Time Series Analysis of Streamflow Data for Mini-hydro Design

Bob Tingleff

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Contents

List of Tables

List of Figures

Abstract

The hydropower potential of Willow Creek, a stream in Northern California, is investigated. Records of fifteen years of daily and monthly mean streamflows are available. One hundred synthetic streamflow sequences are generated to extend the record based on a serial lag-one gamma distribution. The synthetic streamflows are used in conjunction with an economic model of the hydropower plant to produce a range of 100 economic scenarios. The optimal design flow/turbine power are determined. Hydropower is found to be economically feasible on Willow Creek.

Nomenclature

Table 1: Table of Nomenclature

Symbol	Description	Units
q_i	streamflow in time period i	(L^3/t)
β_i	setial correlation coefficient with lag i	$-$
μ	mean streamflow	(L^3/t)
e_i	random streamflow term	(L^3/t)
ρ_k	lag-k serial correlation coefficient	$-$
r_k	sample estimate of lag-k serial correlation coefficient	$-$
γ_ξ	skewness of random streamflow term	$-$
γ_q	skewness of streamflows	$-$
t_i	random standard normal variate	$-$
ξ_i	random standard gamma distributed variate	$-$
IC	hydropower initial costs	$(\$)$
Pr	initial cost per kW of hydropower system	$(\$/kW)$
Pr_1	initial cost per kW of turbine/generator	$(\$/kW)$
Pr_2	initial cost per kW of civil works	$(\$/kW)$
N_0	nominal power output of turbine	(kW)
H	total head of the system	(m)
f, b_0, b_1, b_2, ξ	initial cost equation constants	$-$
OM	annual operating costs	$(\$)$
h	annual number of hours of operation	$(hours)$
P	power output of turbine	(W)
η_T	turbine efficiency	$-$
η_E	electrical efficiency	$-$
Q_m	monthly streamflow	(m^3/s)
Q_R	turbine design flow	(m^3/s)
a, b, c	turbine efficiency equation constants	$-$
R	monthly revenue	$(\$)$
h_m	hours per month	$(hours)$
C_a	avoided cost	$(\$)$

1 Introduction

Hydro-electric power is an important form of renewable energy. While it is now recognized that damming of rivers has significant negative ecological and economic impacts, small-scale hydropower systems have the potential to provide power with fewer negative impacts on the health of the stream (Inversin, 1986). One of the difficulties in designing a small-scale hydropower system is that long-term streamflow records are often lacking for the streams of interest. The designer is forced to seek methods to extend the existing record in order to evaluate the hydroelectric potential.

In this study, the small-scale hydropower potential of Willow Creek, a tributary of the Trinity River in Northern California is investigated. Records of monthly and daily average flows are available for the years 1959–1974. The objective of the study is to extend these records using synthetic streamflows, and thereby gain an improved understanding of the hydropower potential of Willow Creek.

2 Literature Review

Inversin (1986) suggests a number of methods for estimating streamflow for micro-hydro potential in the absence of flow data. The schemes involve either estimating streamflow based on a runoff coefficient, or deriving streamflow in one watershed based on correlations with nearby watersheds. He notes that significant errors are to be expected with these techniques, and that any sizable investment should be based on five to ten years of actual streamflow records.

Runoff estimates can be derived from models based on water budget assumptions. Rainfall-runoff models exist which are stochastic or deterministic, and which model the underlying physical processes with differing levels of complexity (Beven, 2001). Conceptual models are based on mathematical descriptions of the underlying hydrologic processes. All such models need to be calibrated against data.

Regional regression models are based on commonality in parameters based on regional similarities. Watershed area alone has been found to be a poor predictor of average annual streamflow (Vogel et al., 1999), but with the additional parameters mean precipitation and mean temperature, a log-linear regression model performed as well as several years to a decade of data in determining mean annual rainfall. The regression was performed on a regional basis, with the state of California comprising a single region. Rantz (1968) developed correlations between annual runoff and precipitation and potential evapotranspiration (PET) for coastal Northern California streams. The correlations were developed for inland and coastal watersheds based on long-term precipitation records and PET average values. Correlations can be made between short-term streamflow records from one watershed and a nearby watershed for which longer-term data are available. Based on the correlation, streamflow in the target watershed can be extended. This correlation procedure is most successful when the watershed with long-term records (the "donor" site) is downstream of the target site (Laaha and Bloschl, 2005).

Correlations can also be made between existing streamflow records and precipitation data. Hydrograph theory (Viesman and Lewis, 2003) can be used to predict the discharge response to storm events, as well as the groundwater base flow discharge. Stream response to rainfall events can then be generated based on a long-term rainfall records. However, the hydrographs cannot be used to estimate discharge between events or during the dry season without more extensive modeling of the groundwater component.

Wagener and Wheater (2006) note that the prediction of streamflow at ungaged sites is one of the main problems in hydrology. While past attempts have been based on strictly statistical correlations, there are now many attempts to use rainfall-runoff models to more completely capture underlying processes. Model parameters are derived by regional statistical correlations among watersheds for which streamflow records are available. The authors note that success so far has been limited.

Methods of time series analysis can be applied to streamflow data (Chatfield, 1980). Trends, cyclic tendencies, autocorrelations, and stochastic components of a time series can be identified. Based on this analysis, a limited record can be extended. Elshorbagy et al. (2002) investigated whether or not the stochastic component is truly stochastic or is a deterministic process highly sensitive to initial conditions. The later type of process can be investigated with chaos theory. The authors used artificial neural networks (ANNs) to fill in "missing" streamflow data, and concluded that the system showed characteristics of chaotic behavior. Pasternack (1999) assessed many studies which attempted to find chaotic low dimensional attractors in hydrologic time series. He found low levels of success in these attempts.

2.1 Operational hydrology

For control or design purposes, a short-term record can be extended with synthetic streamflows. Fiering (1967) describes the benefits of synthetic streamflows as being restricted to operational situations which depend on the higher moments of the data. The synthetic records preserve the existing (short-term–sample-based) mean and variance. Additional records are generated which preserve these parameters, as well as the presumed underlying distribution. The extended record can be used in simulation studies to examine the performance of an objective function under a larger data set. Fiering and Jackson (1971) provide a method for preserving the underlying parameters of the existing record for normal, lognormal, and gamma distributions. The models are improved by incorporating persistence via autocorrelation. Techniques are provided for finding the correlation between successive events, and adjusting a random component by this deterministic component. The persistence may affect the generated streamflows for one or more time periods.

Box and Jenkins (1976) generalize autoregressive transformations to include non-stationary processes, in which the mean does not remain fixed. The autoregressive-integrated moving average (ARIMA) processes incorporate a backward shift operator, which is a weighted sum of past values describing persistence, a random "noise" term, and a moving-average operator, which is weighted sum of previous noise terms. Ahmed and Sarma (2006) compared a lag-two AR model, a lag-two ARMA model, and an artificial neural network procedure in their ability to synthesize streamflows that matched the historical record. Based on a 40 year monthly average streamflow record, they found that the ANN-synthesized records most closely matched the observed monthly mean and standard deviation, as well as the mean, variance and skew of the overall series. Kuo and Sun (1996) applied ARMA streamflow synthesis to Taiwan, which has low persistence due to steep slopes and high runoff, and extreme variations due to typhoons. Ten day periods are used for reporting rather than months. The year was divided into sections according to weather patterns, and a separate ARMA model was applied to each section.

Low flow frequencies are especially important to estimate for hydropower design. Bowles et al. (1987) compared five stochastic models for their ability to match the historical record with respect to drought years on four Utah streams. They compared a second order AR model, an ARMA model, an ARMA-Markov model (AMAK), a fast fractional Gaussian noise model, and a broken line model (BKL). They found that while the AMAK and ARMA models were best at preserving the persistence in the historical record, the BKL model was best at minimizing the economic loss associated with drought conditions.

Mohammadand et al. (2006) used goal programming to estimate ARMA model parameters for a model with two AR lag coefficients and two MA coefficients. The procedure minimizes the weighted sum of goal deviations as the objective function, and incorporates AR and MA coefficients as constraints. The procedure was found to be sufficient for the purpose, though more computationally intensive than more traditional methods.

Claps et al. (1993) linked conceptual and stochastic representations of hydrologic processes in the development of a periodic independent residual (PIR) ARMA model. The random component represents direct runoff, and is assumed to be proportional to precipitation. Two deterministic components are included - one with a subannual lag representing short-term groundwater storage, and another representing multi-year groundwater storage. Thyer and

Kuczera (2000) also introduced a long-term persistence term to model Australian alternating wet and dry years. A two-state hidden state Markov model was developed to overcome the inability of lag-one AR models to represent the long-term persistence. Spolia and Chander (1977) note that first-order Markov process models do not completely capture the persistence in hydrologic systems, but that the higher-order autoregressive models are unwieldy with respect to parameter estimation, involving a three-step iterative procedure of identification, estimation, and validation. The authors propose a procedure in which a stochastic process is expressed as a linear combination of only uncorrelated random variables, a process known as cannonical expansions. Synthesized streamflows based on cannonical expansions were found to preserve the mean, variance, and correlation–cross-correlation matrix.

3 Model development

The model used here is derived from Fiering and Jackson (1971). The model uses the persistence in streamflows to improve on the synthetic records that could be derived based on the underlying distribution of flows alone. The basic form is,

$$q_i = \mu + \beta_1 q_{i-1} + \beta_2 q_{i-2} + ... + e_i. \tag{1}$$

where

q_i	is	the streamflow at time period i
β_i	is	a serial correlation coefficient
μ	is	the mean streamflow
e_i	is	a random term

The values of the β_i coefficients represent the dependence of the current flows on earlier flows. If β_1 is the only non-zero coefficient, the model is termed lag-one, or Markovian. Fiering and Jackson (1971) note that this model is a distinct improvement over random models without persistence. The lag-one model can be written as,

$$q_i = \mu + \rho_1(q_{i-1} - \mu) + e_i \tag{2}$$

where ρ_1 is the lag-one serial correlation coefficient, derived from the general serial correlation coefficient expression,

$$\rho_k = E[(q_i - \mu)(q_{i+k} - \mu)]/\sigma^2 \tag{3}$$

where $E[X]$ represents the expected value of X, σ^2 is the variance of the distribution, and k is one. The sample estimate of ρ_k is,

$$r_k = \frac{\sum_{i=1}^{n-k} x_i x_{i+k} - \frac{1}{n-k}(\sum_{i=1}^{n-k} x_i)(\sum_{i=k+1}^{n} x_i)}{[\sum_{i=1}^{n-k} x_i^2 - \frac{1}{n-k}(\sum_{i=1}^{n-k} x_i)^2]^{0.5}[\sum_{i=k+1}^{n} x_i^2 - \frac{1}{n-k}(\sum_{i=k+1}^{n} x_i)^2]^{0.5}} \tag{4}$$

For a normally distributed process that is naturally Markovian, the coefficients will follow the relationship,

$$\rho_k = \rho_1^k \tag{5}$$

The adequacy of the lag-one model can be determined by comparing the r_k with ρ_1^k. A plot of r_k with k is called a correlogram. The strength of the serial correlations can be measured by the absolute values of the serial coefficients.

The goal when generating streamflows is to produce synthetic records that preserve the statistics of the existing records, include the mean, variance, skew, and serial correlation coefficients. Fiering and Jackson (1971) describe a method for preserving the statistics of an underlying gamma distribution, which has been found to apply to the present case. Since the sum of gamma variates is not necessarily gamma, it is necessary to introduce a skewness coefficient, γ_ξ, which is the skewness of the random portion only. It is defined as,

$$\gamma_\xi = \frac{1 - \rho_1^3}{(1 - \rho_1^2)^{1.5}}\gamma_q \tag{6}$$

where γ_q is the skew of the flows. If t_i is a standard normal random variate, then,

$$\xi_i = \frac{2}{\gamma_\xi}(1 + \frac{\gamma_\xi t_i}{6} - \frac{\gamma_\xi^2}{36})^3 - \frac{2}{\gamma_\xi} \tag{7}$$

is distributed approximately as gamma with mean zero, variance 1, and skewness coefficient γ_ξ. The lag-one synthetic flows,

$$q_i = \mu + \rho_1(q_{i-1} - \mu) + \xi_i \sigma \sqrt{(1 - \rho_1^2)} \tag{8}$$

are distributed approximately as gamma with mean μ, variance σ^2, skew γ_q, and first correlation coefficient ρ_1 as desired.

3.1 Economic function

The value of the synthetic streamflows is in their use in evaluating an objective function, in this case the costs and benefits of a hydropower system. The key decision to be made in the hydropower design is the design flow. The value of the design flow determines the size of the turbine, the size of the penstock, and the potential power, and thus income, that can be generated. If the system is sized too large for the actual flows, capital expenses will be unnecessarily high. If the system is too small, income will be unnecessarily low.

The model used here for capital costs is based on the relationships found by Kaldellis et al. (2005) to apply for European hydro projects:

$$\begin{aligned}
IC &= PrN_0(1+f) \\
Pr &= Pr_1 + Pr_2 \\
Pr_1 &= \frac{b_0}{N_0^{b_1} H^{b_2}} \\
Pr_2 &= \xi Pr_1 \\
f &= 5 - 10\%
\end{aligned}$$

where

IC	is	the initial cost of the system
Pr_1	is	the cost per kW of the turbine/generator set (€/kW)
Pr_2	is	the cost of the intake and other civil works (€/kW)
N_0	is	the nominal power output of the turbine (kW)
H	is	the total head of the system (m)
f	represents	installation and other costs (%)
b_0	is	3300€
b_1	is	0.122
b_2	is	0.107
ξ	is	a coefficient between 0.8 and 2.0, with larger values for dams and long penstocks

3.2 Operating costs

Annual operating costs are modeled according to the formula developed by Voros et al. (2000),

$$OM = 0.01hN_0 \tag{9}$$

where

OM	is	the annual operating cost
h	is	the annual hours of operation

3.3 Revenue

Annual revenue is based on the hydropower equation,

$$P = \eta_T \eta_E Q g \rho H \tag{10}$$

where

P	is	the average power during a month (W)
η_T	is	the turbine efficiency
η_E	is	the electrical efficiency
Q	is	the monthly streamflow (cms)
g	is	gravitational acceleration (m/s^2)
ρ	is	the density of water (kg/m^3)
H	is	the head (m)

Turbine efficiency for a Francis turbine can be modeled as a function of flow (Voros et al., 2000):

$$\eta_T = \eta_R(a(\frac{Q_m}{Q_R})^2 + b(\frac{Q_m}{Q_R}) + c) \tag{11}$$

where

η_R	is	the rated turbine efficiency (kW)
Q_m	is	the monthly streamflow (cms)
Q_R	is	the turbine design flow (cms)
a	=	-0.537
b	=	1.047
c	=	0.490

Monthly revenue is

$$R = Ph_mC_a \tag{12}$$

where

R	is	the monthly revenue
h_m	is	the number of hours in the month
C_a	is	the “avoided cost” paid by the utility for the generated power

As an energy cost, the avoided cost is expected to increase faster than the overall inflation rate (Laboratories, 2002), and its value can be represented as $C_a(1 + e)^n$ where e is the escalation rate and n is the year. Present values of capital costs, annual operating costs, revenue, loan payments, and salvage value are calculated according to standard methodology (see, e.g., Willis and Finney (2004)).

4 Model Application

Monthly and daily mean streamflows are available for Willow Creek for the years 1959-1974 (USGS, 2007). The relationship between monthly mean flows and the actual flows useable for monthly hydropower is problematic, as seen in Figure 4.1. For much of the month the actual flows during this month would be too low to be useful.

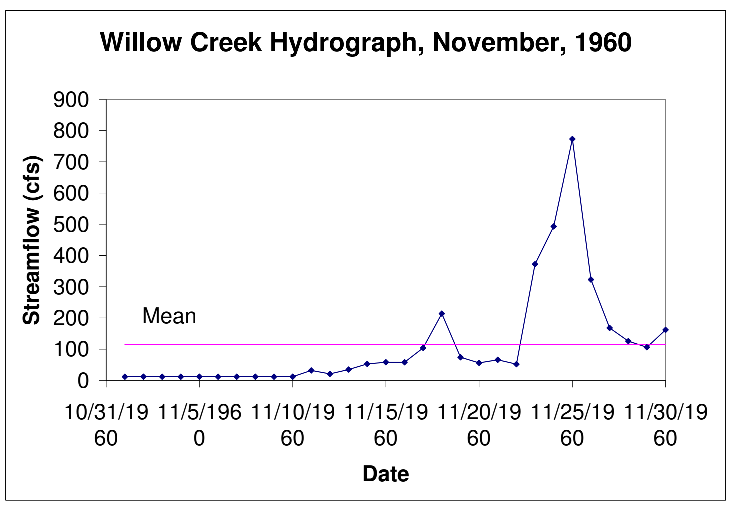

Fig. 4.1: The arithmetic mean streamflow is not necessarily the best representative of the available flow.

The useable flow is in a band around the turbine design flow, which is near the median annual flow (Figure 4.2). A relationship was sought between the daily useable flows, defined at this point as the range between 1.0 cubic meter per second (cms) and 3.5cms, and the monthly means. The monthly average daily available flow is graphed against monthly means in Figure 4.3.

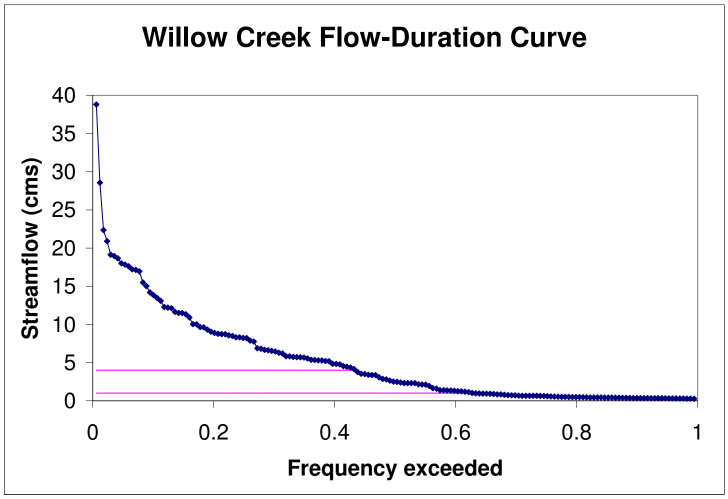

Fig. 4.2: The flows useable for hydropower are centered near the median annual flow.

For monthly means above a certain level, the available flow is at the maximum of 3cms (105cfs). For values under approximately 200cfs, the relationship is close to linear. The choice was made to consider all monthly mean flows above 300cfs as indicating that available flow for the month was at the maximum value of 3cms, and to use the linear relationship found by Microsoft Excel®regression analysis for the remainder of the flows (Figure 4.4). This model overstates the available flows.

With a relationship between monthly means and available flows, the goal is to synthesize monthly mean flows based on the historical record. A probability distribution is needed to represent the variation in monthly streamflows. Figure 4.5 shows the fit between a gamma distribution and the flows of record.

For hydropower purposes, the fit is most important for flows under 300cfs. The standard

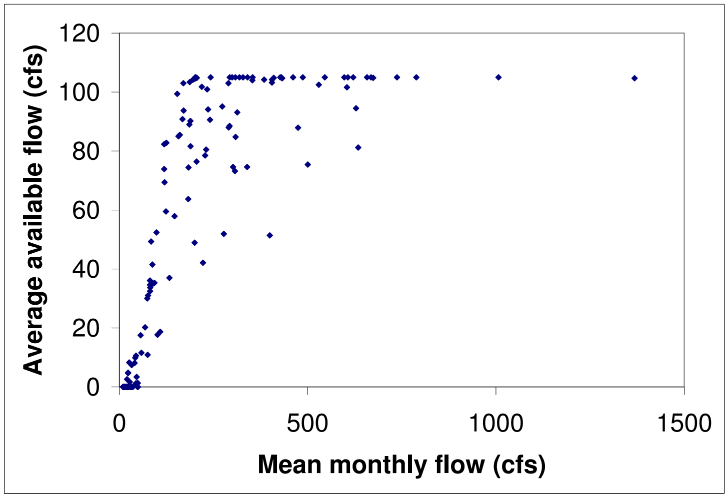

Fig. 4.3: Useable flows are usually at the maximum when monthly mean flows are above 300cfs.

Table 4.1: The one-month serial correlation is highest.

Time lag	Correlation coefficient
1	0.558
2	0.197
3	-0.049
4	-0.207

deviation derived from the data was varied in order to adjust the gamma parameters for a better fit in this region The standard deviation was varied by Excel Solver®to minimize the sum of the squared residuals between the gamma distribution and the observed data in the critical region. The standard deviation changed from 216.5 to 231.3.

The gamma distribution was furthered modified with the lag-one serial correlation coefficient according to Equation 8. The first few correlation coefficients, determined with Equation 4, are shown in Table 4.1. The serial correlation is strong at one month, and declines quickly. The lag-one model was used in this study.

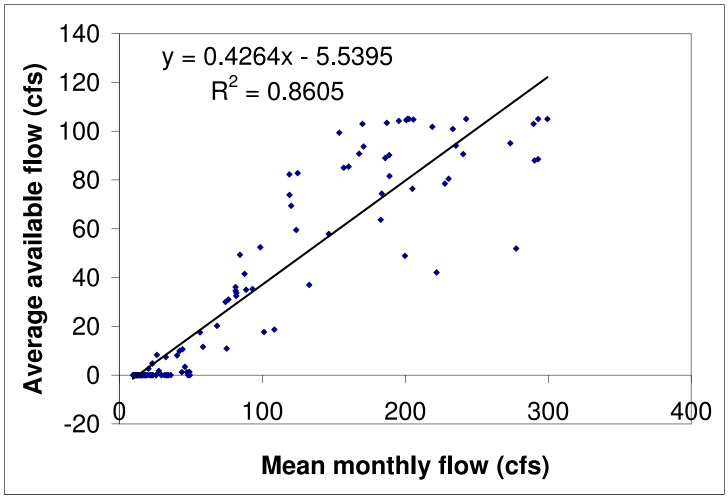

Fig. 4.4: For monthly mean flows below 300cfs, a linear relationship was used between monthly means and available flows.

4.1 Synthesized Flows

A FORTRAN program was developed (Appendix A) and 100 sets of 35 year records of monthly mean streamflows were synthesized according to Equation 8. The FORTRAN "random" function was used to generate random uniform variates between 0 and 1. The Box-Muller technique transforms these into standard normal variates, which are used according to Equation 7. As recommended by Fiering and Jackson (1971), the first 50 years of the synthetic flows were skipped when used in simulations. The statistics of the observed data were preserved in the synthesized flows (Table 4.2).

The synthesized flows were used to simulate the economic returns of hydropower on Willow Creek. The range of present values and internal rates of return (IRR) were found for the modeled configurations. The nominal power of the turbine, and the associated range of flows, were varied to determine the optimal turbine power.

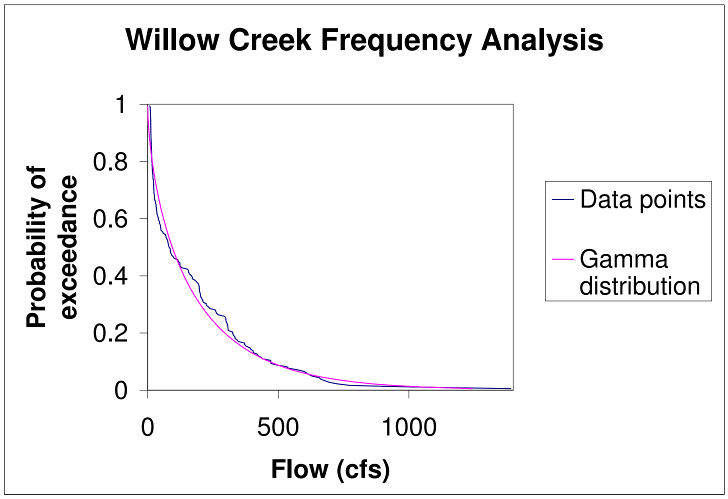

Fig. 4.5: Frequency analysis of monthly means shows a good fit to a gamma distribution.

Table 4.2: The synthesized records preserved the statistics of the data.

Statistic	Data	Synthesized flows
Monthly mean	179	176.8 (s=12.7)
Annual mean	2150	2122 (s=152)
Standard deviation	216 (231)	212.5 (s=13.3)
Skew	2.02	2.05 (s=0.35)
Lag-one coefficient	0.558	0.554 (s=0.02)

5 Results and Discussion

A choice of design flow leads to a nominal turbine power output according to Equation 10. A range of design flows, and the associated turbine powers, was simulated to compare the present values associated with the options. The distribution of present values associated with each option is shown in Figure 5.6. The ten synthetic sequences chosen for simulation were constant across all cases, leading to some contradictory entries in this graph. The sequences chosen were those whose present value was exceeded 10%, 20%, ... 90% of the time when simulated with the assumption of 1650kW. In other scenarios, the rank of sequences varied slightly. The optimal design flow/turbine power rating simulated is 2.5 cms/1960kW. The difference in 35-year present value between the 1960kW median case and the 1800kW median case is 0.6%. The worth of the system falls off for higher power ratings due to higher initial costs, and for lower output systems due to lower revenues. All systems are constrained by the need to leave one cms in the stream.

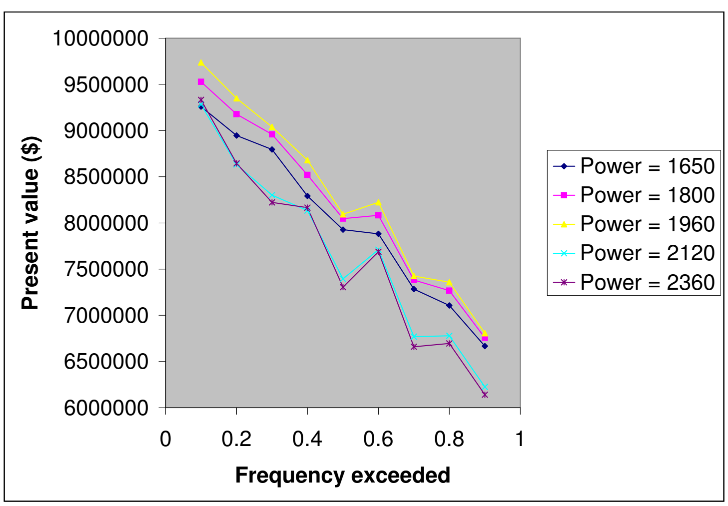

Fig. 5.6: The 100 sets of synthetic streamflows produced a range of 35-year present values for each design flow/turbine power option.

Based on this result for optimal design flow, the base case assumptions include a nominal power of 1960kW, capital costs as determined by Equation 9, and other assumptions as shown in Table 5.3. O&M costs vary by year according to actual turbine output.

Table 5.3: The assumptions used in the base case are shown.

Design flow	2.5cms
Head	100m
Nominal turbine power	1960kW
Initial costs	$4,048,802
Loan amount	80%
Loan rate	7%
Loan term	15 years
Loan payment	$355,629
Discount rate	5%
Escalation rate	2%
Periodic maintenance	Turbine rebuild in year 20

The median present value among the 100 sets of 35-year synthetic records was $5.7 million. The present value determined by the model was $4.2 million for the scenario whose present value was exceeded by 90% of the synthetic sets. The distribution of present values is shown in Figure 5.7. The mean of the distribution is $5.8 million, and the standard deviation is $1.2 million. The risk of a non-positive outcome is zero according to this model.

The annual net income for the median scenario is shown in Figure 5.8. After the loan is paid, annual net income is positive in every year except the 20th year, which is modeled as the year of a $200,000 turbine upgrade.

The internal rate of return (IRR) for three synthetic scenarios is shown in Table 5.4. The most optimistic scenario shown is based on the synthetic records which lead to a present value that exceeds 90% of the modeled present values. The discount rate was varied in a trial and error manner to find the rate with a zero present value. The results indicate a 10% probability of the IRR exceeding 21%, a median expectation of IRR of 16%, and a 90% chance that the IRR will exceed 13%.

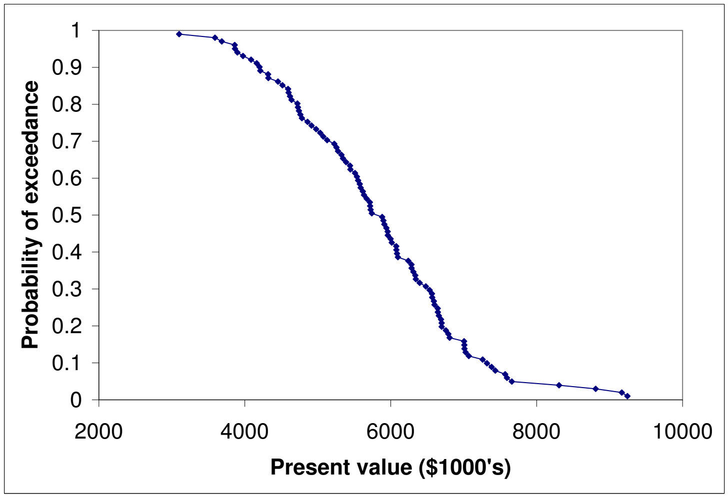

Fig. 5.7: The distribution of 35-year present values for the base case begins at $3 million.

Table 5.4: The internal rate of return is shown for three stochastic streamflow scenarios.

Synthetic streamflow scenario	Internal Rate of Return
Exceeds 90%	21%
Median	17%
Exceeds 10%	13%

The simulated economic returns are dependent on the rate of increase assumed in the price paid by the utility for the generated power. In the base case, an escalation rate of 2% was assumed. As this rate increases, the returns likewise increase (Table 5.5).

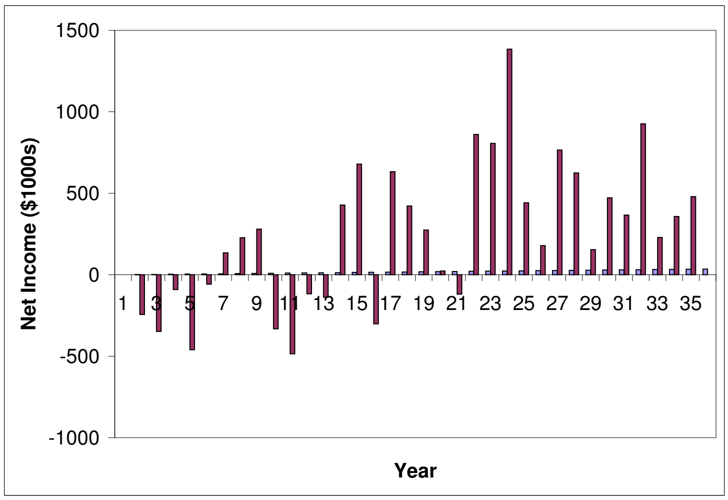

Fig. 5.8: The net income for the median synthetic streamflows varies year to year.

Table 5.5: The internal rate of return changes as the escalation rate in the price paid for generated power is varied.

Escalation rate	Internal Rate of Return
1%	16%
2%	17%
3%	18%
4%	19%
5%	20%

6 Conclusions

Based on the assumptions made here with respect to initial costs and operating costs, hydropower on Willow Creek has good economic potential. The optimal design flow and turbine power are 2.5cms and 1960kW. All scenarios studied had positive 35-year life cycle benefits. The median internal rate of return generated according to the synthetic streamflows was 17%. Internal rates of return were above 21% for 10% of the stochastic streamflow scenarios.

The synthetic streamflows contained some short-term sequences that are not realistic for the Mediterranean climate of California. However, on a long-term basis, they provide a valuable tool to help assess the economic risks and benefits of a hydropower plant dependent on stochastic streamflows.

References

Ahmed, J. and Sarma, A. (June 2006). "Artificial neural network model for synthetic streamflow generation." *Water Resources Management*.

Beven, K. J. (2001). *Rainfall-Runoff Modelling the Primer*. John Wiley and Sons, Ltd.

Bowles, D., James, W., and Kottegoda, N. (1987). "Initial model choice: an operational comparison of stochastic streamflow models for drought." *Water Resources Management*, 1, 3–15.

Box, G. E. and Jenkins, G. M. (1976). *Time Series Analysis Forecasting and Control*. Holden-Day.

Chatfield, C. (1980). *The Analysis of Time Series: An Introduction*. Chapman and Hall.

Claps, P., Rossi, F., , and Vitale, C. (1993). "Conceptual-stochastic modeling of seasonal runoff using autoregressive moving average models and different scales of aggregation." *Water Resources Research*, 29, 2545–2559.

Elshorbagy, A., Simonovic, S., and Panu, U. (2002). "Estimation of missing streamflow data using principles of chaos theory." *Journal of Hydrology*, 255, 123–133.

Fiering, M. B. (1967). *Streamflow Synthesis*. Harvard University Press, Cambridge.

Fiering, M. B. and Jackson, B. (1971). *Synthetic Streamflows*. American Geophysical Union, Washington D.C.

Inversin, A. (1986). *Micro-Hydropower Sourcebook*. NRECA International Foundation.

Kaldellis, J., Vlachou, D., and Korbakis, G. (2005). "Techno-economic evaluation of small hydro power plants in Greece: a complete sensitivity analysis." *Energy Policy*, 33.

Kuo, J.-T. and Sun, Y.-H. (1996). "An ARMA-type section model for average ten-day streamflow synthesis." *Water Resources Management*, 10, 333–354.

Laaha, G. and Bloschl, G. (2005). "Low flow estimates from short stream flow records - a comparison of methods." *Journal of Hydrology*, 306.

Laboratories, S. N. (2002). "Life cycle costing." *http://sandia.gov/pv/docs/LCcost.htm*.

Mohammadand, K., Eslami, H., and Kahawita, R. (2006). "Parameter estimation of an ARMA model for river flow forecasting using goal programming." *Journal of Hydrology*, 331, 293–299.

Pasternack, G. B. (1999). "Does the river run wild? Assessing chaos in hydrological systems." *Advances in Water Resources*, 23, 253–260.

Rantz, S. (1968). *Average Annual Precipitation and Runoff in North Coastal California*. U.S.G.S.

Spolia, S. and Chander, S. (1977). "Streamflow simulation - a model based on cannonical expansions." *Journal of Hydrology*, 35, 279–298.

Thyer, M. and Kuczera, G. (2000). "Modeling long-term persistence in hydroclimatic time series using a hidden state Markov model." *Water Resources Research*, 36, 3301–3310.

USGS (2007). "Usgs 11529800 willow c nr willow c ca." *http://waterdata.usgs.gov/ca/nwis/dv/?site_no=11529800&referred_module=sw*.

Viesman, W. and Lewis, G. L. (2003). *Introduction to Hydrology*. Pearson Eduction, Inc.

Vogel, R. M., Wilson, I., , and Daly, C. (May/June 1999). "Regional regression models of annual streamflow for the United States." *Journal of Irrigation and Drainage Engineering*.

Voros, N., Kiranoudis, C., and Maroulis, Z. (2000). "Short-cut design of small hydroelectric plants." *Renewable Energy*, 19, 545.

Wagener, T. and Wheater, H. S. (2006). "Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty." *Journal of Hydrology*, 320, 132–154.

Willis, R. and Finney, B. (2004). *Environmental Systems Engineering and Economics.* Kluwer Academic Publishers.