Rainfall Analysis for Mine Water Management System Design and Operation

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ABSTRACT

A need exists for probabilistic design in mine water resource management systems conducive to risk analysis to determine "optimal" levels of reliability in operation. Time series techniques of monthly rainfall are investigated for their potential in providing simulated data suitable for probability analysis. The statistical fluctuations in the Oenpelli rainfall series, Northern Australia, may be described by first normalising and then standardising the monthly rainfall series, the remaining component being a simple Gaussian process with zero mean and unit variance. Free water volume data produced from a hypothetical tailings dam water balance model was found to be suitable for probability analysis and hence risk assessment.

INTRODUCTION

In Australia as in the rest of the world, mining operations are being required to comply with tighter environmental regulations[1,2]. In most situations water is the primary medium for the transport of mine related solutes from the mine into the wider environment. To comply with the tighter environmental regulations the mining companies need to be confident that the mine water resource management systems (WRMS) will operate within preset reliability criteria.

The primary purpose of the mine WRMS is to supply the water needs of the process plant and the mining operation. There is now a secondary design requirement for the WRMS; that it shall meet the environmental requirements. Water retention ponds are often sized by considering both the environmental and operational requirements.

Mine retention pond water yield estimation typically includes an input of monthly rainfall which is converted to a water volume via a rainfall/runoff model. An appropriate monthly rainfall series for the mine site is usually derived from site data and/or data from a site within the region. This rainfall series becomes the input to the rainfall/runoff model.

Traditionally, to obtain an indication of possible response variations, sub-strings of monthly rainfall are randomly selected from the rainfall series and concatenated to form new strings of the required length[3,4]. These generated synthetic series are then entered into the yield determination process to provide a qualitative estimate of water yield variation.

The above method of generating synthetic rainfall data produces only pseudo random series. Results from any subsequent statistical analysis based on the generated series are thus biased. The probability of bias will be increased if the original data contains a rare event, since its occurrence is likely to be incorporated into the synthetic series.

In this paper, we overcome this problem by utilising time series techniques to simulate rainfall series. A hypothetical one square kilometre tailings dam located at Oenpelli, 260km east of Darwin, Northern Australia, is used in the assessment of our proposed method. It is noted that Oenpelli's rainfall is monsoonal with the wet covering the months November to April.

RAINFALL ANALYSIS AND MODEL DEVELOPMENT

The rainfall time series can be broken down into three main components:

1) deterministic changes such as trends or slippage,
2) periodic changes of the year and month, and
3) random components or white noise.

The determination of the underlying rainfall model for Oenpelli thus consisted of breaking down the original Oenpelli series into the three components. The monthly rainfall series for Oenpelli is shown in Figure 1a.

Deterministic components(eg. trends) should be removed first from the raw data series. The greenhouse effect has been identified as a possible source of deterministic change in rainfall. The Oenpelli annual series was examined for trend by fitting a linear regression model and testing for significance in its slope. It is found that the slope is insignificant at the 5% level and therefore no deterministic component seems apparent.

Typically annual rainfall series are independent[5] but can exhibit periodicy as was found by Narayana Iyengar[6] for the Indian Peninsular, India. Annual periodicy in the extended time series is quantified by an examination of the auto-correlation statistic. The annual Oenpelli time series is also found to be independent, with auto-correlation coefficients all less than the upper and lower significant bounds.

The majority of statistical analysis techniques used in the literature are based on the assumption of normality in the sampling distribution. If the data are non-normal, one may consider transforming the data to produce a normal series[7]. The Power transform is a common method of normalisation (Box and Cox, 1970):

$$Y_{v,t} = (X_{v,t} + C)^{P} \quad t=1, \ldots, 12 \tag{1}$$

Figure 1a OENPELLI
MONTHLY RAINFALL

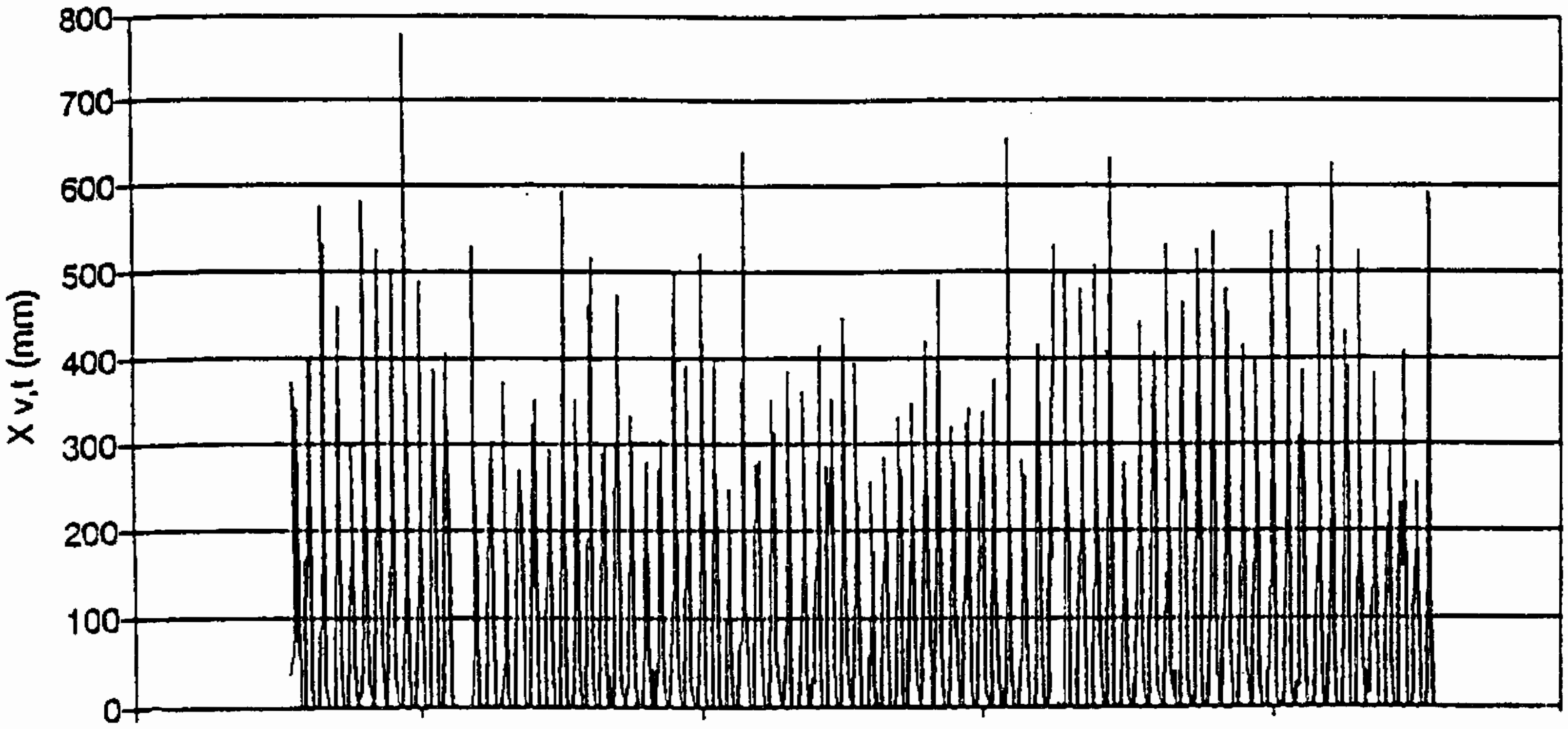


Figure 1b NORMALISED (SQRT)

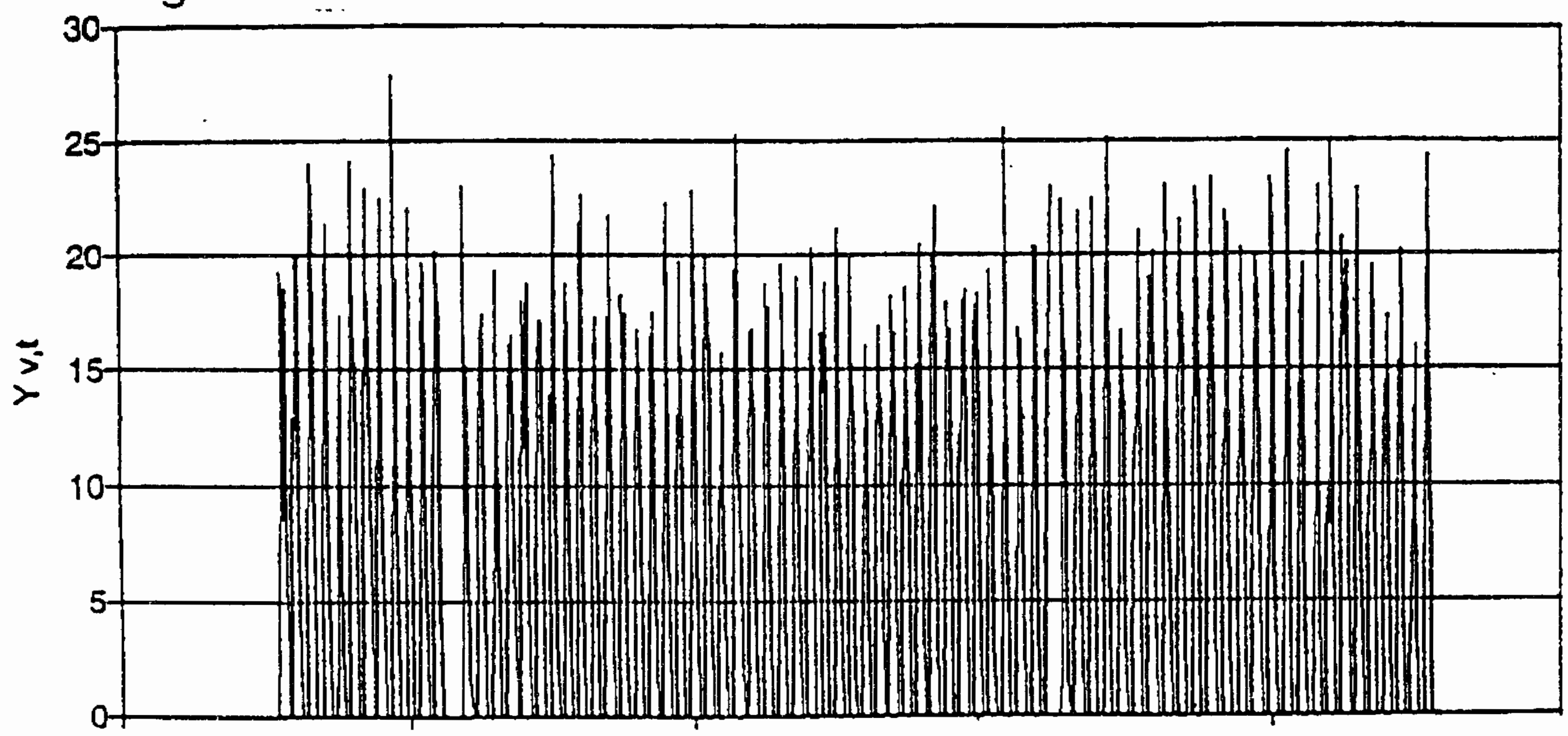
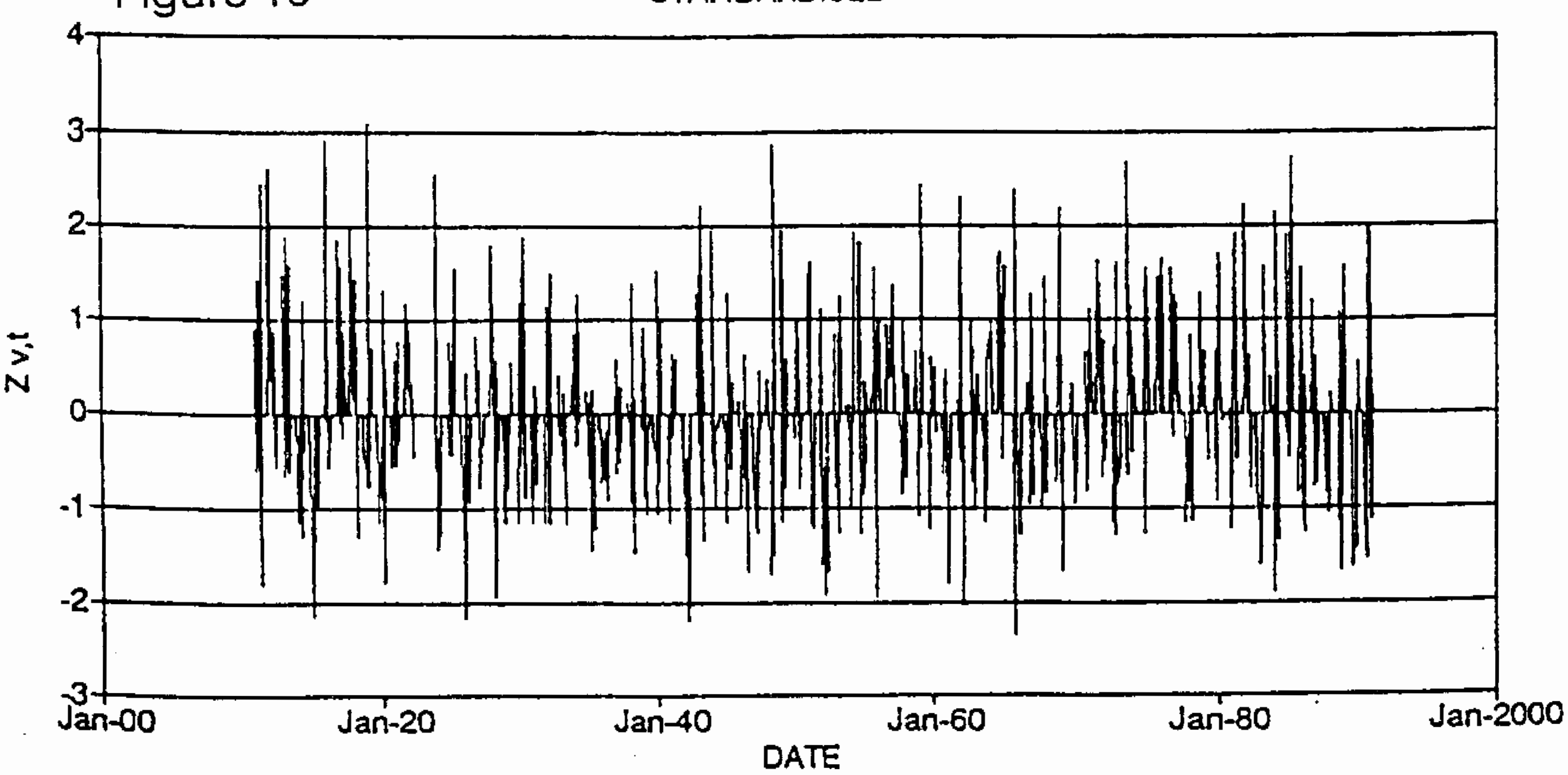


Figure 1c STANDARDISED



where $Y_{v,t}$ is the transformed series; v = year,
$X_{v,t}$ is the original series,
C is a constant, and
P denotes the power required to yield normality.

Transforms with P=0 (and c= 0.1, representing the logarithm transform) and P=0.5 (representing the square-root transform) were considered in this study. The transformed series are then visually examined using box-whisker plots and tested for normality using the Kolmogorov-Smirnov test. The transformation with P=0.5 is selected and the transformed series is plotted in Figure 1b.

It should be pointed out that the dry season data are insufficient for transformation. These months are characterised with few data points above zero. Many more years of data (about 1000 samples) would be required to form a basis of its underlying distribution. However, since the dry season rainfall rarely impacts on the operation of the WRMS, it is assumed that the rainfall for the months May to September are negligible and the series may be reduced to seven months.

The dominating periodicy in monthly rainfall data is contained within the monthly mean and standard deviation(5), see Figure 2(a). The next step in selecting an appropriate model for the wet season months can be facilitated through the standardisation:

$$Z_{v,t} = (Y_{v,t} - \overline{Y_t}) / \sigma_t \tag{2}$$

where $Z_{v,t}$ is the standardised 7-month wet season series,
$\overline{Y_t}$ is the sample mean for month t, and
σ_t is the sample standard deviation for month t.

The resulting series is plotted in Figure 1c. Sample statistics for the normalised Oenpelli series are given in Table 1.

TABLE 1 SAMPLE PERIODIC MEANS & STANDARD DEVIATIONS FOR THE NORMALISED SERIES

MONTH	OCT	NOV	DEC	JAN	FEB	MAR	APR
MEAN	3.9632	9.8787	14.550	17.884	17.442	16.318	7.472
SD	3.4356	3.4547	3.2949	3.2362	3.5425	4.2846	4.890

The standardised wet season series is tested for auto-correlation but no significant auto-correlation is evident as shown in Figure 2(b). Our findings are consistent with those of Narayana Iyengar(6). Although the absence of auto-correlation at this stage is not guaranteed, any remaining periodicy may be accounted for using auto-regressive or auto-regressive moving-average modelling techniques.

The remaining component of the monthly rainfall series appears to be random and may be described by a simple Gaussian process with zero mean and unit variance, N(0,1), ie. a white noise model.

Figure 2a AUTO-CORRELATION PLOT
NORMALISED DATA (Y v,t)

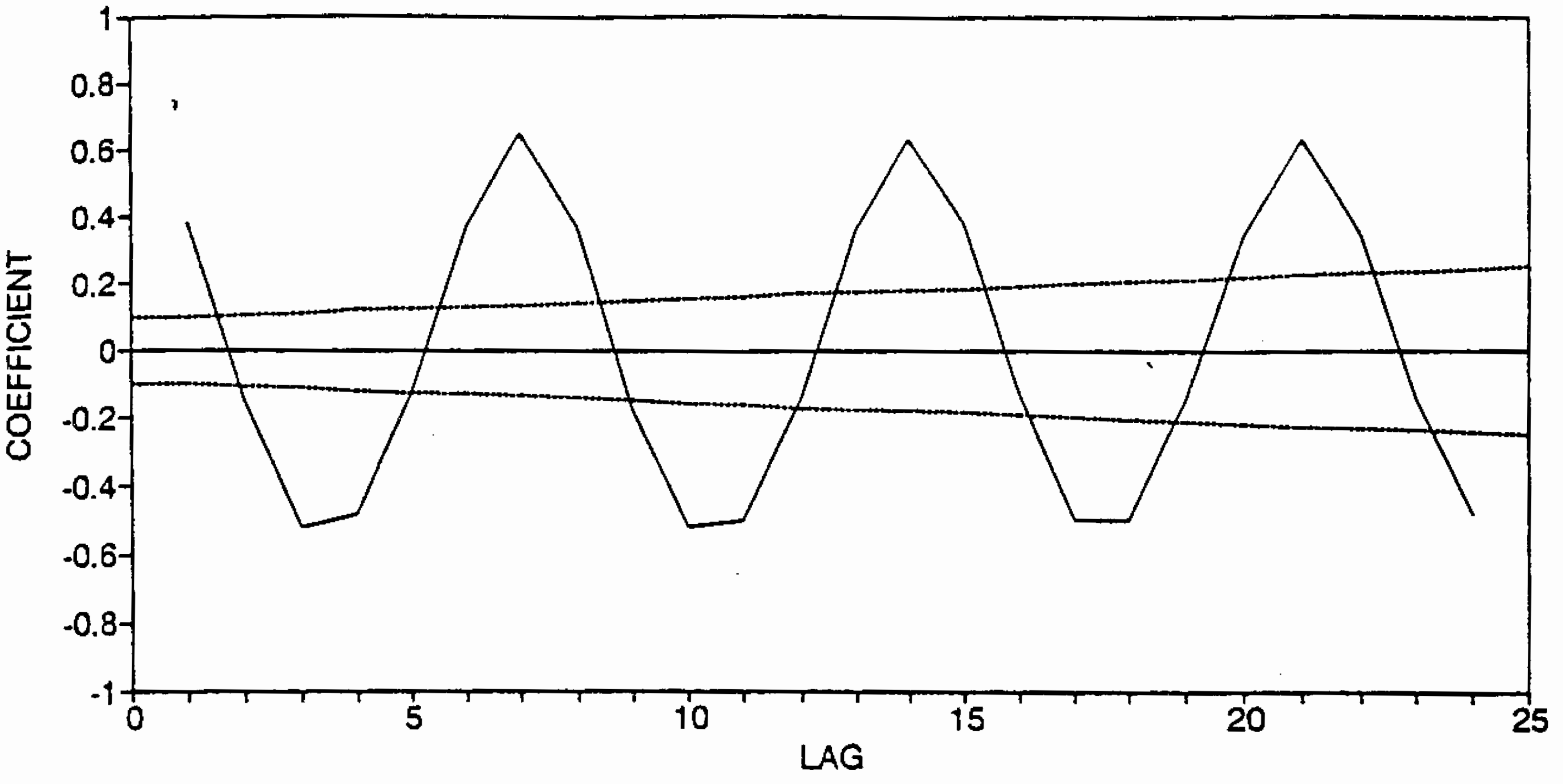
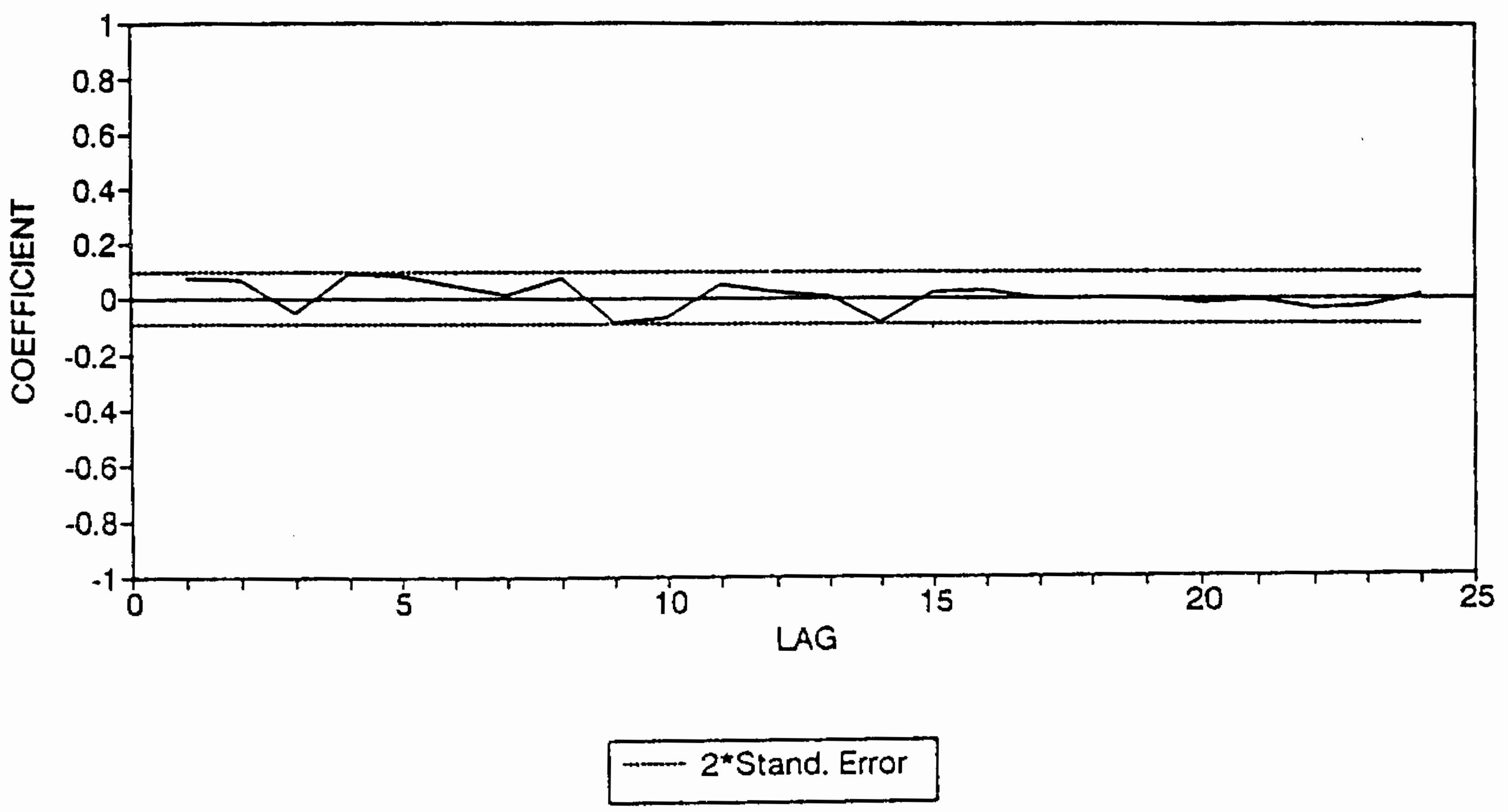


Figure 2b AUTO-CORRELATION PLOT
STANDARDISED DATA (Z v,t)



The final stage of the time series analysis process involves model validation. The N(0,1) model was used to generate 19 sets of simulated 10 year monthly rainfall series. The monthly median, maximum and minimum values for the simulated and actual series are compared in Table 2.

TABLE 2 ACTUAL AND SIMULATED SERIES STATISTICS

STATISTIC	OCT	NOV	DEC	JAN	FEB	MAR	APR
ACT-MEDIAN	10	89	190	291	271	248	71
SYN-MEDIAN	15	95	207	314	316	245	47
ACT-MAX	168	366	583	777	655	602	414
SYN-MAX	186	347	573	716	708	705	348
ACT-MIN	0	3	55	135	113	48	0
SYN-MIN	0	1	45	59	31	35	0

It is found that the simulated rainfall series have similar characteristics to those of the actual rainfall. Consequently, the rainfall model developed should be adequate for generating simulated rainfall series for the Oenpelli region.

The process of back transfer has been applied to generate simulated rainfall series,

$$X_{v,t} = (\sigma_t \times Z_{v,t} + \overline{Y}_{v,t})^2 \tag{3}$$

The four steps are thus:

1) Generate a series of 7 by v random values ($Z_{v,t}$) from the N(0,1) model, v being the years of the series of interest.
2) To each $Z_{v,t}$ generated in step 1, multiply by the corresponding sample standard deviation and then add the sample mean.
3) Inverse transform the data by squaring the values from step 2 giving $X_{v,t}$ for the seven month series.
4) Expand the seven month wet season series by adding in the five dry season months, the latter being assumed to contribute nil rainfall.

PROBABLE PERFORMANCE OF THE TAILINGS DAM

The hypothetical tailings dam consists of an above grade ring dyke, with a catchment area of $10^6 m^2$ defined by the top of the retaining wall. The dam is operated as a no release system where the only water out is either by evaporation or recycle into the process plant. In months of no rainfall, water is transferred from other parts of the WRMS for evaporation from the dam. Seepage in or out of the dam is assumed to be zero.

The monthly free water volume within the dam is calculated by:

$$
\begin{aligned}
W_t &= W_{t-1} - O_t + I_t \\
O_t &= (Evaporation)_t + (Recycle)_t \\
I_t &= (Rainfall)_t + (freeW)_t + (Wtansfer)_t
\end{aligned}
\tag{4}
$$

where W_t is the free water volume at time t,
freeW is the input of free water from the process line during time t,
Wtransfer is the amount of water transferred to the tailings dam from other parts of the WRMS.

For the hypothetical tailings dam, we have preset the parameters as follows:

Recycle to the mill = 100,000m^3/month
Free water input = 105,000m^3/month
Wtransfer = 50,000m^3/month
Evaporation = as per Table 3

It should be remarked that the above values represent a typical WRMS encountered in practice. In running the model both the quantities of evaporation and water recycle to the mill will be modified if there is insufficient water supply for these two processes within the dam.

TABLE 3 TAILINGS DAM MONTHLY LAKE EVAPORATION

MONTH	SEP	OCT	NOV	DEC	JAN	FEB
EVAP(m)	0.195	0.220	0.195	0.200	0.180	0.145
MONTH	MAR	APR	MAY	JUN	JUL	AUG
EVAP(m)	0.160	0.170	0.150	0.145	0.155	0.185

To demonstrate the practical applicability of the proposed technique nineteen rainfall series of length ten years are generated using the model developed. Also, a ten year sequence of observed data is randomly selected from the actual Oenpelli rainfall. The 19 simulated series reflects the minimum number of series required for the statistical analysis at the 5% significance level. The free water volume of the actual rainfall series, together with the corresponding averages and 95% confidence limits across the 19 simulated series, are plotted in Figure 3.

Typical questions that may be of interest to the WRMS designer and/or operator are:

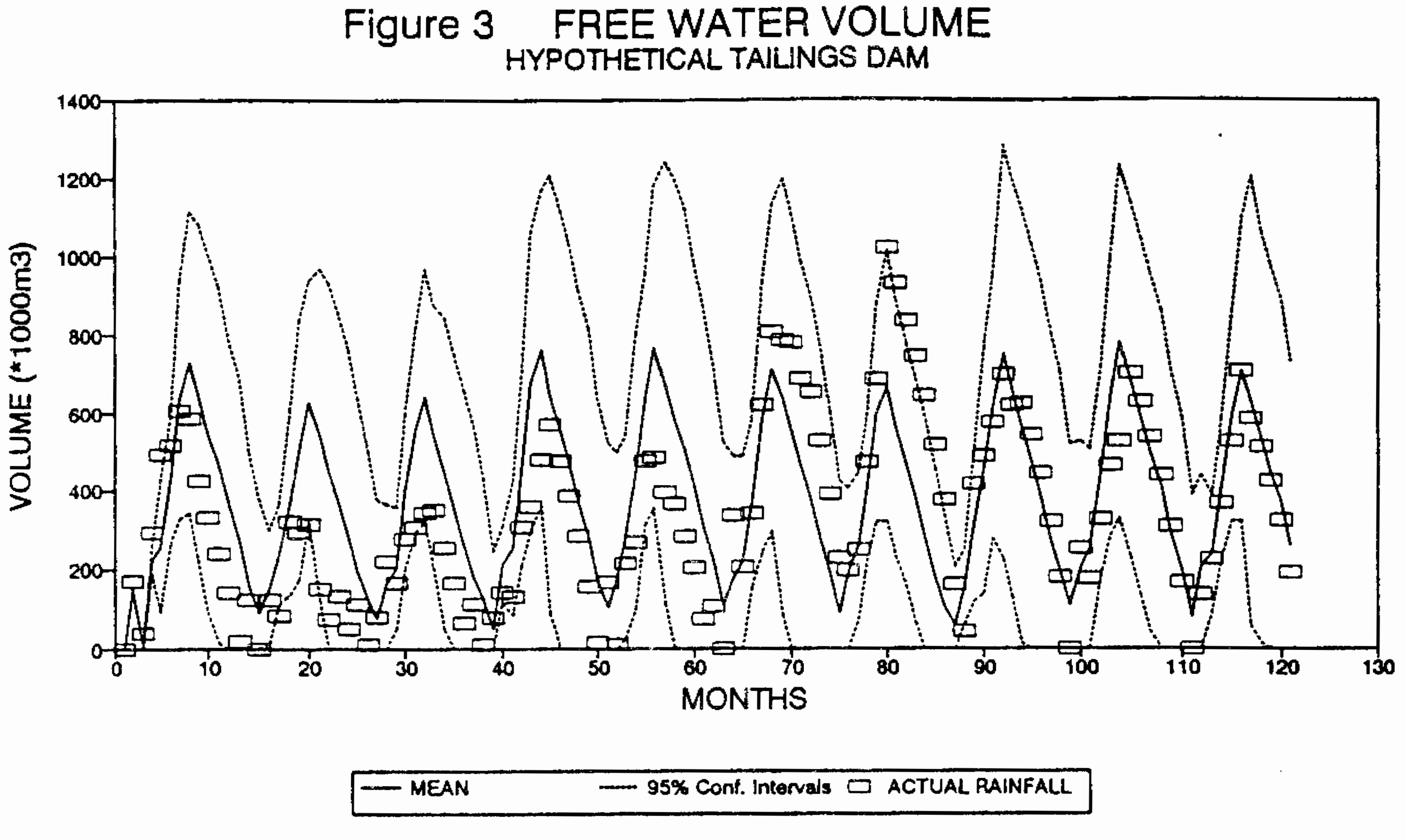
1) How often will the free water volume fall below 100,000m^3?
2) How often will the free water volume exceed 500,000m^3?
3) Assuming no tails are deposited within the dam or adjusting for the tailings input, what is the free board required to reduce the chance of an over topping of the dam to less than 1 year in 50 years?, 1 year in 100 years? or 1 year in 1000 years?.

Based on the model output, we arrive at the following calculations, with numbers in brackets denoting the respective 95% confidence intervals:

(1) 7 months [76 months, 1 months],
(2) 39 months [0 months, 91 months],
(3) Using the Weibull distribution, as the data are non normal, the free board required

is 1.07m, 1.58m, and 2.3m, respectively.

Although the above exercises are based on a hypothetical tailings dam, they nevertheless demonstrate the usefulness of this technique in the design and/or operation of a WRMS.



CONCLUSIONS

The statistical fluctuations in the original rainfall process of Oenpelli may be described by first normalising and then standardising the monthly rainfall series. Since the combined process results in a white noise series, implying no auto-correlation, it is not possible to forecast the fluctuations within the model. However, time series techniques do provide a means for probabilistic design and evaluation, conducive to risk analysis.

In terms of input into water yield analysis, our method will take only marginally more time than the existing practice to generate rainfall series. But the proposed technique is preferable because the associated simulated series are randomly generated and thus representative of the underlying structure of the original sample series.

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