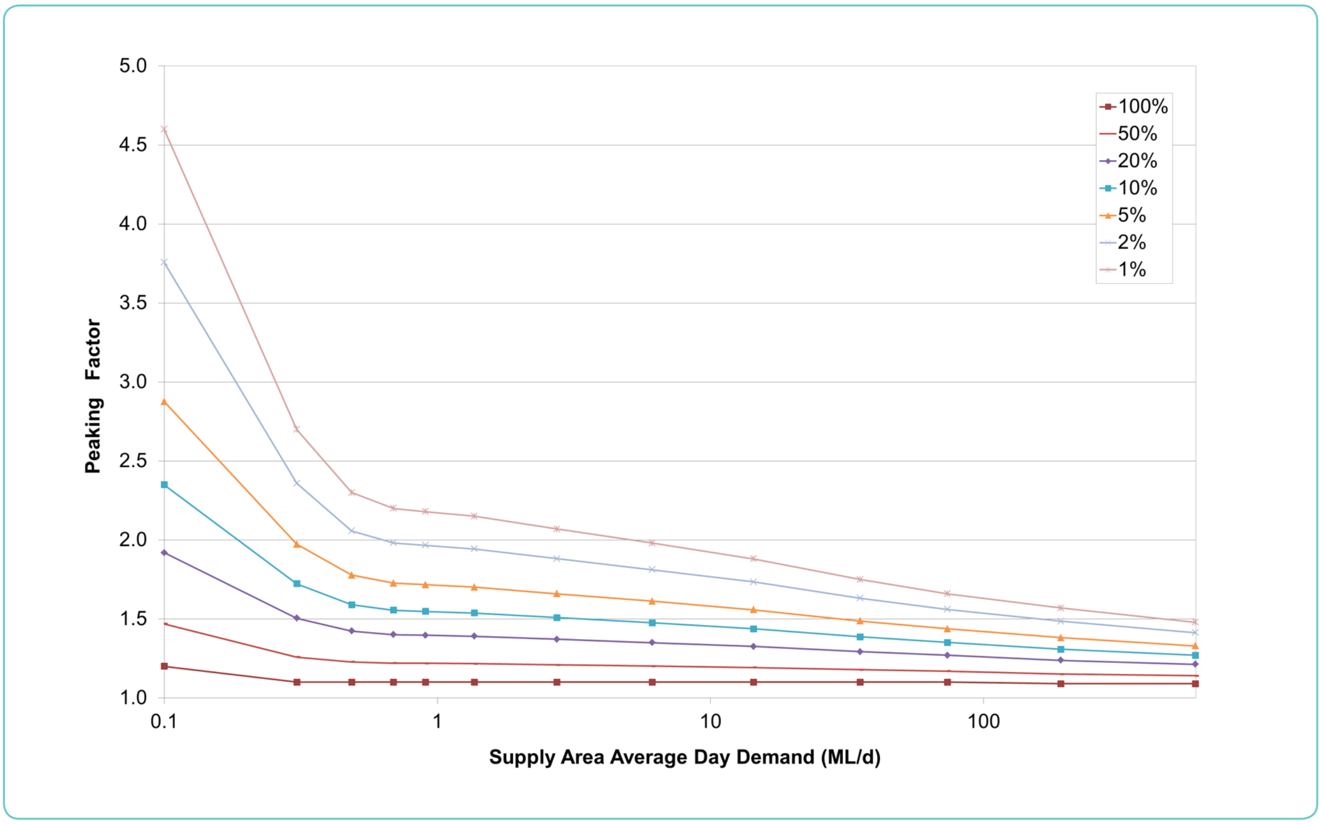


Figure 8: 30 Day Peaking Factor Exceedance Probability Profiles

Note: Peaking factors are plotted on the Y axis (log scale) and exceedance probabilities are plotted on the X axis (log scale) for each data bin. As for Figure 5, the representative probability exceedances are shown as solid red lines and the 5% and 95% confidence limits are shown as broken black lines. All plots are for storage adjusted peaking factors.

Table 2 tabulates the 30 day peaking factor values used for the preparation of the Figure 8 exceedance probability profiles.

Table 2: 30 Day Peaking Factors

RI	Supply Area Demand (*ML/d*)												
(*Year*)	0.1	0.3	0.5	0.7	0.9	1.4	2.7	6.1	14.4	35	74	192	597
1	1.20	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.09	1.09
2	1.47	1.26	1.23	1.22	1.22	1.22	1.21	1.20	1.19	1.18	1.17	1.15	1.14
5	1.92	1.51	1.42	1.40	1.40	1.39	1.37	1.35	1.33	1.29	1.27	1.24	1.21
10	2.35	1.72	1.59	1.56	1.55	1.54	1.51	1.48	1.44	1.39	1.35	1.31	1.27
20	2.88	1.97	1.78	1.73	1.72	1.70	1.66	1.61	1.56	1.49	1.44	1.38	1.33
50	3.76	2.36	2.06	1.98	1.97	1.94	1.88	1.81	1.73	1.63	1.56	1.49	1.41
100	4.60	2.70	2.30	2.20	2.18	2.15	2.07	1.98	1.88	1.75	1.66	1.57	1.48

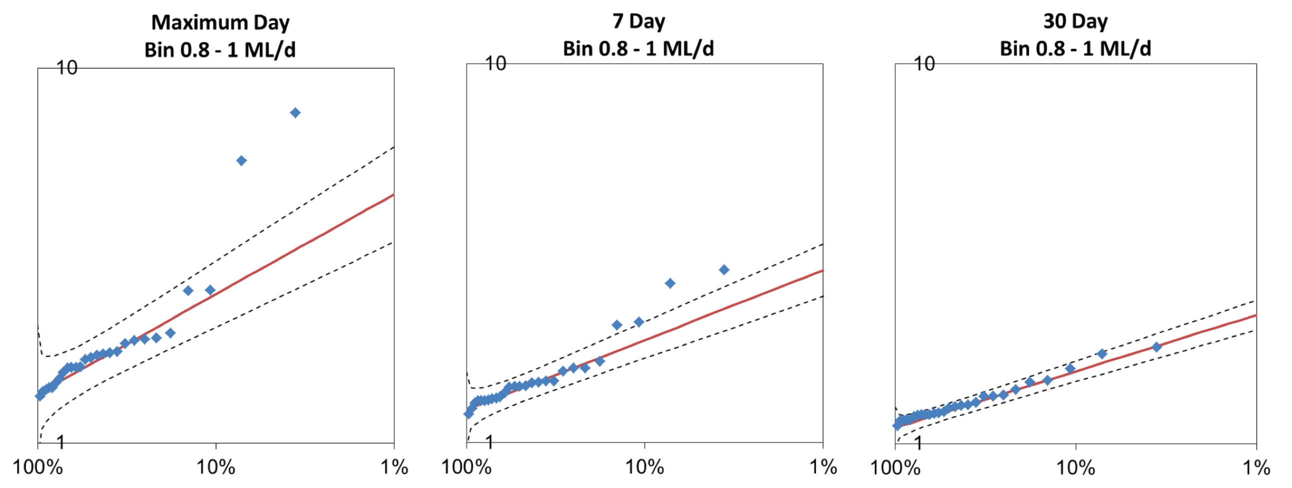
PEAKING FACTOR VALIDATION

Bin Plot Outliers and Exceedance Probability Compliance

The presence of outliers on some of the bin plots shown on Figure 5 might generally be explained by some points not being removed through the data acceptance processes discussed earlier, or by the arbitrary bin range selection, and would fall within the confidence limits if the bin ranges were modified.

While these explanations might be correct, a more robust assessment of the validity of these outliers, and the process adopted for selection of the representative exceedance probability lines is needed. That assessment follows.

It was noted that the presence of outliers reduces when viewing the respective Maximum Day, 7 day and 30 day bin plots. Figure 9 shows, as an example, the data plots for the 0.8-1 ML/d demand bin which demonstrate the reduced presence of outliers and the more closely confined confidence limits of the 7 and 30 day data as compared to the Figure 5 MD data.



Note: Peaking factors are plotted on the Y axis (log scale) and exceedance probabilities are plotted on the X axis (log scale) for each data bin. As for Figure 5, the representative probability exceedances are shown as solid red lines and the 5% and 95% confidence limits are shown as broken black lines. All plots are for storage adjusted peaking factors.

Figure 9: Confidence Limit Band Width Reductions with Increases in Persistence

The 7 Day and 30 day plots benefit from much of the "noise" associated with the MD plots, shown on Figure 5, being removed by the averaging processes. Those processes also reduce the MD, 7 Day and 30 day standard deviations of the plot data respectively from 0.264 to 0.176 to 0.172. This, in turn, reduces the confidence limit band widths as calculated using equation (6). This observed reduction in data standard deviation provided an opportunity to further check the validity of the Figure 5 plots.

The Goodrich Formula relationships discussed above showed that good correlations could be made with actual persistence data curves. Indeed, as discussed previously, flow meter data records with a correlation coefficient of less than 0.95 were rejected. Back-calculation of the 1 Day peaking factors from the independently prepared 7 and 30 day values using equations (3) and (4) was thus carried out using EXCEL *Goal Seek* to determine the MD peaking factors associated with those 7 and 30 Day peaking factors.

The back-calculations were carried out for the full range of AD and recurrence interval values given in Table 1, and were found to have an average of 1.02 times the Table 1 MD values, and 20 and 80 percentiles of 0.98 and 1.06 times those MD values. This close agreement in the MD values confirms the validity of the methodology based on fitting the representative probabilities to make the data lie within the 5% and 95% confidence limits.

Variability in Data Source Areas

The SEQ water supply authorities service a population of about 3.1 million people over an urban area which extends in a north-south direction for almost 200 km. There are demand differences between the five treated water distribution authorities. QUU's non-residential component is over 30% compared to the other four distribution authorities which have non-residential components nearer to 20%, and average residential water consumptions vary from about 165 to 200 litres per capita per day within the overall SEQ supply area.

The accepted data records used for the probability analyses came from the six SEQ water supply authorities as follows: Seqwater, 6, QUU, 143, Unitywater, 131, Redland Water, 50, Gold Coast City Council and Logan City Council, 39. The question then is whether the probability exceedance profiles described by Figures 6 and 8 are also valid for the individual supply areas?

This was tested by breaking down the data in the Figure 5 MD plots to show their sources, and replacing the overall upper and lower confidence limits with 5% and 95% limits which only applied to the source data. Figure 10 shows the results for the QUU and Unitywater sourced data in the 1-2 ML/d demand bin, and the QUU and Gold Coast City Council (GCCC) sourced data in the 100-400 ML/d demand bin. The figure appears to confirm that the adopted exceedance probabilities are also applicable to individual source areas within the overall SEQ supply area.

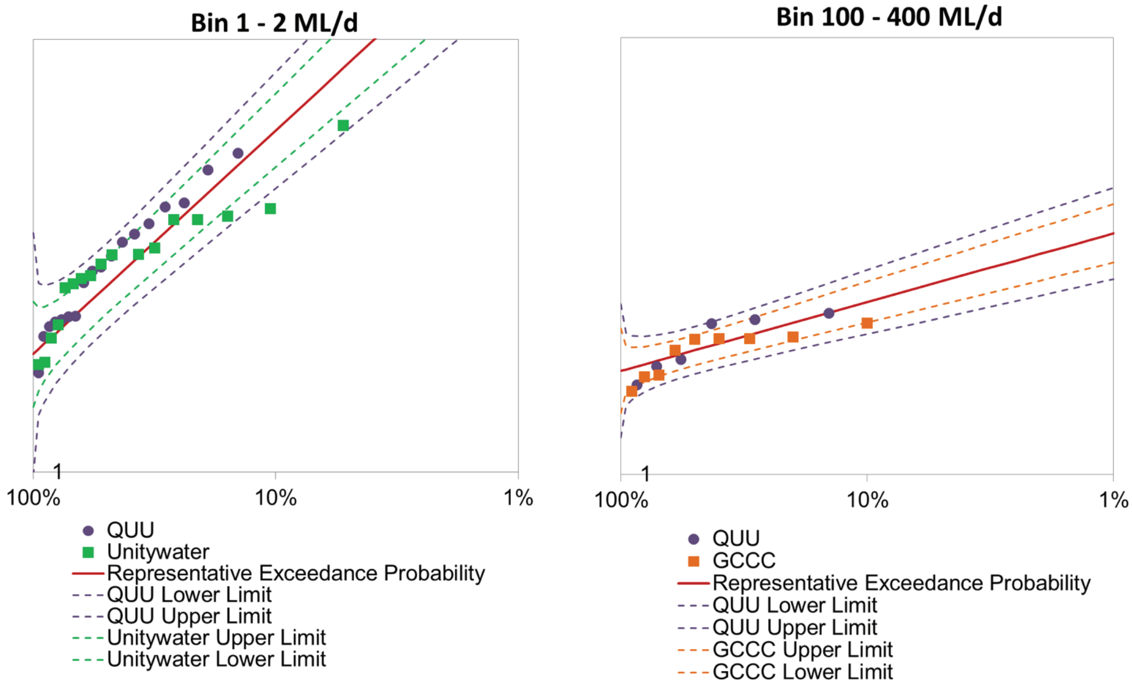


Figure 10: Bin Data by Source

Extrapolation of Exceedance Probabilities

The intent of this document was to produce stochastic peaking factors for the full range of demands applied to the SEQ supply area but this was difficult to achieve for those peaking factors applying to the whole 800 ML/d supply area. This is an important aspect of this paper's stochastics because its outcomes could be used for making assessments impacting on over 3 million people. Data could only be created by the combination of separate flow meter records. The 400-800 ML/d plot on Figure 5 shows that only six data points were available for that bin, and the calculated maximum exceedance probability was less than 9%, equivalent to a RI of only about 12 years. Care clearly needs to be taken when making long extrapolations from that limited base and use of either a log-normal or Gumbel distribution is recommended.

CONCLUSIONS

Demand data for the stochastic preparation of water supply peaking factors can be sourced from annual daily flow meter records kept for billing purposes, but the data base can be much increased by the interrogation of data loggers associated with the operation of pressure reduction valves supplying demand management areas. Data records used for stochastic assessment need to be near continuous over their twelve month periods and desirably have a coefficient of uniformity of 0.95 or greater. The location of storages within the data supply areas was found to have only a minor impact on the resultant peaking factors.

Peaking factors can be represented stochastically for any demand percentile by separating the demand data into a series of bins, and undertaking exceedance probability analyses of each bin's data while retaining the data within 5% and 95% confidence limits. The use of regression analyses on each bin's data was not found to be an effective method for undertaking the exceedance probability analyses. Persistence relationships based on the Goodrich Formula using Maximum Day and 30 Day peaking factors allow peaking factors for intermediate periods to be estimated.

The peaking factors prepared in this document were for the south-east Queensland supply which services a population of over 3 million people and extends over a distance of nearly 200 km. Testing found that the peaking factors also met acceptable confidence limits for individual supply areas within the overall supply area. The prepared stochastic peaking factors for the SEQ supply area therefore need only be defined by their AD demand and recurrence interval.

The data available for the preparation of the probability assessments for the large AD demand supply areas was limited and care needs to be taken when making extrapolations. It is expected that the addition of future flow meter records will allow these probability assessments, and their extrapolations, to be carried out with more confidence.

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THE AUTHOR

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Lee has investigated stochastic methods for the reliability analysis of water supply distribution systems using both optimisation and hydraulic modelling techniques. Those methods have also included the development of the relationships between tank storage volumes, inflow rates and demand persistence. His has been engaged by several south-east Queensland water supply authorities to assess their failure risks with the aim of minimising storage volumes, and in turn system water age.

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