British Journal of Multidisciplinary and Advanced Studies:
Agriculture, 5(4),10-26, 2024
Print ISSN: 2517-276X
Online ISSN: 2517-2778
Website: https://bjmas.org/index.php/bjmas/index
Published by European Centre for Research Training and Development-UK

Development of Stochastic Models for Flows of Kainji Reservoir System

Mohammed J. Mamman.[1], Otache, Y, Matins[2], Abubakar Sadiq[3] Abdullahi S.M. Musa[4],
[1]Department of Crop Production Technology,College of Agriculture Mokwa, Niger State Nigeria.
[2]Department of Agricultural and Bio Resources Engineering,Federal University of Technology, Minna, Niger State, Nigeria.
[3,4]Department of Agricultural and Bioresources EngineeringAbubakar Tafawa Balewa University, Bauchi
Email:ikwan1565@gmail.com

doi: https://doi.org/10.37745/bjmas.2022.04130 Published July 13, 2023

Citation: Mamman M.J., Otache, Y.M., Sadiq A. and Musa A.S.M. (2024) Development of Stochastic Models for Flows of Kainji Reservoir System, British Journal of Multidisciplinary and Advanced Studies: Agriculture, 5(4),10-26

ABSTRACT: *Dams are infrastructural systems critical for hydropower generation, flood control and river navigation. They are systems branded by their multifarious, dynamic, and stochastic behaviors. The recurrent variation in the hydrological and meteorological variables poses a higher probability of dam failure, highlighting the need to improve pertinent risk valuation approaches to forecast failure risks, bearing in mind the uncertain states of such variables. This study Develops stochastic models for reservoir system state. It relates system storage, dependability, and yield to the incidence, scale, and period of reservoir system let-downs and similarly to associate unchanging -state reliability 1-q, to the N-year no-failure system reliability p. A two – state Markov process was employed in the development of the stochastic reservoir models. Two states of the reservoir system were defined, the states are failure state and non-failure. Specifying entirely the dualistic Markov equation, an estimation of (r) and (f) were done. The relationship between the resilience index and the probability that a regular year follows a failure year (r) and the likelihood that a failure year follows a regular year f were established using linear regression models. Correlation coefficients* R^2 *and standard error estimates were used to determine the extent of correlation and linearity of the models. Furthermore, the general regression models for establishing relationship between the reservoir system states i.e., failure state and non-failure state were developed. The value of Annual reliability (Ra) obtained depicts that the reservoir is substantially reliable at 0.96 reliability; also the unconditional return period of failure years (72years) substantiates the reliability of the reservoir. Again, the r, f and Average length of reservoir failure (UL) values obtained indicates strong reliability of Kainji reservoir. From the analysis of the reservoir system state the probability of failure years following a regular year was determined to be 0.014 which implies low probability of occurrence of system state f, the probability of regular year following a failure year was estimated as 0.99. The annual reliability Ra was estimated as 0.96, this indicated that the reservoir is significantly reliable. This can be seen from the estimate of the unconditional return period of failure years (72 years) and the average length of return period of 1 year. From the parameter values computed for the reservoir system state it is clear that the reservoir system is significantly reliable. In conclusion stochastic models were developed for the reservoir system state, and used to evaluate the state of the reservoir.*

Keywords: *Probability distribution models, predicted inflow, Kainji dam, Goodness of fit tests*

INTRODUCTION

The state of the art for optimal water reservoir operations is rapidly evolving, driven by emerging societal challenges. Changing values for balancing environmental resources, multisectoral human system pressures, and more frequent climate extremes are increasing the complexity of operational decision making Giuliani, (2021)

Water balance dynamics of the reservoir are piece-wise deterministic and are driven by a stochastic regime-switching inflow process (Hidekazu and Yumi 2020). Water resource systems have helped together people and their economy for many eras. The services provided by such systems are in manifold. Yet in numerous areas, water resource systems are not capable to meet the requirements, or even the basic desires, for unsoiled fresh water, nor can they support and uphold robust bio diverse ecosystems (Daniel, *et al*., 2005). Inadequate water resource systems reflect let-downs in planning, management and decision making, and at stages wider than water.

Operations of reservoirs are increasingly noteworthy in the water cycle (Hanasaki *et al*., 2006; Padowski *et al*., 2015; Wada *et al*., 2017) and support regional growth and development by increasing water accessibility for various economic subdivisions, contributing renewable electricity production, and mitigating flood risks (Billington & Jackson, 2017). Current estimates (Grill *et al*., 2019) submit that current dams control around 50% of the all rivers worldwide. This figure is predictable to grow speedily following the generated new interest in dam construction (World Bank, 2009), which poses the challenge of designing their upcoming operations (e.g., Bertoni *et al*., 2019; Geressu & Harou, 2015; Mortazavi-Naeini *et al*., 2014) to safeguard water and energy supplies in rapid developing African and Asian countries (Zarfl *et al*., 2015). Rapid changes in climate and society suggest an urgent need to re-operate existing infrastructures (Benson, 2016), particularly in systems that are failing to produce the likely benefits that inspired their construction (Ansar *et al*., 2014; Sovacool *et al*., 2014).

Among the processes used in planning and in managing of reservoirs include; time and volume reliabilities. By definition time period reliability shows the proportion of time during an operating horizon for which the reservoir can meet the specified demands while volume reliability is that volume of water given as a section of the total target demand during the operating horizon.

The reservoir evaluation is conventionally done applying procedures which comprise time based reliability of hundred percent. Nevertheless, to design a reservoir system that are massive amenities at hundred percent dependability may not be economical. Furthermore, sometimes in operating reservoirs, due to unforeseen forms or nature of demand or drought, all the targeted demands cannot be provided. Occurrences of these nature are referred to as failure times or period. Henceforward as reported in Lele (1987), Loucks (1998) and Adeloye (1997), recognition of failure period as a reality in designing stage of reservoirs is necessary and the involvement of performance indices such as reliability and vulnerability to control the performance of reservoirs during this period is desirable.

Reliability represents the time based probability in which reservoir can provide all the design demand which vulnerability exhibits the severity of failure (Hashimoto; 1982; Adeloye, 2001). For instance, reliability of 98% indicates the reservoir is able to provide all the design demand in 98% of the operational period and the vulnerability of 30% indicates the reservoir may not be able to provide 30% of the target demand during the failure period and it is necessary to find an alternative water resource during this period.

In broad, there are two methodologies to the determination of the yield or storage capacity of a reservoir system. One method applied in the USA, which involves the determination of the no-failure yield (often called the firm yield) which can be met over a particular planning period with a specified reliability. The other approach applied in Australia and somewhere else is to determine the yield which can be delivered with a specified steady-state reliability (1 - q). Regrettably, these two approaches are often seen as unrelated and disconnected. Both of these schools of thought can be connected using a two-state Markov model, resulting to completely consistent estimates of the reliability of reservoir systems, notwithstanding which school of thought one happens to follow. According to Vogel *et al*., (1996), when the sequent peak algorithm is used to determine the smallest reservoir system design capacity (S) required to guarantee regular or failure-free operation over an *n*-year planning period with probability *p*, then *p* is a probability over that planning period. If one applies the two state Markov model, the probability of consistent (failure-free) operation over an *n*-year period, *p*, is basically the probability of normal operations in the first year (1 — q), times the probability that successive years continues free of failures:

$$p = (1 - q)(1 - f)^{n-1} \quad (1.0)$$

The equation above relays the index of reliability usually applied in the USA (the probability p of failure-free operations over an *n*-year period) to the index of reliability frequently applied in Australia and somewhere else (the steady-state system reliability (1 — q). Furthermore, one can use the two-state Markov model to compare S-R-Y relationships developed using completely different understandings of system reliability Richard (1996).

A Markov chain (MC) is a stochastic method that defines a sequence of recurring or acyclic changes between the states of a given process (or variable) over discrete or unceasing time intervals. (Ahmad *et al*., 2021).

Reservoir State Modelling

Mosaad (2018), developed a simulation model that was applied to the Ruhr river reservoirs system in Germany. An adaptive neuro-fuzzy inference system, Thomas–Fiering model and hidden Markov model were incorporated in a simulation model. The set of model input included the time of the year, reservoir storage, inflow and Standardized Rainfall Index; and the target output was the reservoir release. Their results revealed that the proposed approach could be a good tool at the real-time operation stage to quickly check operational alternatives due to emergency events or planning and real-time incongruence.

A two-state Markov model relates system storage, reliability, and yield to the frequency, magnitude, and duration of reservoir system failures (Vogel *et al*., 1994). In addition, the two-state Markov model allows relate steady-state reliability 1-q, to the N-year no-failure system reliability p. Additional advantage of the two-state Markov model is its easiness and therefore its simplicity of manipulation. Vogel *et al*., (1994), reported that Klemes, (1967); Stedinger *et.al*., (1983); and Vogel (1987) have effectively exploited two-state Markov model for representing sequences of reservoir surplus and failures. Nevertheless, those studies have not given direct link between the two-state Markov model and a simple reservoir system model.

McMahon and Vogel (1996), reported that Klemes (1977), showed that the number of discrete storage states necessary to assess the reliability of a storage reservoir with a desired level of accuracy is customarily well above two states (McMahon and Vogel, 1996). It is usually infeasible for an over-year reservoir system to pass from full (state 1) to empty (state 2) in one year, as a result most investigators have applied more than two states to model reservoir state transitions. Conversely, if one describes one state as the failure state and another as the non-failure state, according to Vogel and Bolognese (1995) a two-state Markov model of reservoir state transitions gives a satisfactory description of the frequency and magnitude of reservoir system failure durations. Figure 1.1 illustrates the two basic reservoir transition states.

Print ISSN: 2517-276X
Online ISSN: 2517-2778
Website: https://bjmas.org/index.php/bjmas/index
Published by European Centre for Research Training and Development-UK

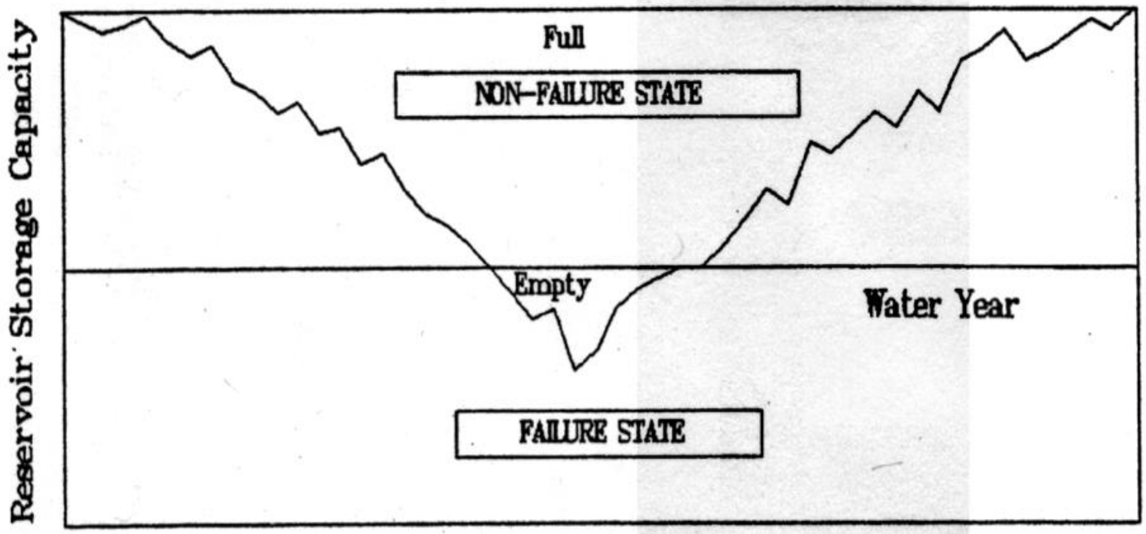


Fig. 1.1: Reservoir system state for two State Markov Model (Vogel, 1994)

The failure of reservoir system is the inability of a reservoir system to deliver the contracted demand in a given year (Vogel, 1994.). Failures of water supply for within – year systems tend to be short- lived, in comparison with over- year systems, since within – year systems tend to refill on an annual basis. Naturally, all reservoir systems exhibit some combination of over- year and within – year behaviour (Vogel, 1996).

A failure state happens when the water in storage plus the inflow during year *t* are less than the contracted demand $\alpha\mu$, where α is demand and μ mean inflow. Vogel (1996), assumed that the states associated with

$$Y_t, t = 1, \ldots, N \qquad (1.3)$$

form a Markov chain with probability transition matrix:

$$A = \begin{bmatrix} 1-r & r \\ f & 1-f \end{bmatrix} \qquad (1.4)$$

where f = probability that a failure year follows a regular year, and r = the probability that a regular year follows a failure year. The probabilities of the states of the Markov chain are given by:

$$Y_{t+1} = Y_t A \qquad (1.5)$$

As t increases, Y_t reaches a steady-state and the solution to equation (1.7) becomes

British Journal of Multidisciplinary and Advanced Studies:
Agriculture, 5(4),10-26, 2024
Print ISSN: 2517-276X
Online ISSN: 2517-2778
Website: https://bjmas.org/index.php/bjmas/index
Published by European Centre for Research Training and Development-UK

$$\lim_{t\to\infty} Y_t \begin{bmatrix} \frac{f}{r+f}, & \frac{r}{r+f} \end{bmatrix} \quad (1.6)$$

Thus, the steady-state probability that the reservoir will be in the failure or regular states are $f/(r + f)$ and $r/(r + f)$ regardless of the initial state of the reservoir system (Vogel *et al.*,1995). The steady state system reliability (1 - q) can be related to the two-state Markov model using

$$q = 1 - \frac{r}{r+f} \quad (1.7)$$

Equation (1.7) provides the link between the two-state Markov model and S-R-Y relationships based upon a steady-state probability of failure.

To specify fully the two-State Markov model, one requires an estimate of r and f in equation (1.7). Estimation of the transition probability r is accomplished by first recalling its definition as the probability that the reservoir system transfers from the failure (empty) state to the normal (non-empty) state. The failure state is defined as the condition when the water in storage plus the inflow for that period Q_t are less than the demand ($\alpha\mu$). Once a failure has occurred, r becomes the conditional probability:

$$r = P\{ Q_{t+1} \geq \alpha\mu | Q_t < \alpha\mu |\} \quad (1.8)$$

which can be approximated, as shown by Vogel & Bolognese (1995), to be:

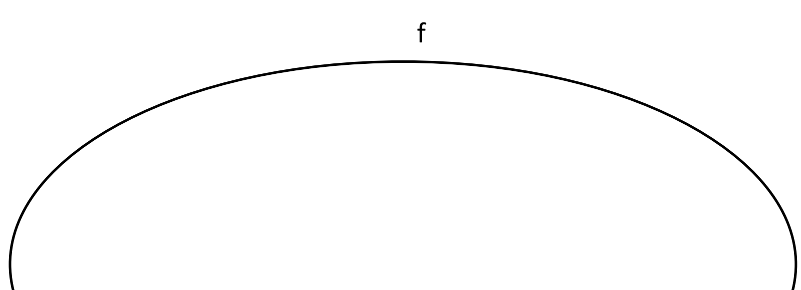
$$r = \phi \left[\frac{\frac{m-\rho(2\pi)^{-1/2}}{\phi(-m)\exp(\frac{m^2}{2})}}{\sqrt{1-\rho^2}} \right] \quad (1.9)$$

when Q follows an AR(1) normal process with ϕ denoting the *cdf* of a standard normal random variable. Note that equation (1.9) reduces to

$$r = \phi\ (m) \quad (2.0)$$

when ρ = 0. Once r is determined from equation (1.9), f is easily found by rearranging equation (1.9) to obtain:

$$f = r \left[\frac{q}{1-q} \right] \quad (2.1)$$



British Journal of Multidisciplinary and Advanced Studies:
Agriculture, 5(4),10-26, 2024
Print ISSN: 2517-276X
Online ISSN: 2517-2778
Website: https://bjmas.org/index.php/bjmas/index
Published by European Centre for Research Training and Development-UK

Fig. 1.2: Two- state Markov model of reservoir system states (Vogel *et al*., 1987)

Vogel *et al*., (1987) in his work established that the probability function for the length of a reservoir system failure for a two-state Markov model is given by:

$$P\{L = \ell\} = r\,(1-r)^{\ell-1} \text{ for } \ell \geq 1 \qquad (2.2)$$

where L is the length of a failure sequence. Since L is geometrically distributed, it has mean E[L] = 1/r, variance Var [L] = (1 — r)$/r^2$, and coefficient of variation C_v [L] = (1 - r)$^{1/2}$. This theoretical description of the length of reservoir system failures has been confirmed via simulation by (Vogel and Bolognese, 1994).

2.0 Materials and Methods

2.1 Development of a Stochastic Model for Reservoir System State

2.1.1 Model Structure or Topology

In other to relate system storage, reliability, and yield to the frequency, magnitude, and duration of reservoir system failures and also to relate steady-state reliability 1-q, to the N-year no-failure system reliability p a two – state Markov process was employed in the development of the stochastic reservoir model. Two states of the reservoir system were defined, one state as the failure state and another as the non-failure state.

The row vector $Y_t = (Y_{1t}, Y_{2t})$ was taken to specify the probability that a reservoir is in either: (1) failure state; or (2) regular (non -failure state) in year t. Failure state of the reservoir was taken as when the water storage plus the inflow during the year t are less than the contracted demand $\alpha\mu$ usually taken as the ratio of the mean annual flow. Vogel (1995) assumption was adopted; that the states associated with Y_t, t = 1………N form a Markov chain with transition probability matrix.

$$A = \begin{bmatrix} 1-r & r \\ f & 1-f \end{bmatrix} \qquad (2.3)$$

where f = probability that a failure year follows a regular year, and r = the probability that a regular year follows a failure year, Y_t = reservoir state at time t, Y_{1t}, Y_{2t} = reservoir states at (1) and (2) i.e., failure state and non-failure state. Vogel (1995) assertion that the steady-state probability that the reservoir will be in the failure or regular states are *f*/(*r* + *f*) and *r*/(r + *f*) regardless of the initial state of the reservoir system was employed in the model development.

2.1.2 Model Parameter Estimation

To specify fully the two-State Markov model, an estimation of *r* and *f* were done. Estimation of the transition probability *r* was achieved by first recalling its definition as the probability that the reservoir system transfers from the failure (empty) state to the normal (non-empty) state. The failure state is defined as the situation when the water in storage plus the inflow for that period Q_t are less than the demand $\alpha\mu$. Once a failure has occurred, *r* becomes the conditional probability: The probability that a regular year follows a failure year *r* was estimated using the relationship.

$$r = (1 - f) \quad (2.4)$$

The probability that a failure year follows a regular year *f* was determined using the relationship

$$f = 1 - p^{\left[\left(\frac{1}{N-1}\right)\right]} \quad (2.5)$$

Where *p* is the reliability of the reservoir over N period (Vogel *et al*., 1987). The values of *p* and N were assumed to be 0.5 and 50years respectively as suggested by (Vogel *et al*., 1987). The annual reliability of the reservoir was determined from the inflow, storage and the demand of the reservoir, equation (2.6) was employed in determining annual reliability of the reservoir R_a. (Nawaz 1999) The definition of failure by Vogel *et al.*, (1987) that a failure occurs when the inflow plus the storage is less than the demand, failure occurs was employed.

$$R_a = \frac{number\ of\ non\ failure\ years}{number\ on\ record} \quad (2.6)$$

The unconditional return period T* of the failure years was determined employing equation (2.7) and (2.8).

$$T* = 1 + f/f \quad (2.7)$$

$$T* = \frac{2-p^{\left[\left(\frac{1}{N-1}\right)\right]}}{1-p^{\left[\left(\frac{1}{N-1}\right)\right]}} \quad (2.8)$$

The average length of reservoir failure was determined using equation (2.9) (Vogel & Bolognese, 1994).

$$U_L = \frac{1}{r} \quad (2.9)$$

2.1.3. Performance Evaluation.

The connection between the resilience index and the likelihood that a regular year follows a failure year *r* and the probability that a failure year follows a regular year *f* were established using linear regression models. Correlation coefficients R^2 and standard error estimates were approached to determine the extent of correlation and linearity of the models. Furthermore, the general regression models for establishing relationship between the reservoir system states i.e., failure state and non-failure state is of the form.

$$\rho = a + b\vartheta + c\tau + \varepsilon \quad (3.0)$$

Where a, b, c are model parameters (ε) is the error term.

3.0 Results and Discussion

3.1 Stochastic Model for Reservoir System State

The reservoir system state was evaluated by determining system state parameters i.e., probabilities of failure, annual reliability, unconditional return period of the failure years, resilience and average length of reservoir system failure. The results computed are as presented in table 4.9.

Table: 1.1. Calculated values of Probabilities of failure, Annual reliability, Return period and Length of Time

parameter	Parameter values
f	0.014
p	0.50
r	0.99
Ra	0.96
T*	72years
U_L	1year

f = probability of failure year following regular year, r = probability of regular year following failure years, *p* = Reliability of the reservoir over N period, Ra = Annual reliability, T* = Unconditional return period of the failure years, U_L = Average length of reservoir failure

Table 1.1 shows the values of the probability that a failure year follows a regular year (f), reliability of reservoir over (N) period (p), the probability that a regular year follows a failure year (r), annual reliability (Ra) and unconditional return period of failure years (T*) obtained from the application of the stochastic (Markov) model and reliability relationships. Similarly the length of reservoir failure (U_L) is also shown. The value of R_a obtained depicts that the reservoir is substantially

Print ISSN: 2517-276X
Online ISSN: 2517-2778
Website: https://bjmas.org/index.php/bjmas/index
Published by European Centre for Research Training and Development-UK

reliable at 0.96 reliability; also the unconditional return period of failure years (72years) substantiates the reliability of the reservoir. Furthermore, the *r*, *f* and U_L value obtained indicates strong reliability of Kainji reservoir. From the analysis of the reservoir system state the probability of failure years following a regular year was determined to be 0.014 which implies low probability of occurrence of system state *f*, the probability of regular year following a failure year was estimated as 0.99. The annual reliability Ra was estimated as 0.96, this indicated that the reservoir is significantly reliable. This can be seen from the estimate of the unconditional return period of failure years (72 years) and the average length of return period of 1 year. From the parameter values computed for the reservoir system state it is clear that the reservoir system is significantly reliable, adopting the recalibrated policy could yield better performance of the reservoir system.

The developed models for the reservoir system state are presented in table 1.2.

Table: 1.2 Developed Markov models for Reservoir System State

Developed Models	R^2	Se
m = - 42.5 + 46.4r	0.8033	0.002
$m = 1519r^2 - 2855r + 1342$	0.982	
$m = 45.6 - 41.8L$	0.8176	0.006
$U_L = 0.997126 + 1.1204f$	0.9988	0.000889
$m = 3.935 - 46.4f$	0.8033	0.005
$m = 0.064f^{-0.96}$	0.999	
$r = 1.- f$	0.99999	0.0000
$r = 0.005f^2 - 0.018f + 0.029$	0.974	

m = resilience, U_L = length of time of failure, *r* = probability of regular year following a failure year, *f* = probability of failure year following a regular year.

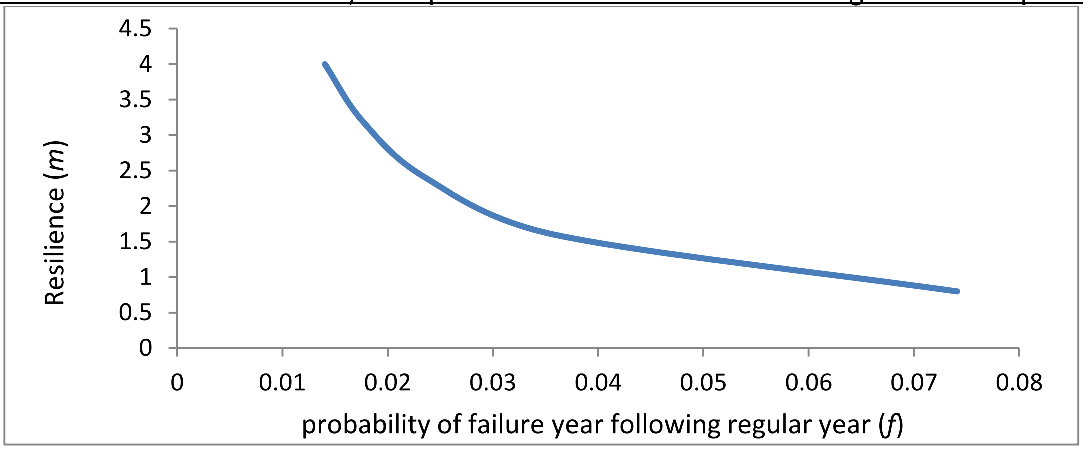


Fig. 1.3: Relationship between resilience (*m)* and probability of failure year following regular year (*f)*

Figure 1.3 shows that as reservoir resilience increases the probability of failure year following regular years decreases the more the resilience m the less the *f* value, this indicate that *f* is inversely proportional to m, meaning that resilient reservoirs (within year systems) have smaller *f* values.

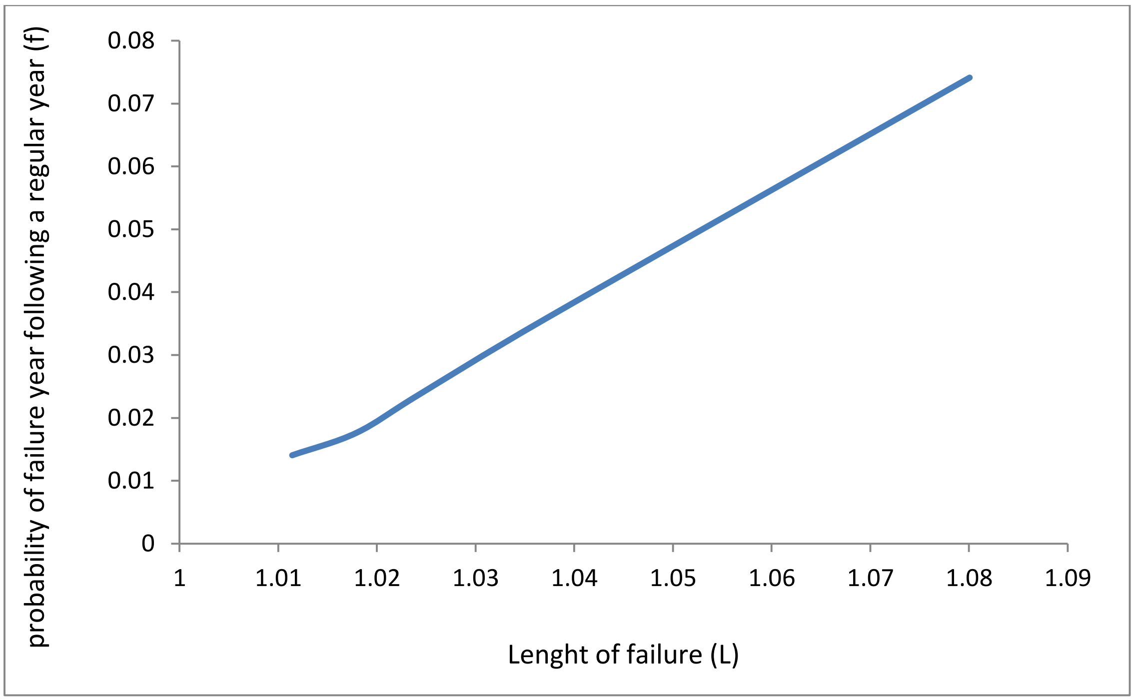


Fig. 1.4: Relationship between Length of failure (L) and *f*

Figure 1.4 shows the relationship between length of failure and the probability of failure year following a regular year *f* it indicates that as *f* increases L also increases. Meaning that *f* is directly proportional to L.

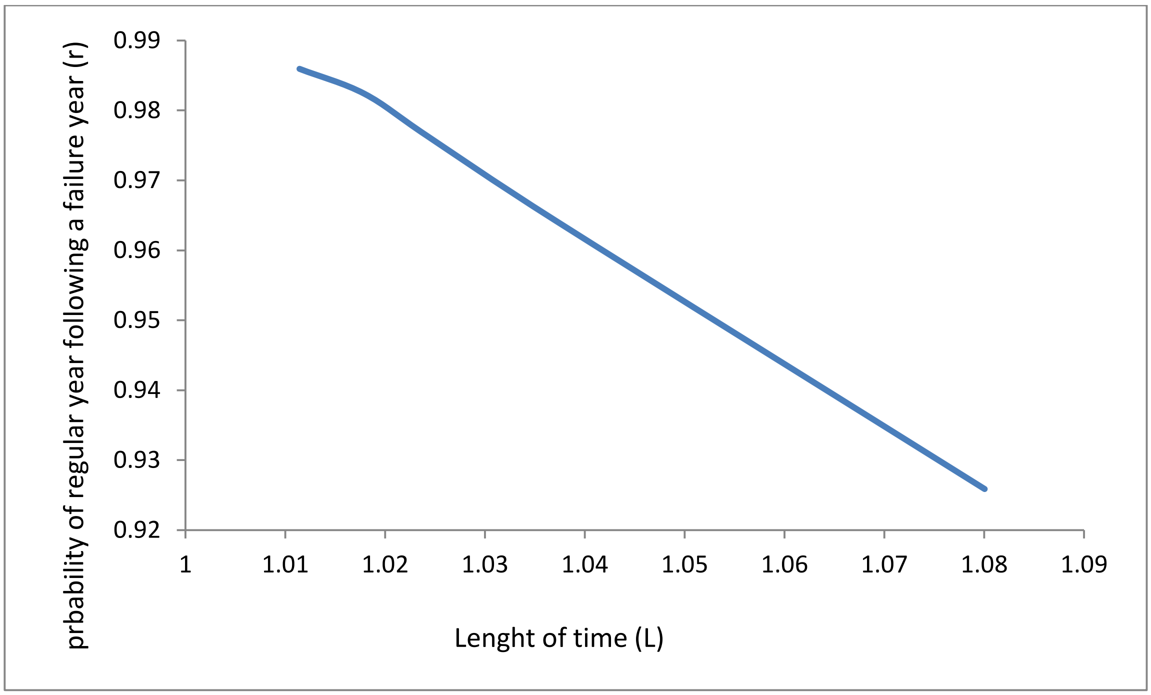


Fig. 1.5: Relationship between *L* and *r*

In figure 1.5 shows the relationship between E(L) and r, the figure depicts that as r increases the length of failure E(L) decreases i.e., r is inversely proportional to L.

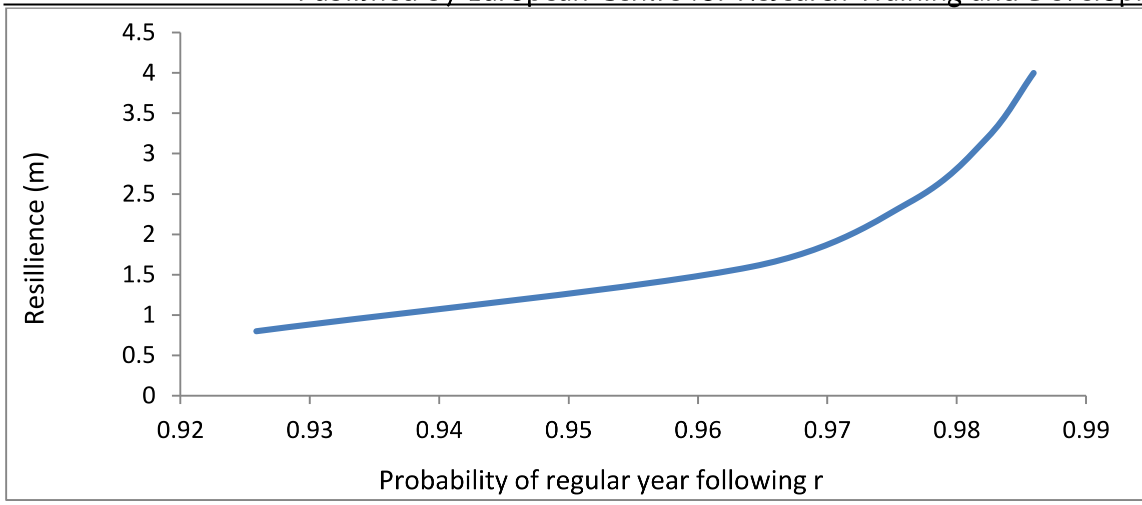


Fig. 1.6: Relationship between *m* and *r*

Figure 1.6 shows the relationship between r and m, it could be observed from the figure that the more the reservoir resilience i.e., the reservoir behave more of a within year system (m >1), the higher the r value, substantiating the reliability of the reservoir.

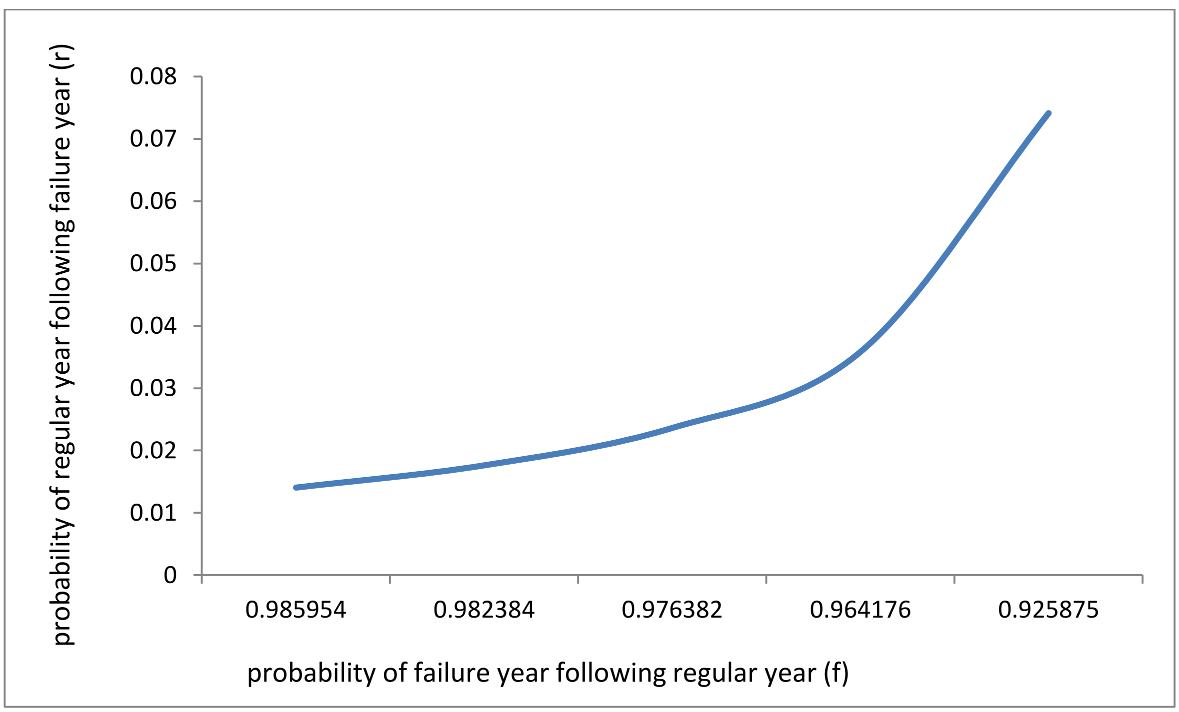


Fig. 1.7: Relationship between *f* and *r*

Figure 1.7 shows the relationship between *f* and r the relationship translates that as r increases *f* also increases indicating direct proportionality between r and *f*.

Conclusion

A stochastic model was developed for the reservoir system state, and used to evaluate the state of the reservoir. The reservoir system state was evaluated by determining system state parameters i.e., probabilities of failure, annual reliability, unconditional return period of the failure years, resilience and average length of reservoir system failure.

The value of R_a obtained depicts that the reservoir is substantially reliable at 0.96 reliability; also the unconditional return period of failure years (72years) substantiates the reliability of the reservoir. Furthermore, the *r*, *f* and U_L value obtained indicates strong reliability of Kainji reservoir.

From the parameter values computed for the reservoir system state it is clear that the reservoir system is significantly reliable, adopting the recalibrated policy could yield better performance of the reservoir system. Entice

4.0 References

Adeloye, A. J., Montaseri, M., & Garmann, C. (2001). Curing the Misbehavior of Reservoir Capacity Statistics by Controlling Shortfall during Failures Using the Modified Sequent Peak Algorithm. *Water Resources Research*, 37(1), 73-82

Ahmed Badr, S.M., Ahmed Yosri; Sonia Hassini, A.M.A ; and Wael El-Dakhakhni, F. (2021). Coupled Continuous-Time Markov Chain–Bayesian Network Model for Dam Failure Risk Prediction. Journal of Infrastructure Systems · December 2021 J. Infrastruct. Syst., 2021, 27(4): 04021041

Ansar, A., Flyvbjerg, B., Budzier, A., & Lunn, D. (2014). Should we build more large dams? The actual costs of hydropower megaproject devel-opment. Energy Policy, 69, 43–56.

Benson, R. (2016). Reviewing reservoir operations: Can federal water projects adapt to change. Columbia Journal of Environmental Law, 42, 353.

Bertoni, F., Castelletti, A., Giuliani, M., & Reed, P. M. (2019). Discovering dependencies, trade-offs, and robustness in joint dam design and operation: An ex-post assessment of the Kariba Dam. Earth's Future, 7(12), 1367–1390

Billington, D., & Jackson, D. (2017). Big dams of the new deal era: A confluence of engineering and politics. University of Oklahoma Press

Daniel,G.F., & Fedoski, E. (2005). The Potential Role of Water in the Landscape System: Conceptualisation to Address Growing Human Landscape Pressure, *Seojournal*, 33(4), 45 -56

Geressu, R. T., & Harou, J. J. (2015). Screening reservoir systems by considering the efficient trade-offs?informing infrastructure investment decisions on the blue nile. Environmental Research Letters, 10(12), 125008.

Giuliani , M., Lamontagne J.R., Reed, P.M., Castelletti, A.(2021). A State-of-the-Art Review of Optimal Reservoir Control for Managing Conflicting Demands in a Changing World. Water resources research. Volume57, Issue12.

Grill, G., Lehner, B., Thieme, M., Geenen, B., Tickner, D., Antonelli, F. (2019). Mapping the world's free-flowing rivers. Nature, 569(7755).

Hashimoto, T., Loucks, D.P., Stedinger, J. (1982). Reliability, resilience and vulnerability for water resources system performance evaluation. Water Resources Research. 18 (1), 14- 20.

Hanasaki, N., Kanae, S., & Oki, T. (2006). A reservoir operation scheme for global river routing models. Journal of Hydrology, 327(1), 22–41

Hidekazu, Y. Yumi, Y. (2020). Regime-switching constrained viscosity solutions approach for controlling dam-reservoir systems. https://www.researchgate.net/publication/338447077

Klemes, V. (1967). Reliability Estimates for a Storage Reservoir with Seasonal Input. *Journal of Hydrology* 7(2), 198- 216.

Klemes,V. (1977). Storage Mass-Curve Analysis in a Systems-Analytic Perspective. Water Resources Research., 15(2): 359-370

Lele, S.M. (1987). Improved Algorithms for Reservoir Capacity Calculation Incorporating Storage–Dependent Losses and Reliability Norm, Water Resources. Research. 23 (10), 1817–1820.

Loucks, D. P., Stedinger, J. R., & Haith, D. A. (1981). Water Resources System Planning and Analysis," Prentice - Hill, Englewood Cliffs, New Jersey, United State of America, USA.

Loucks, D. P. (1998). Quantifying Trends in System Sustainability, Journal of Hydrological Science. 42 (4), 503–507.

Loucks, D.P., & Eelco, V.B. (2005).Water Resources Systems Planning and Management An Introduction to Methods, Models and Applications. United Nations Educational, Scientific and Cultural Organization 7, place de Fontenoy F-75352 Paris 07 SP, 231- 332.

Mcmahon, T.A., & Mein, R.G. (1996). River and Reservoir Yield, Water Resources Publications, Col., USA.

Mortazavi-Naeini, M., Kuczera, G., & Cui, L. (2014). Application of multiobjective optimization to scheduling capacity expansion of urban water resource systems. Water Resources Research, 50(6), 4624–4642

Mosaad K. (2018). Data-driven stochastic modeling for multi-purpose reservoir simulation. Journal of Applied Water Engineering and Research Volume 6, 2018 - Issue

Nawaz, N.R., Adeloye, A.J., Motasari, M. (1999). The Impact of Climate Change on Storage – yield Curves for Multi- Reservoir Systems. Nordic Hydrology 30 (2):29-146

Phien, H.N. (1993). Reservoir Storage Capacity with Gamma Inflows. *Journal of Hydrology*, 146, 384–388.

Richard, M. V., Neil, M.F., & Raph, A.B. (1995). Storage –Reliability-Resilience –Yield Relations for North Eastern United States. *Journal of Water Resources Planning and Management*. (121) 5.

Sharad , K., & Jain, D. (2010). Investigating the behavior of statistical indices for performance assessment of a reservoir. *Journal of Hydrology* 391 (2010) 90–96. Indian Institute of Technology, Roorkee 247667, India.

Sovacool, B., Gilbert, A., & Nugent, D. (2014). Risk, innovation, electricity infrastructure and construction cost overruns: Testing six hypotheses.

Stedinger, J.R., & Taylor, M.R. (1982). Synthetic Stream Flows Generation: Effect of Parameter Uncertainty. Water Resources Research, 18 (4), 912–923.

Silva, A.T., & Portela, M. M. (2012). Disaggregation Modeling of Monthly Stream Flows Using A New Approach of the Method of Fragments, *Hydrological Sciences Journal*, 57(6).

Vogel, R. M. (1985). The Variability of Reservoir Storage Estimates. PhD Thesis Presented to Cornell University, Ithaca, New York, USA.

Vogel, R. M., & Stedinger, J. R. (1987). Generalised Storage – Reliability -Yield Relationships. *Journal of Hydrology*. (89), 302-326.

Vogel, R. M., & Fennessey, N.M. (1994). Flow Duration Curves I: A New Interpretation and Confidence Intervals." *Journal of Water Resources Planning and Management, 120(4), 485-504.*

Vogel, R.M., Bolognese, R. A. (1995). Storage–reliability–resilience–yield relations for over-year water supply systems. Water Resources Research. 31 (3), 646–653.

Vogel, R. M., & Mcmahon T.A. (1996). Approximate Reliability and Resilience Indices of Over-Year Reservoirs Fed By Ar(1) Gamma And Normal Flows. *Hydrological Science Journal*, 41(10):75–96.

Vogel, R.M., Lane, M., Ravindrian, R. S., & Kirshen, P. (2007). Storage Reservoir Behavior in the United States. *Journal of Water Resources Planning and Management, American Society of Civil Engineers*, 125(5), 246-257.

Wada, Y., Bierkens, M., de Roo, A., Dirmeyer, P., Famiglietti, J., Hanasaki, N., et al. (2017). Human-water interface in hydrological modeling: Current status and future directions. Hydrology and Earth System Sciences Discussions, 1–39.

Wurbs, R. A. (1993). Reservoir-System Simulation and Optimization Models. *Journal of Water Resources Planning and Management. 119(4), 456 -477.*

World Bank. (2009). Directions in hydropower (Tech. Rep.).

Zarfl, C., Lumsdon, A., Berlekamp, J., Tydecks, L., & Tockner, K. (2015). A global boom in hydropower dam construction. Aquatic Sciences, 77(1), 161–170