ABSTRACT

Title of Thesis:	RELIABILITY-BASED MODELING FOR MISSOURI RIVER DAM SYSTEM
	Zihui Ma, Master of Science, 2020
Thesis Directed By:	Dr Gregory B. Baecher, department of Civil Engineering and Environmental Engineering

Recently, the dam failure types shift from traditional causes to operational risk. Since the operational components have complex internal and external interactions, we take them into an integrated system. Moreover, the Monte-Carlo simulation method was applied to develop a reliability-based model to study the system performance. Our approach incorporates different sources of uncertainty. This model allowed us to evaluate the reliability and availability of the system. The system reliability analysis helps us understand the relationship between failure modes and safety decisions made. In further, the model allows experimenting on operational strategies. This thesis presents the framework we have developed and illustrated the results and analysis of our application in the Missouri River mainstem reservoir system. In addition, four scenarios have been applied to explicit the impacts of modeling system

with different maintenance strategies. Besides, we used the stochastic time-series inflow instead of our historical data to evaluate the system performance.

RELIABILITY-BASED MODELING FOR MISSOURI RIVER DAM SYSTEM

by

Zihui Ma

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Table of Contents

List of Tables

List of Figures

1. Introduction

Hydropower dams are an integral part of the world's surface water resource system and provide significant social and economic benefits. However, many existing hydropower systems were built decades ago, and the components of these aging infrastructure facilities have caused increasing numbers of dam incidents or failure. The consequences of a dam failure can be catastrophic, resulting in immense damage to environmental, economic, and casualties. Common traditionally identified reasons of dam failure include 1) sub-standard construction materials, crack, erosion, slides, 2) inadequate spillways, 3) geological instability, 4) extreme inflows, 5) human, computer or design error 6) increased external load due to unusual weather, and 7) earthquakes. ("Dam Failure," 2020)In contrast, many cases indicate that failure did not result from the above reasons but an unfortunate and unforeseen combination of more or less routine things (Hartford et al., 2016).For example, a moderately high but no extreme inflow occurs; a sensor fails to provide a warning for an unexpected reason; one or more spillway gates are unavailable due to maintenance. None of these is particularly dangerous by itself but can lead to a failure when they occur in combination.

Therefore, the safety assessment of a dam becomes more biased on how to analyze and evaluate operational risks for the whole system. The operation of a large and complex hydropower facility system requires careful management and continuous planning. This factor needs to be considered for both the daily operations and maintenance of hydropower systems and emergency operations required during flood events(Patev et al., 2017).

Various researchers have proposed the use of stimulation employing the Monte-Carlo approach. This method is a numerical procedure for generating random numbers based on certain probability distribution ((Motevalli et al., 2015). After defining the uncertain variables which affect system performance, specific probability distributions are generated based on each variable's inherent and natural variability. In each repetition of the procedure, the random combination uncertainty of inputs is taken into account. Consequently, this approach can resolve the uncertainty of the water system, services for access to the performance of reservoirs and analysis the reliability of hydropower systems.

The present study uses the Monto-Carlo simulation in commercial software application GoldSim™. This software provides a module with reliability modeling and risk analysis together. In our project, we created an existing model of the Missouri River mainstem reservoir system based on a reliability-based method to investigate the performance of reservoir cascades and treat risk and uncertainty in operational planning. Four scenarios were tested to evaluate the effects of different maintenance schedules. A time-series river hydrology element was also added to the simulation model to learn more about the dynamic behavior of the reservoir system.

2. Literature Review

The cascades are several dams in a row along a river. These involve multi-purposes and many uncertainties, and the computational burdens of analyzing such a system is a major obstacle. Nevertheless, Karamouz & Mousavi (2003)using a method that included driven stochastic dynamic programming (DDSP) and Fuzzy stochastic dynamic programming (FSDP) to predict the uncertainty of the reservoir operation of Dez and Karun dams. Turgeon (2007) studied optimal multi-reservoir operation using stochastic dynamic programming (SDP) and Optimal Reservoir Trajectory (ORT) approaches. Celeste & Billib (2009)examined the optimal reservoir operation policies using Implicit (ISO), explicit stochastic optimization (ESO), and parameterization simulation optimization (PSO) approaches. Hakimi-Asiabar et al.(2010)applied self-learning Genetic Algorithms (SLGAs to derive optimal operating policies for the multi-reservoir system.

Current engineering approaches to dam safety are mostly based on probabilistic risk analysis (PRA). PRA primarily addresses the capability of a dam to withstand extreme hydrologic loads or the demands caused by earthquakes and the dam’s capacity to withstand resulting ground shaking (Hartford & Baecher, 2004). It principally considers risk as associated specific chains of events that may occur using event trees, but many interactions and feedbacks among the chains of events ignored.

In recent years, the reliability-based methodology has gained recognition both in academics and engineering practice. In structural design, it is particularly useful for evaluating existing structures and offers the possibility of rational integration of information concerning a certain object.(Westberg, 2010).Westberg described and demonstrated the capability of applying the reliability-based methodology for the assessment of concrete dams. Since every dam is a unique prototype, the reliability-based analysis enables those unique characteristics to be taken into consideration and to reduce the uncertainties. By offering good possibilities to implement additional information available from investigations, testing, monitoring, etc. System reliability analysis is a valuable tool to define system failure modes.

Accordingly, this methodology has also been applied to operational goals. Zhou et al. (2014) integrated reliability-based methods with hydro system optimization modeling, incorporated both qualitative and quantitative reliability analysis methods, and developed a model that formally treat risk and uncertainty in operations planning. Similar to this study. Baecher et al. (2019) , developed an operational risk model to evaluate the availability of individual components and systems in order to identify system weakness and corrective actions relative to maintenance.

Both Zhou et al.(2014) and Baecher et al. (2019) have applied the simulation to better understanding the reliability of the complex system. Moreover, Karamouz & Mousavi (2003) have applied simulation to study the operational uncertainty of large scale reservoir systems in Iran. Tilmant et al. (2014) have applied simulation to analyze the performance of a stochastic dual dynamic programming (SDDP) model, which determines the economic value of storage in a cascade of multipurpose reservoirs in Euphrates River basin.

Monte Carlo simulation is one of the most used simulation methods, and it is beneficial for modeling problems with uncertainty in the inputs. For example, Sharma (2016) analyzed geotechnical slope stability using the Monte-Carlo method. By comparing it with a deterministic approach, he found that the Monte-Carlo method was more adaptable since the deterministic approach used input parameters assigned single-valued rather than using the spatial variation for these inputs. Motevalli et al., (2015) used Monte-Carlo simulation to analyze the operational criteria of the reservoirs system regarding inflow uncertainty. Meanwhile, Rohaninejad & Zarghami (2012) combined Monte Carlo and the finite difference method to predict the behavior of embankment dams after impounding. The results indicated the robustness of this combination method and can efficiently implement in monitoring dam performances.

The Monte Carlo simulation approaches have become increasingly common in engineering applications involved in a variety of benefits. 1) simulation allows complex systems interactions to be modeled easily compared with the use of closed-form analytical models, 2) the system can evolve into any feasible state, 3)simulation allows external or internal interactions readily included, and 5)the numerical precision of simulation results is independent of the complexity of the system being modeled. It depends only on iterations performed (Hartford et al., 2016).

In a Monte-Carlo simulation, the model runs many times with uncertain variables sampled with different values each time. These realizations generate a probability density function (PDF) or cumulative density function (CDF) for the outputs. Based on these CDFs, the risk level representing the confidence bonds (5% and 95%), mean or median, or any other desired level of probability can be obtained.

GoldSim™ is a valuable tool for Monte-Carlo simulation. Except providing a more accurate representation of uncertainty, it allows the user to create detailed and accurate representations than can be achieved with even the most sophisticated risk and reliability methodology (*A Dynamic Simulation Approach to Reliability Modeling and Risk Assessment Using GoldSim*, 2017). Compared to traditional approaches to reliability modeling, *GoldSim*™ has the advantage that:

a) The external environment can be readily modeled, which can affect and interact with the system.
b) It allows for complex operating rules.
c) It allows for complex interdependencies.

These features and capabilities contribute to *GoldSim*™ being powerful in creating realistic models. For instance, Patev et al.(2017) used *GoldSim*™ to model the behavior of the spillway and hydropower plant components during phased plant operations. For estimating the uncertainty of flood characteristics, Ahmadisharaf et al., (2018) developed a semi-distributed hydrologic model in *GoldSim*™ to simulate the rainfall-runoff process. Goharian et al.(2017) introduce a new approach to assess vulnerability by integrating the water resource system, and the system was modeled in *GoldSim*™.

3. Project overview

3.1. Project purpose

This project takes mainstream dams on the Missouri river as a cascade system. It uses *GoldSim*™ software to develop an operational reliability-based model to evaluate the components' performance as well as the effects of their interactions to analyze the operational risk in the system. Our goal is to use simulation to better understand the reliability of hydropower, the flow control systems, and the relationship of reliability to maintenance. Operational factors are important to reliability and operational factors, system engineering is difficult to model, and that is why a simulation approach was used.

On the other hand, we followed four scenarios provided by Corps engineer (the owner) to examine the performance of the reservoir with different maintenance schedules. The Corps aims to gain the sense that how the varieties repair and rehabilitation periods would affect the system, how long they can take out the service off the turbines, and whether they need to take multiple turbines at once or at discrete time.

3.2. System project location

The Missouri River is the longest one in the united states. The system consists of six mainstream dams that extend from the Fork Peck reservoir in northeastern Montana to Gavins Point Dam in southeastern South Dakota and northeastern Nebraska (*Master Water Control Manual*, 2018). The total of the mainstream reservoirs contain about 72.4 MAF (million acre-feet) of storage capacity and drain about 529,350 square miles (updated in 2018). The map of the Missouri river basin is shown below in *Figure 1*:

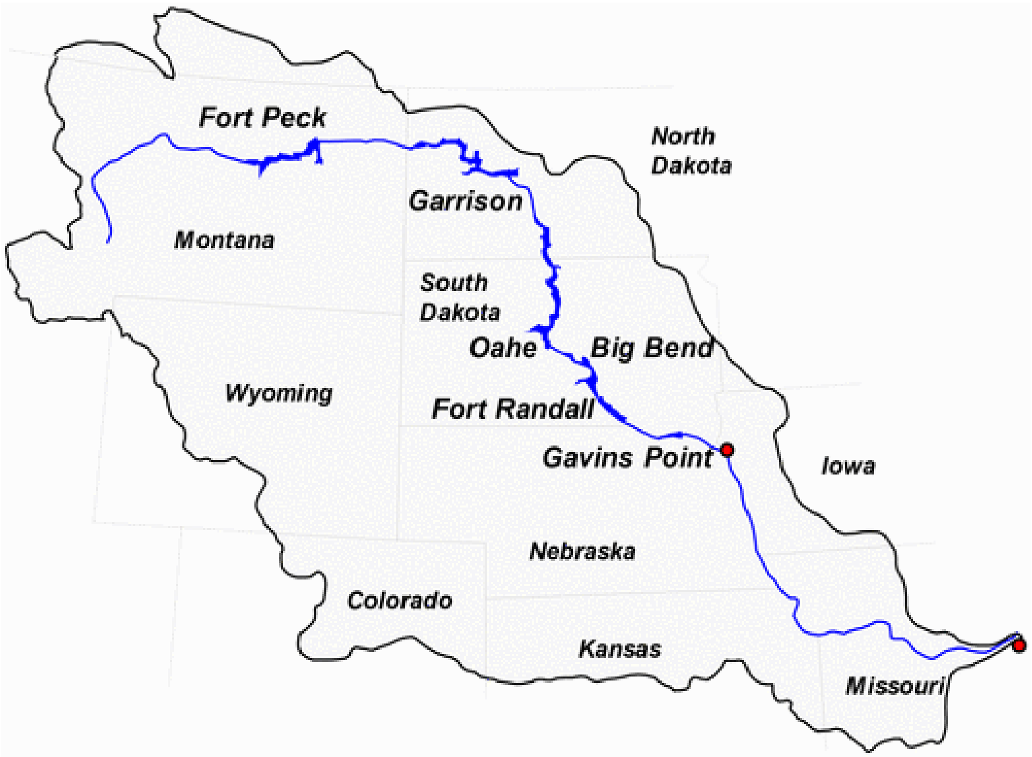


Figure 1: Map of Missouri river basin with the mainstem (Grigg, 2020)

Characteristics of the mainstem dam's and their locations are summarized in Table 1.

	Fort peck Dam-Fort peck lake	Garrison Dam-Lake Sakakawea	Oahe Dam-Lake Oahe	Big Bend Dam-Lake Sharpe	Fort Randal Dam – Lake Francis Case	Gavins Point Dam-Lewis&Clark Lake
Location of Dam	Near Glasgow	Near Garrison	Near Pierre	Upstream Chamberlain	Near Lake Andes	Near Yankton
State	MT	ND	SD	SD	SD	SD

River mile	1771.5	1389.9	1072.3	987.4	880	811,1
Total & increment drainage areas in square miles.	57,500	181,400 – 123,900	243,490 – 62,090	249,330 – 5,840	263,480 — 14,150	279,480 – 16,000

Table 1:Summary of location data for each dam archive from Missouri water manual

3.3. System physical component

This section overviews the major physical components of the six hydroelectric systems. The typical hydroelectric system (*Figure 2*) consists of a reservoir, control gates, penstocks, water turbines, and generators. The dam is constructed at a high level to ensure enough water could be stored. The height of the water level determines the capacity of the reservoir and how much energy can generate. The water flow through the penstocks to the turbines, the gates open controlled by the amount of water released. Then the water will continue to be taken into the turbine, and the turbine is mechanically coupled with electric generators. Once the kinetic energy of the water drives the turbine, it generates electricity.

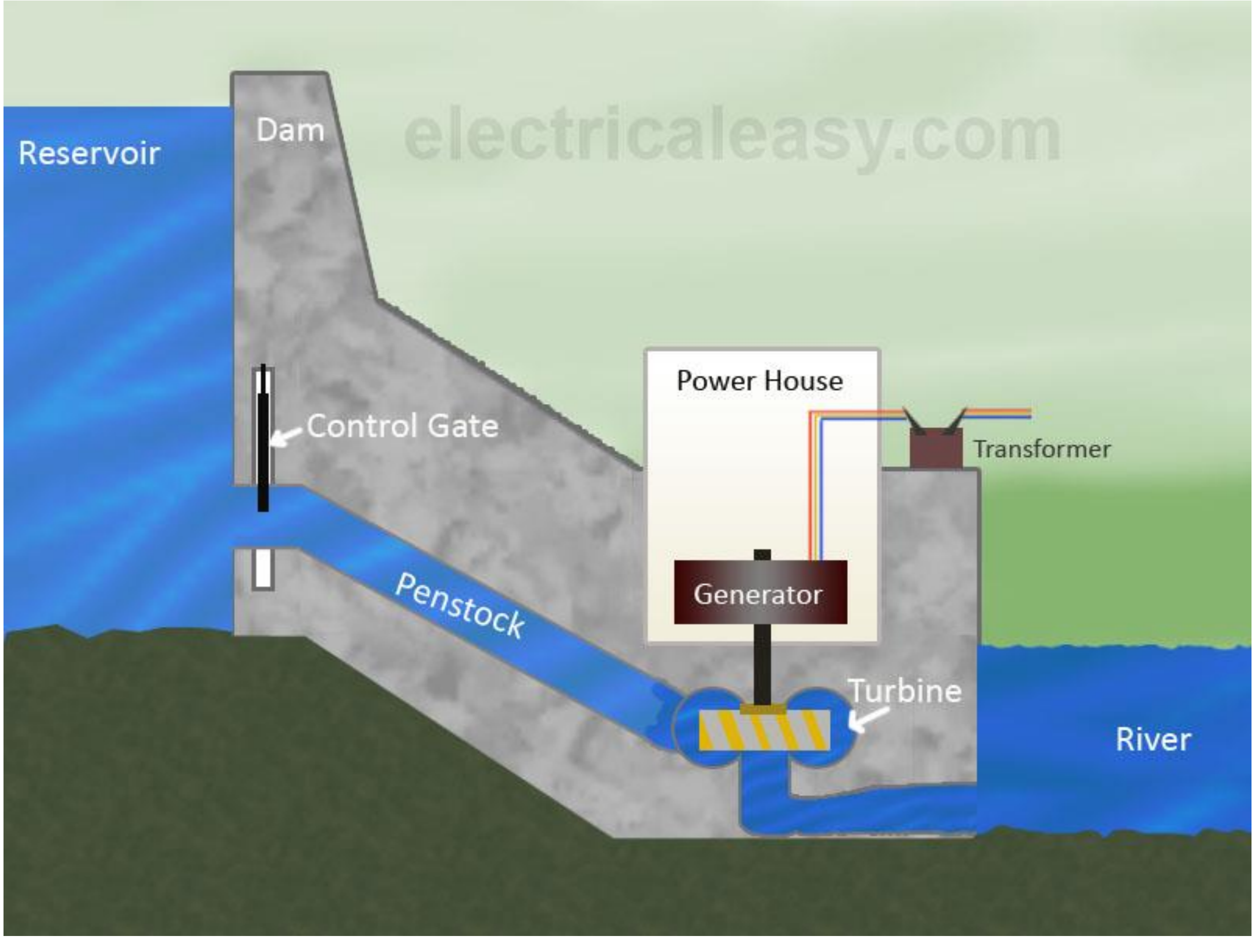


Figure 2: Typical Hydroelectric system layout (Kiran, 2015)

As the main component of this system, the reservoir assumes the primary goal to control flood storage and maintain the reliable water supply. The reservoir has a complex subsystem controlled by a subsystem’s various interactions. The key parameters for operating the reservoir are as following:

- *Water Level*: it is defined as the water level measured at a specific gauge and at a particular time.
- *Inflow*: it defined as total inflow into the reservoir from all sources.

- *Discharge*: it defined as the overall flow released from the reservoir through all spillway facilities, turbines of the hydropower station.
- *Storage*: it described as the volume of water stored in the reservoir.

Multiple pools for a single reservoir are defined to use for different purposes. An example of a multi-pool reservoir is shown in Figure 3, and each dam's annual pool-duration relationship curve can found in Appendix 8.1:

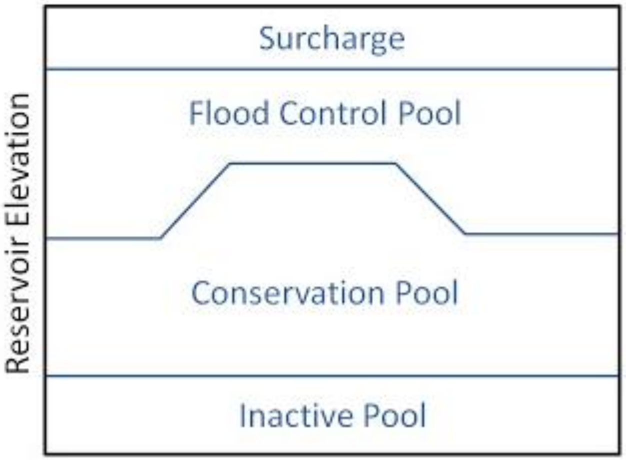


Figure 3:Reservoir Pools example

Inactive Pool: also called the dead pool. Within this level, there are no outlets to drain the water.

Conservation Pool: this pool is used to store water temporarily for power generation, recreation, navigation, irrigation, municipal, and industrial water supply (Jason, 2011). The top of the conservation pool varies seasonally because of additional storage needs during part of the year.

Flood Control Pool: usually, this pool is to remain empty except during the times following a flood event. Scheduling releases from this zone is typically in a controlled manner of spillway gates operation.

Surcharge Pool: this is storage reserved for the retention of extreme or unpredictable flood flows.

3.4. Engineering data

3.4.1. Fort Peck Dam

The top of Fort peck dam elevation is 2280.5 ft in mean sea level. It contains sixteens 40’ x 25’ vertical lift gates at the right bank, the gates are electrically operated and can be individually controlled from the service bridge. Design discharge capacity at elevation 2253.3 ft —which is the top elevation of spillway gates closed — is 275,000 CFS. Moreover, the discharge capacity at the maximum operating pool is 230,000 CFS.

There are five Francis turbines inside the Fort peck dam. This type of turbine consists of five internal components which are 1) Sator, 2) Rotor,3) Excitor, 4) Transformers, and 5) Governors. See the diagram in *Figure 4*. All of these components work dependent but interact with others. It turns to be failed if one of these gets a problem. It has been used popularly, because of its wide range of heads and flows, also the high efficiency.

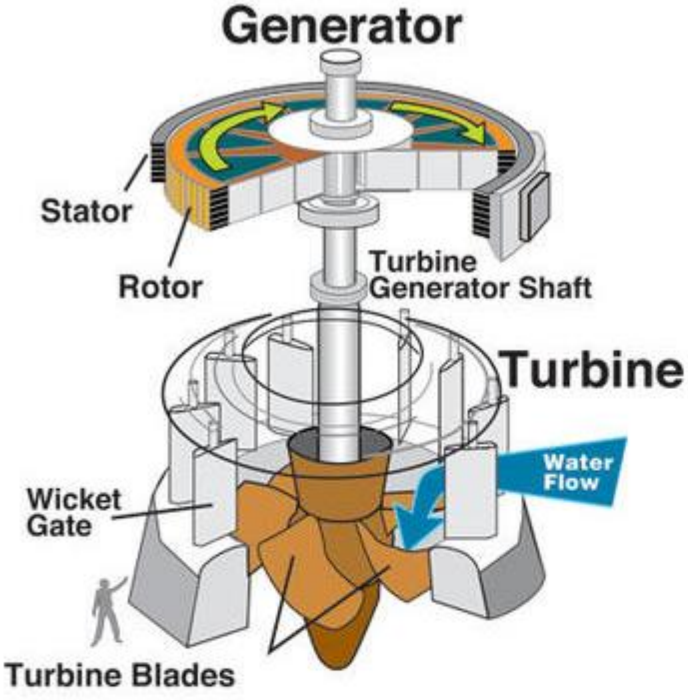


Figure 4: Diagram of a Francis turbine (credit: U.S.Army Corps of Engineers)

3.4.2. Garrison Dam

The highest elevation of Garrison is 1875 ft. It contains 28 spillway gates and 5 Francis type turbines. The 28 Tainter spillway gates are each 40’ wide and 29’ high, which contribute the design discharge capacity is 827,000 at 1858.5 ft. The crest elevation is 1825 ft. The discharge capacity at the maximum operating pool is 660,000 CFS.

3.4.3. Oahe Dam

Oahe embankment has a top elevation of 1666.0 ft. The Oahe spillway is a remote spillway located on the right bank and controlled by 8 Tainter gates at 50’ x 23.5’ size. The discharge capacity at the maximum operating pool is 80,000 CFS. The turbines of Oahe dam also used Francis type, and it has seven of that.

3.4.4. Big Bend Dam

The maximum dam height is 95ft, and the top elevation is 1440ft. There are eight Tainter gates control the spillway. Each tainter gate is 40 feet long and 38 feet high. Design discharge capacity at 1433.5ft is 390,000 CFS, and at the top of the exclusive flood control zone is 270,000 CFS. Eight hydraulic turbines installed in the Bid bend dam.

3.4.5. Fort Randall Dam

The dam has the top elevation at 1395ft. The spillway has 21 tainter gates controlled. Each gate is 40 feet long and 29 feet high. The discharge capacity of the maximum operating pool is 508,00 CSF, and the maximum operating pool is 1375 ft. In Fort Randall dam, eight Francis hydraulic turbines installed to generate power.

3.4.6. Gavins Point Dam

The top elevation of the Gavins Point dam is 1234ft, and the maximum operating pool elevation is 2250ft. The discharge capacity at maximum operating pool elevation is about 508,000 CFS, and 620,000 CFS at the maximum level attained during routing of the Spillway Design Flood (SDF). The spillway gates are fourteen 40’ x 30’ Tainter gates, and the turbines are three Kaplan type hydraulic turbines.

3.5. Current water control plan for the system

The Missouri master water control manual describes the water control plan for the system, and it covers all the criteria for the management of the system, including the operational regulation during drought, flood, and regular runoff periods. The Cops has direct responsibility for an update of the water control plan if any possible changes in the future.

4. Development of the GoldSim™ Model

We could not get adequate data on the entire system at this time, so we narrowed scope, the scope for a longer term is on many dams. Still, since the time limitations and the quality of data we had, we have only developed the model of the biggest dam – the Garrison dam – as our first stage of the project.

GoldSim™ reliability module leverages the power dynamic fault tree analysis Monte-Carlo framework. The dynamic fault tree simulation allows the analyst to develop a representation to check the system's reliability and then observe the system's performance. It also allows the multiple independent failure modes to be defined for each component and observe the availability of the system as well as each dependent. In the next section, the framework for developing the reliability-based model will be introduced.

Besides, we used two different ways to analyze our model. The first way is taking the historical data as input, and it applied to our general model plus the four scenarios. The other way is to replace these historical data with stochastic time-series, which has been developing the simulate inflow.

4.1. Model preparation

USACE provided us with the daily data inflow from the year 1967 to the year 2018 which will be used as historical input. All engineering data and operation rules were obtained from Master Water Manual. Our model start simulates in the year 1984 and simulated for 70 years; because we only have the first thirty-five years (1984 -2018) data available, thus, the historical inflow data of Garrison were repeated for every thirty-five years.

4.2. Reservoirs modeling

The reservoir operated based on policies that involve multiple pools where are divided into surcharge, flood control, conservation, and inactive pool zones (See Figure 3). The property for the Garrison dam could be summarized in Table 2.

Storage Capacities, acre-feet	
Exclusive Flood control (Elev. 1850-1854)	1,495,000
Flood control (Elev. 1837.5-1850)	4,211,000
Conservation zone (Elev. 1775-1837.5)	12,951,000
Dead zone (Elev. 1673-1775)	4,794,000

Table 2: Multiple Pool zone for Garrison dam

Table 3 summarizes the physical water level constrains for the Garrison dam.

	Garrison
Initial_Pool_Elevation (ft)	1840.6
Top_Dam_Embankment(ft)	1875

Table 3: Physical constrains of the Garrison dam

The difference between the upstream daily inflow and outflow of spillways and turbines will change the reservoir elevation. The initial storage capacity for each reservoir could read from the *storage capacity rating* table. This table was given the storage capacity by looking up at a specific pool elevation. Knowing the initial pool elevation, we can quickly obtain the initial storage capacity, and then the model can run the simulation. Contrarily, if we have data for the reservoir capacity, we can reverse the storage capacity table – the *reservoir elevation rating table* – to get the number for elevation. Both *storage capacity rating* table and *reservoir elevation rating* table are actual daily data recorded in 2018. The amount of daily inflow may not be entirely stored in reservoirs, and it will go through the turbines and spillway gates at sometimes and then flow out to the next dam. Therefore, the simple operation system represented in *GoldSim*™ looks like in the following:

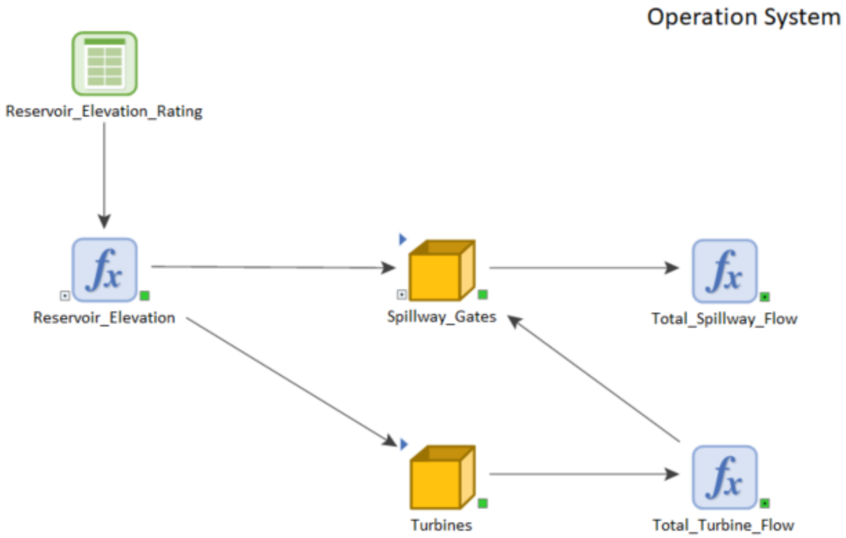


Figure 5: Snapshot of the operation system in GoldSim™

4.3. Turbines modeling

The *power unit rating* table relates to power generation as a function of discharge and headwater elevation. Once we know two of these parameters, we could obtain the other one incorporates with this look-up table.

At this point, we developed a correlation equation of power head and discharge. Surprisingly, the results fit good polynomial lines for the first top-three dams (take Garrison as an example, see Figure 6) but results for the bottom three dams (take Fort Randall as an example, see Figure 7) were unreasonable. The powerhead we calculated is subtracted from the lowest permanent pool zone elevation from reservoir elevation.

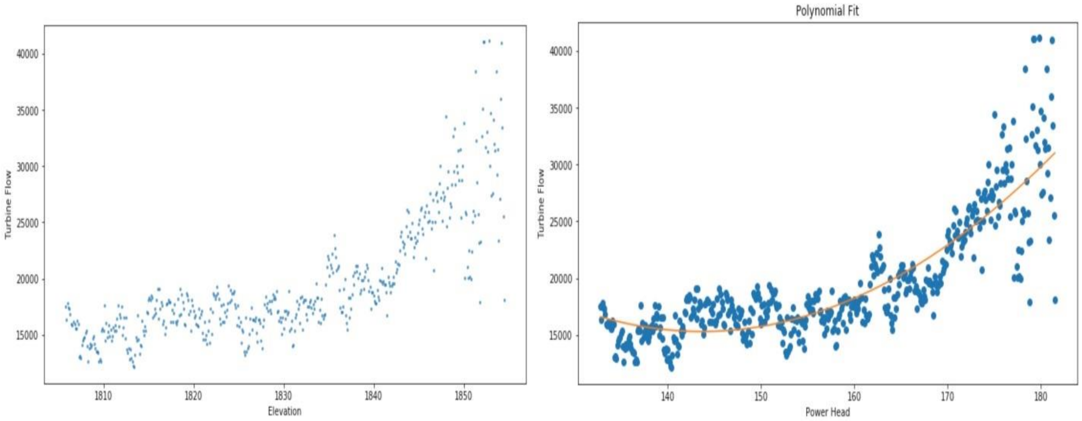


Figure 6: Plots of Garrison Dam's Turbine Flow Vs. Elevation and Turbine Flow Vs. Power Head (Source: Lingyao Li)

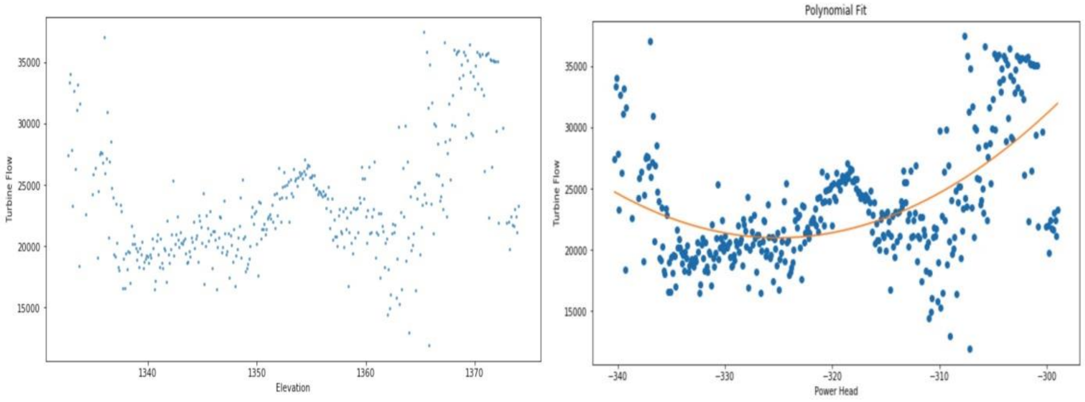


Figure 7: Plots of Fork Randall Dam's Turbine Flow Vs. and Turbine Flow Vs. Powerhead (Source: Lingyao Li)

The results give us the confidence to study the first three dams rather than the bottom three dams. Each turbine generates power when the water flows out; meanwhile, some amount of water may flow out over the spillways. The diagram for this working mechanism looks like *Figure 8*:

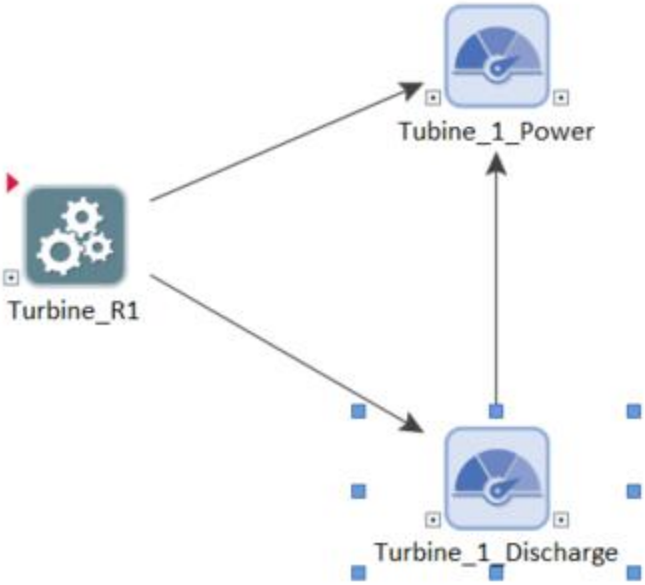


Figure 8: The outputs relate to Turbines

Figure 9 shows the major components of turbines incorporated into the system reliability model:

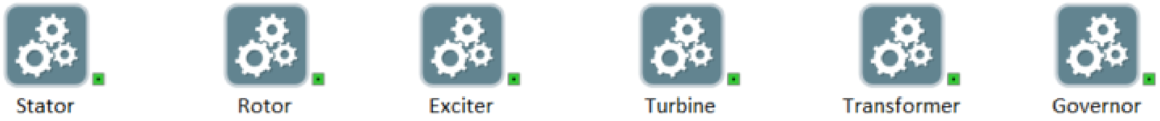


Figure 9: Typical Turbine inner system

4.4. Gates modeling

The gates open to release water not only to avoid overtopping of the dam but also to support other authorized purposes such as downstream environmental flows. While the elevation reaches out to the base flood control elevation, we need the gates to drain. The operation rules for gates should follow two aspects: discharge and reservoir elevation.

1. If the upstream daily inflow is more than the amount of turbine outflow and,
2. The reservoir pool reaches the maximum normal operation pool level, but within the maximum operating pool elevation, gates opened.

To determine how much height needs to lift for the gates is dependent on pool elevation and the difference between upstream daily inflow and the outflow. *Spillway rating curve* indicated the information we need for gates operation rules to ensure the system regulation. Note the stage-discharge shown in this curve is the sum of all gates.

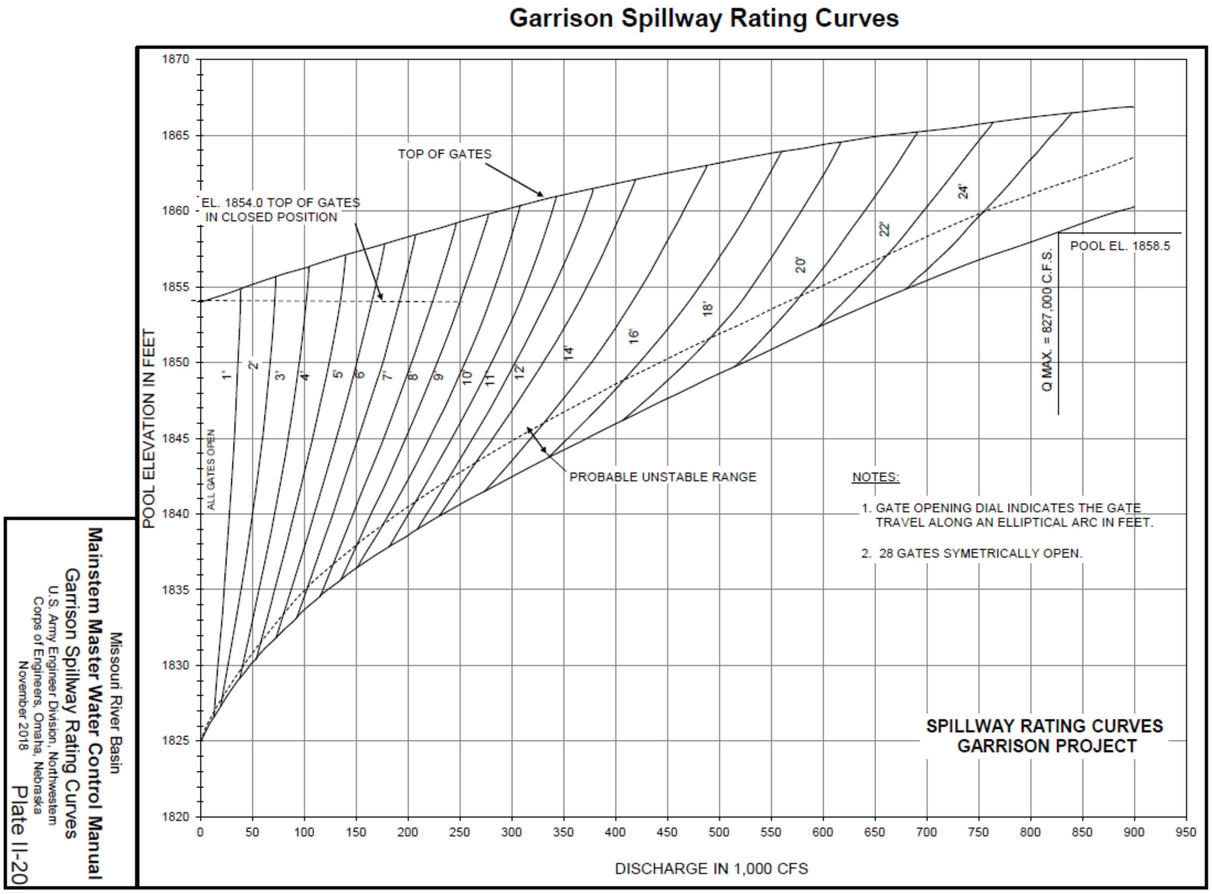


Figure 10: Spillway rating curve example – Garrison dam

The in-demand failures of spillway gates are complex and controlled by the gate's components. The major components of the spillway gates shown in *Figure 11*:

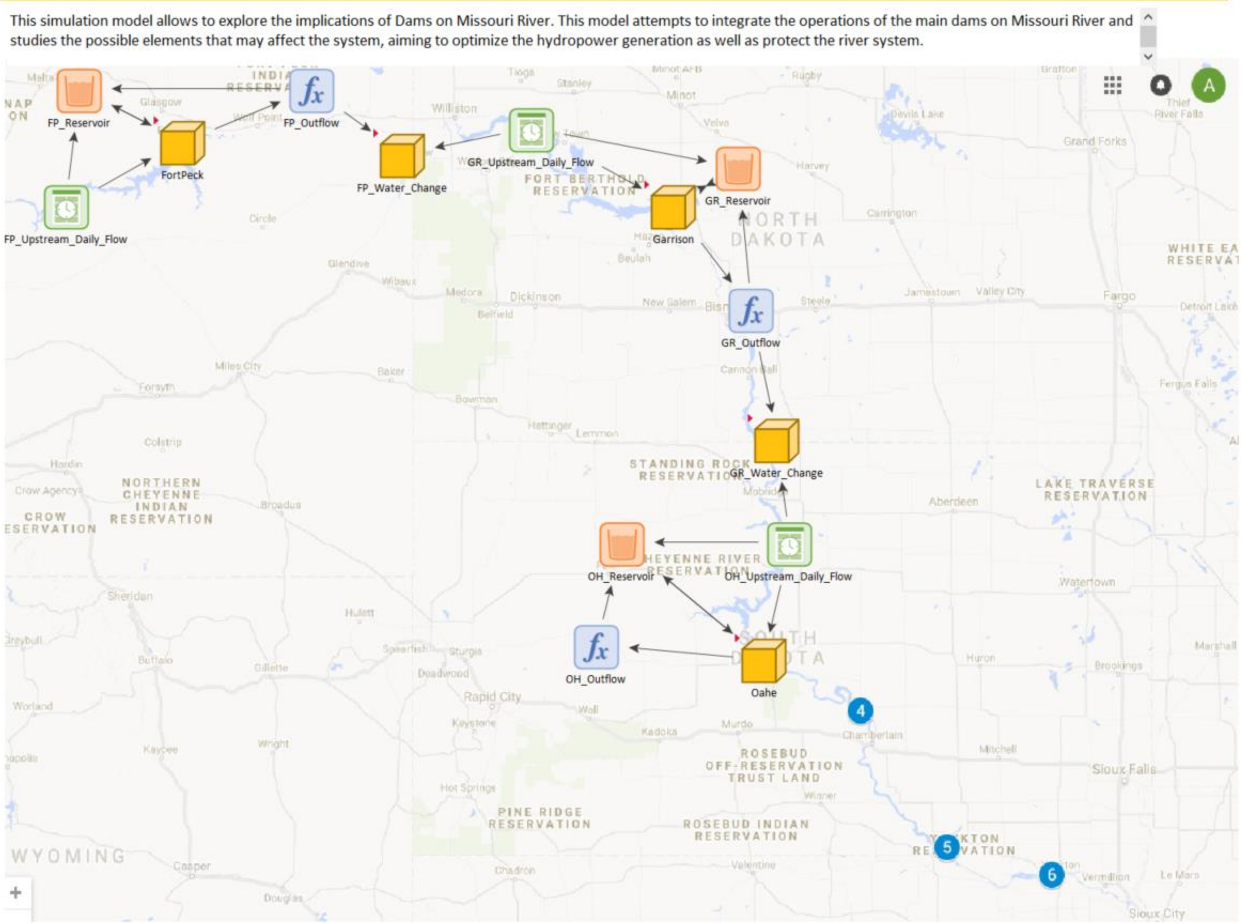
Figure 11: Spillway Gates inner system

Moreover, here are some key equations we used in the model:

- Total_Spillway_Flow = Sum of discharge through all gates
- Total_Turbine_Flow = Sum of discharge through all turbines
- GR_outflow = Garrison.Total_Spillway_Flow+Garrison.Total_Turbine_Flow

4.5. Model overview

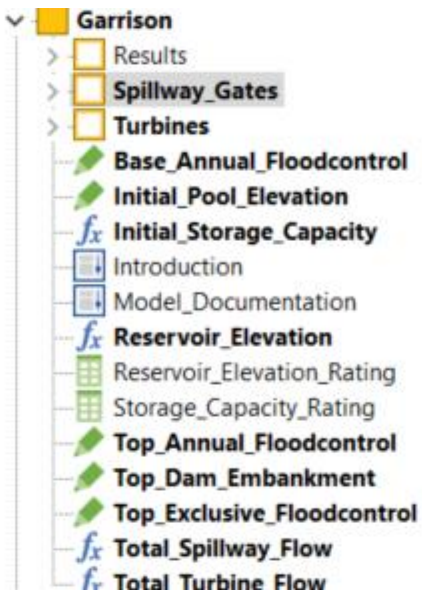
Figure 12 gives a graphicly view of each dam's interaction and location.



This simulation model allows to explore the implications of Dams on Missouri River. This model attempts to integrate the operations of the main dams on Missouri River and studies the possible elements that may affect the system, aiming to optimize the hydropower generation as well as protect the river system.

Figure 12: Missouri River Mainstem dams system model overview

Since we only focus on Garrison at this time, the structure of Garrison dam components could simply view in Figure 13.



- Garrison
  - Results
  - Spillway_Gates
  - Turbines
  - Base_Annual_Floodcontrol
  - Initial_Pool_Elevation
  - Initial_Storage_Capacity
  - Introduction
  - Model_Documentation
  - Reservoir_Elevation
  - Reservoir_Elevation_Rating
  - Storage_Capacity_Rating
  - Top_Annual_Floodcontrol
  - Top_Dam_Embankment
  - Top_Exclusive_Floodcontrol
  - Total_Spillway_Flow
  - Total_Turbine_Flow

Figure 13 Garrison Dam inner structure shown in GoldSim™ browser

4.5.1. Reliability elements

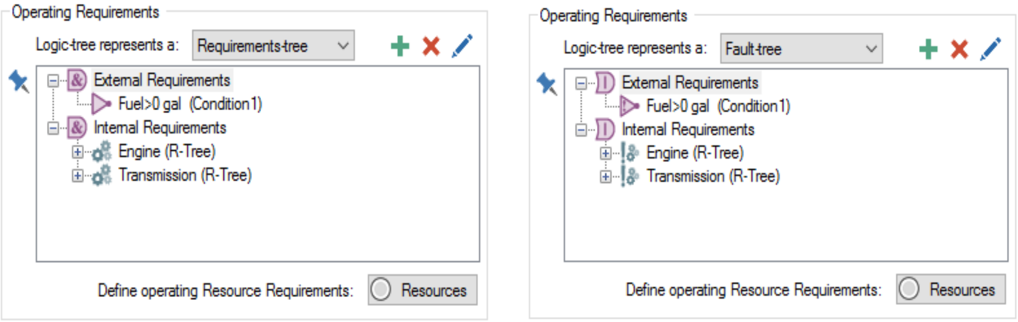
In our model, we choose the reliability elements – ‘function element,’ which continuously operates once it turned on. The default icon for our function elements look like this:

Once we create one function element, the element’s dialog appears and requires to specify each primary property. In the next section, we illustrated how we fulfill those properties.

4.5.2. Logic tree

The GoldSim™ provides two types of logic trees to define operating requirements, which are the ‘requirement-tree’ and ‘fault-tree.’ The former one evaluates elements operate in true order, and the later one evaluates to false in order.

Under the box of operational requirements, we have two AND-Gates – one for external requirements and one for internal requirements. The external requirements AND-Gate will be empty as initial created and refer to outside requirements/conditions while the internal requirements used for the requirements/conditions that are inside the element – such as child elements.

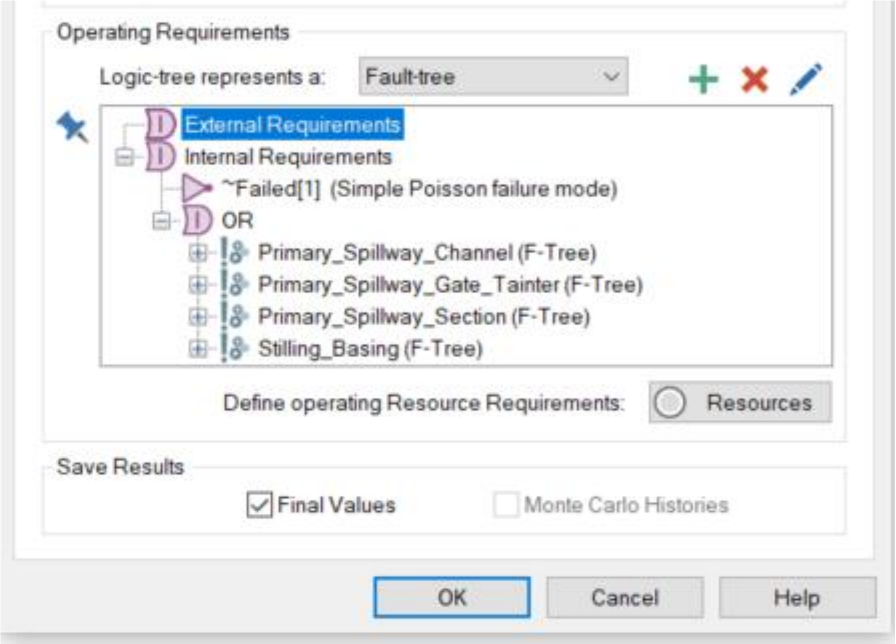


Logic-tree represents a: Requirements-tree

Logic-tree represents a: Fault-tree

Figure 14: Example of Requirements-tree and Fault-tree

The spillways gates and turbines controlled by different internal components operations. The two figures displayed below represented the operation requirements for gates and turbines, respectively.



Operating Requirements

Logic-tree represents a: Fault-tree

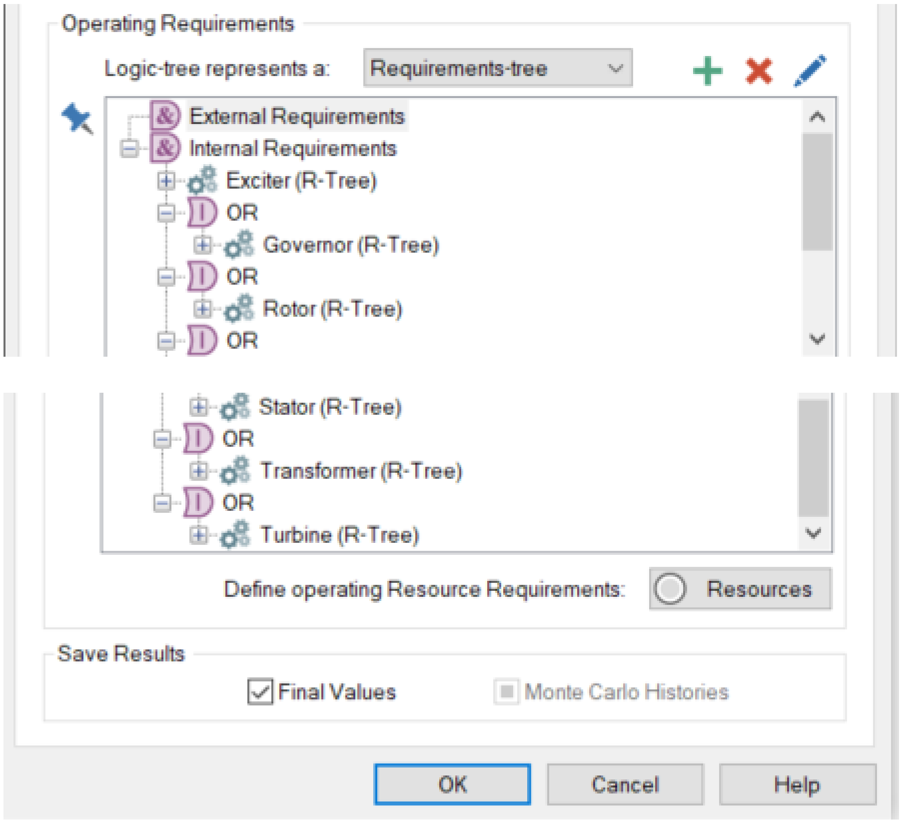
- External Requirements
- Internal Requirements
  - ~Failed[1] (Simple Poisson failure mode)
  - OR
    - Primary_Spillway_Channel (F-Tree)
    - Primary_Spillway_Gate_Tainter (F-Tree)
    - Primary_Spillway_Section (F-Tree)
    - Stilling_Basing (F-Tree)

Define operating Resource Requirements: ○ Resources

Save Results

☑ Final Values ☐ Monte Carlo Histories

Figure 15: Operation requirements for gates



Operating Requirements

Logic-tree represents a: Requirements-tree

- External Requirements
- Internal Requirements
  - Exciter (R-Tree)
  - OR
    - Governor (R-Tree)
  - OR
    - Rotor (R-Tree)
  - OR
    - Stator (R-Tree)
  - OR
    - Transformer (R-Tree)
  - OR
    - Turbine (R-Tree)

Define operating Resource Requirements: ○ Resources

Save Results

☑ Final Values ☐ Monte Carlo Histories

Figure 16: Operation requirements for turbines

4.5.3. Failure modes

Each component inside the dam system interacts by one or more others. Since the adverse performance of each component remains uncertain, the result of their interaction is uncertain as well. Therefore, we introduce statistic distribution to access the reliability of the particular component in order to determine when the failure occurs.

Weibull distribution is particularly useful to predict product life and quality than other statistic distributions because it can characterize a wide range of data trends, including increasing, constant, and decreasing failure rates (*Unlocking Weibull Analysis*, 2013). Moreover, the Weibull distribution generally provides valuable results to help explain the item's failure characteristics. For example, it reveals the point at which the component will have failed and given us the estimated time that component needs to be fixed or replaced.

Here are some essential terms in Weibull distribution (2-parameter):

1) The PDF (Probability density function) is given by:

$$f(t) = \frac{\beta}{\eta} \cdot (\frac{t-\gamma}{\eta})^{\beta-1} \cdot e^{-(\frac{t-\gamma}{\eta})^{\beta}}$$

Where,

$\frac{\beta}{\eta} \cdot (\frac{t-\gamma}{\eta})^{\beta-1}$ = hazard rate/failure rate.

β = shape parameter/slope factor.

η= scale parameter, also called the characteristic life parameter.

$\gamma =$ location parameter.

2) The relationship between those parameters is distinct.

   When $\beta < 1$, the failure rate is decreasing, which indicates that the component is more likely to fail at the early stage of its life. Also, the Weibull PDF is the same as the gamma distribution.

   When $\beta = 1$, the failure rate is constant, which the Weibull PDF will be equivalent to the exponential distribution, and the component failed randomly.

   When $\beta > 1$, the failure rate is increasing, the component wearing out at an increasing rate as time passed.

   When $\beta = 2$, the failure rate linearly increasing, and the Weibull PDF becomes the Rayleigh distribution.

3) The Weibull CDF equation is:

$$F(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}}$$

   If you assume that *t*= η, then the CDF reduces to:

$$F(t) = 1 - e^{-1} = 0.632$$

   It defined as at which 63.2% of the component has failed.

In Goldsim, they support Weibull analysis as two different methods to define the best fit distribution – one is characteristic life &slope factor, and the other is mean life &slope factor. According to the data we have, we used the former one to define our failure modes in our reliability model. The slope factor and characteristic life for each component present in *Table 4* below.

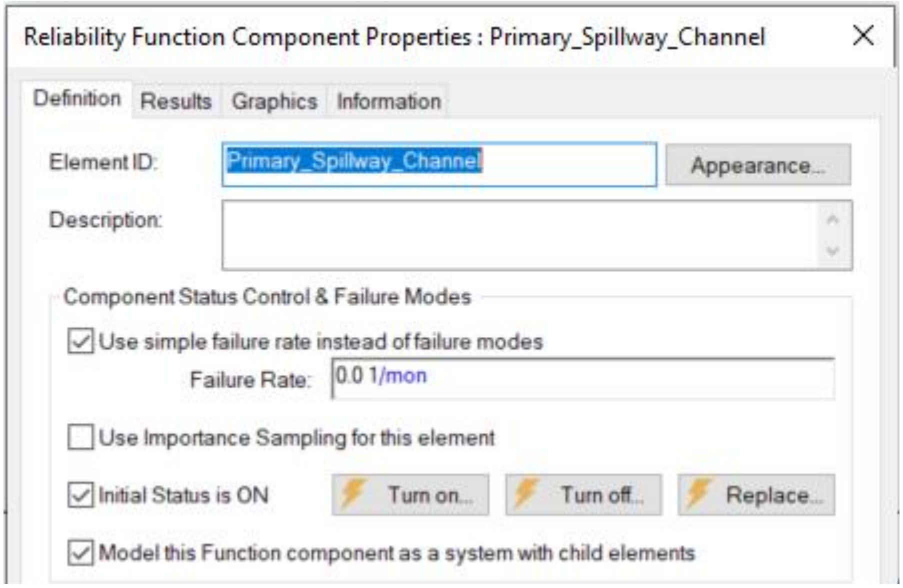
Components				β	η (Yr)
Gates	Primary_Spillway_Channel	Channel_bottom_concrete		2.9	75

		Channel_Sides_concrete		2.9	75
		Concrect_Channel_Inlet-Structu		2.9	75
		Scour_protection		3.5	158
	Primary_Spillway_Gate_Tainter	Anchorages		4.3	91
		Basic_Structure		3.8	85
		Contro_Cables		4.7	47
		Elevtric_Motors		2.9	45
		Lifting_Cables		3.8	85
		Operationg_Equitment_Mechanical	Break	3.4	35
			Couplings	4.1	60
			Gate_Wheels	4.1	60
			Lifting_Stem and Guides	4.1	60
			Open gates	4.1	60
		Power_ cable480V		4.7	47
		Seals		4.1	60
	Primary_Spillway_Section	Downstream_Face		4	156
		Gate_Pier		4	156
		Main_Structure		4	156
		Upstream_Face		4	156
	Stilling_Basing	Basic_Structure		2.9	75
		End_Sill		2.9	75
		Foundation		2.9	75
		Training_Walls		2.7	75
Turbines	Exciter			4.8	61
	Governor			2.5	80
	Rotor			4.9	98
	Stator			3.3	62
	Transformer			3.3	66
	Turbine			3	102

Table 4: Slope factor and characteristic life parameter for each component's summary

From the table above, only the most internal components have the failure rate. However, for the first- or second-order components which dominated by lowest-order components, they do not have the failure modes and with the simple failure rate at 0.01/month.

If the failure rate were constant, then checked the “use simple failure rate instead of failure modes” box. Example of the gate’s component – “*Primary _Spillway_Channel*” dialog shown below as *Figure 17*.



Reliability Function Component Properties : Primary_Spillway_Channel

Element ID: Primary_Spillway_Channel

Description:

Component Status Control & Failure Modes

☑ Use simple failure rate instead of failure modes

Failure Rate: 0.0 1/mon

☐ Use Importance Sampling for this element

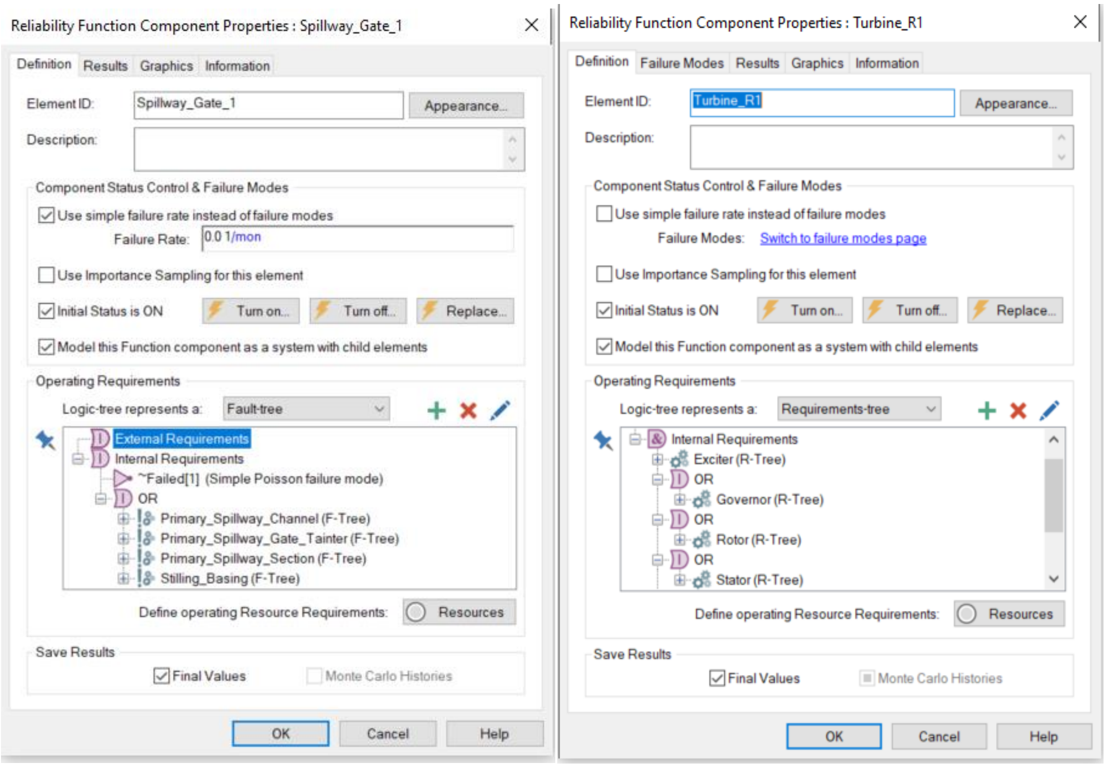
☑ Initial Status is ON

☑ Model this Function component as a system with child elements

Figure 17: Simple Failure rate checkbox

4.5.4. Elements dialog summary

All gates have the same dialog, and so does turbines do. See the dialog detail in snapshots for gates and turbines below.



Reliability Function Component Properties : Spillway_Gate_1

Element ID: Spillway_Gate_1

Description:

Component Status Control & Failure Modes

☑ Use simple failure rate instead of failure modes

Failure Rate: 0.0 1/mon

☐ Use Importance Sampling for this element

☑ Initial Status is ON

☑ Model this Function component as a system with child elements

Operating Requirements

Logic-tree represents a: Fault-tree

- External Requirements
- Internal Requirements
  - ~Failed[1] (Simple Poisson failure mode)
  - OR
    - Primary_Spillway_Channel (F-Tree)
    - Primary_Spillway_Gate_Tainter (F-Tree)
    - Primary_Spillway_Section (F-Tree)
    - Stilling_Basing (F-Tree)

Define operating Resource Requirements:

Save Results

☑ Final Values ☐ Monte Carlo Histories

Reliability Function Component Properties : Turbine_R1

Element ID: Turbine_R1

Description:

Component Status Control & Failure Modes

☐ Use simple failure rate instead of failure modes

Failure Modes: Switch to failure modes page

☐ Use Importance Sampling for this element

☑ Initial Status is ON

☑ Model this Function component as a system with child elements

Operating Requirements

Logic-tree represents a: Requirements-tree

- Internal Requirements
  - Exciter (R-Tree)
  - OR
    - Governor (R-Tree)
  - OR
    - Rotor (R-Tree)
  - OR
    - Stator (R-Tree)

Define operating Resource Requirements:

Save Results

☑ Final Values ☐ Monte Carlo Histories

Figure 18: Spillway Gates and Turbines dialog in GoldSim

4.5.5. Simulation approach summary

After finished the modeling, the system runs time simulations in GoldSim$^{\text{TM}}$ following the flow chart of Figure 19. The realization for our thesis is ten with each simulation time-steps is 25569, the total irritation time for the system is 255690.

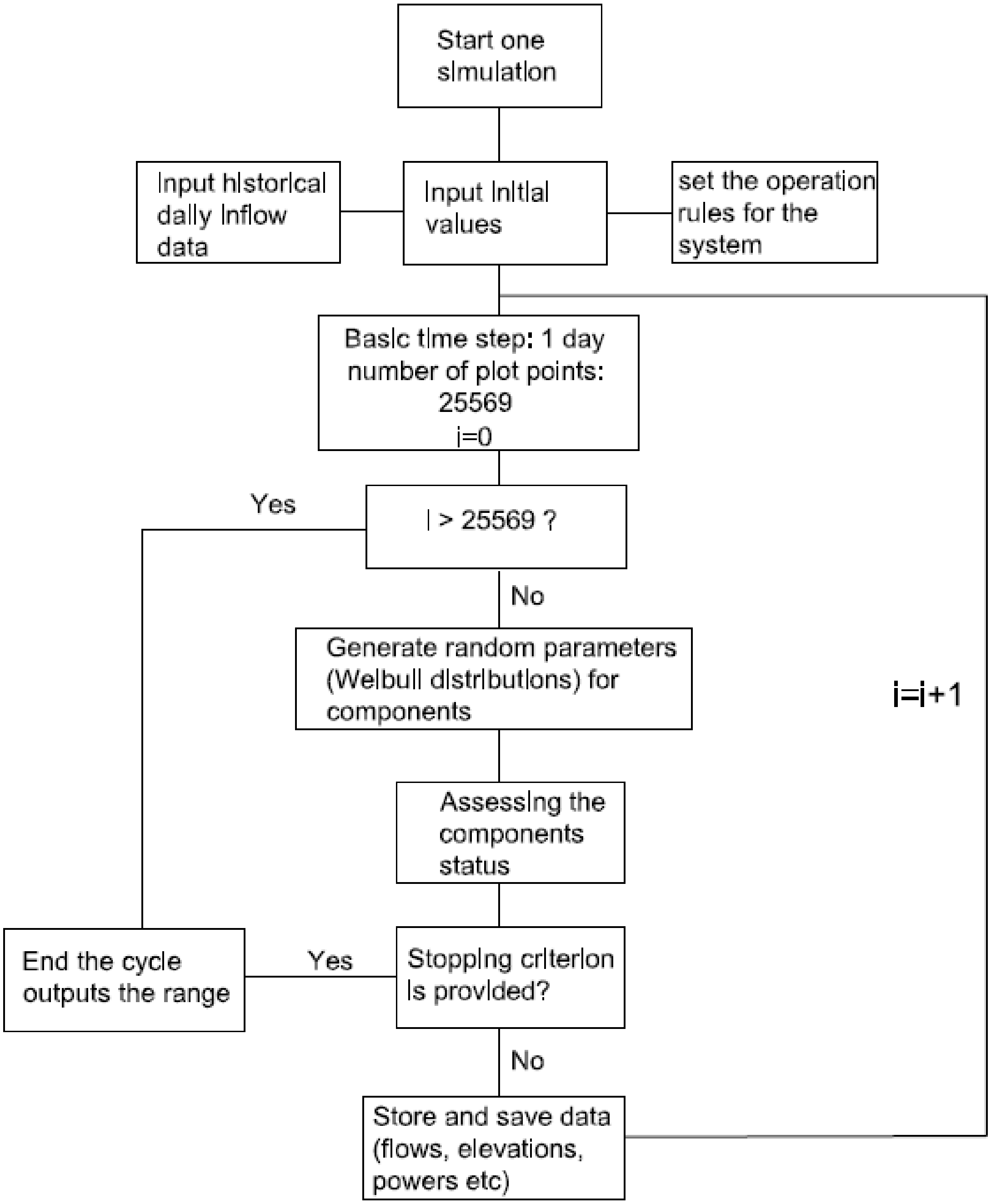


Figure 19: Monte Carlo simulation flow chart for GoldSim^{TM}

4.6. Four scenarios

Based on different maintenance schedules provided by Corps, four scenarios have been processed to exam the impacts of the system in terms of power generation, downstream flows, and pool elevations. Each scenario generated based on the data we collected as aforementioned. Again, all the study objectives based on the Garrison dam. The conditions for corresponding scenarios explained as following:

Scenario 1: Assumed the turbine 1 out of work for the first six months and 70 years of the simulation was conducted.

Scenario 2: For this scenario, the Corps wants to see the overall impacts while stopping the multiple turbines at once. The simulation time for the model is 70 years, and five cases contained in this scenario.

Case 1: Turbine 1 offline for six months in the beginning.

Case 2: Turbine 1 and turbine 2 both offline for six months in the beginning.

Case 3: Turbine 1, turbine 2 and turbine 3 offline together for six months in the beginning.

Case 4: Turbine 1, turbine 2, turbine 3 and turbine 4 offline together for six months in the beginning.

Case 5: All five turbines offline together for six months in the beginning.

Scenario 3: For this scenario, the turbine 1 will be offline once ten years, and it happened in the first year. The repairing time was last for a year. The stimulation time for the model is 70 years as well.

Scenario 4: In this scenario, five cases conducted. In case 1, the turbine 1 was work for the first year and offline afterward. Case 2 is based on case 1, but the turbine 2 was taken out after the second year. Similarly, case 3 was turbine 3 offline after third years and remained the same conditions of case 2. And so forth for the rest of the cases. All cases simulated in 70 years.

The change of pool elevations regarding each scenario exhibited in *Figure 25*. The x-axis denotes the period of stimulation years while the y-axis is the reservoir elevation in feet. Maximum reservoir elevation (Top of the dam) for Garrison found in Missouri Mainstem Master Manual 2018, which is 1875ft (*Master Water Control Manual*, 2018). Additionally, five legends were defined as below to better view the results.

Reservoir_Elevation1= Case 1 results happened in the corresponding scenario. For example, in Figure 25(2), it represents the results of case 1 in scenario 2.

Reservoir_Elevation2 = Case 2 results happened in the corresponding scenario. For example, in Figure 25(2), it represents the results of case 2 in scenario 2.

Similarly,

Reservoir_Elevation3 = Case 3 results happened in the corresponding scenario.

Reservoir_Elevation4 = Case 4 results happened in the corresponding scenario.

Reservoir_Elevation5 = Case 5 results happened in the corresponding scenario.

5. Results and analysis

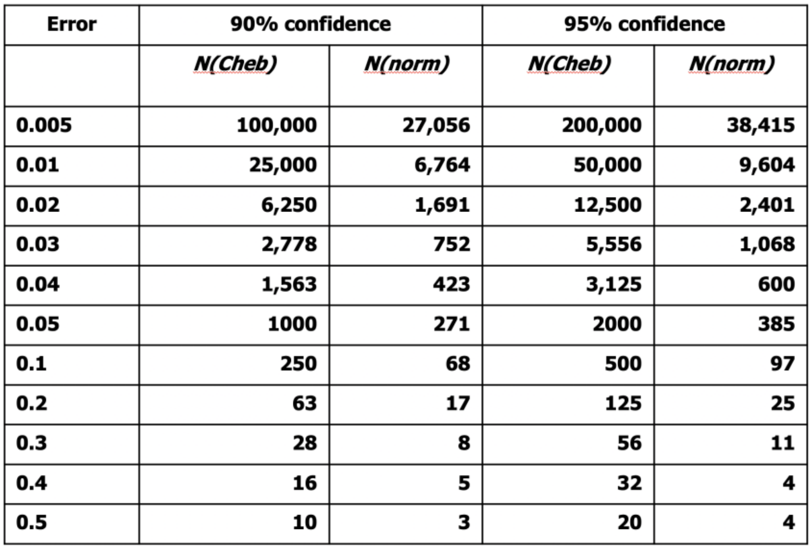
The results are divided into two parts. One is the graphic outputs, and the other is the reliability statistic results of components. Those results came from our 70-years simulation model based on historical inputs. Additionally, the results of replacing with stochastic time-series forecasting inflows will be presented at the end of this chapter.

The results are divided into two parts. One is the graphic outputs, and the other is the reliability statistic results of components. Those results came from our 70-years simulation model based on historical inputs. Additionally, the results of replacing with stochastic time-series forecasting inflows will be presented at the end of this chapter.

When a simulation is run more than once, somewhat different results are obtained for each iteration, because it’s a random process. Consequently, the differences occur across the simulations observed. Given that the current simulations all use the historical record of hydrologic inflows there is no variation among the iterations in water flow. The main variations occur in the component performance realizations. These vary from one 70-year simulation to the next.

Only ten 70-yr simulations were performed. Thus, the error in the statistical average across these iterations is large. Table xx shows these errors in the mean as a function of non-parametric and Normal error assumptions.

The present study, however, has not sought to estimate precise failure rates, but to understand trends in the patterns of turbine and spillway failures as a function of maintenance programs. Understanding the trends involved averaging results over the sets of independent turbines and gates, which to some extent reduces the sampling error. Nonetheless, in future studies a greater number of long-time simulations will be needed, especially when stochastic as opposed to historically observed reservoir inflows are used.



Error	**90% confidence**		**95% confidence**	
	N(Cheb)	***N(norm)***	***N(Cheb)***	***N(norm)***
0.005	**100,000**	**27,056**	**200,000**	**38,415**
0.01	**25,000**	**6,764**	**50,000**	**9,604**
0.02	**6,250**	**1,691**	**12,500**	**2,401**
0.03	**2,778**	**752**	**5,556**	**1,068**
0.04	**1,563**	**423**	**3,125**	**600**
0.05	**1000**	**271**	**2000**	**385**
0.1	**250**	**68**	**500**	**97**
0.2	**63**	**17**	**125**	**25**
0.3	**28**	**8**	**56**	**11**
0.4	**16**	**5**	**32**	**4**
0.5	**10**	**3**	**20**	**4**

Table 5:MC error rates on the mean assuming non-parametric and Normal errors

5.1. Graphics results- historical data

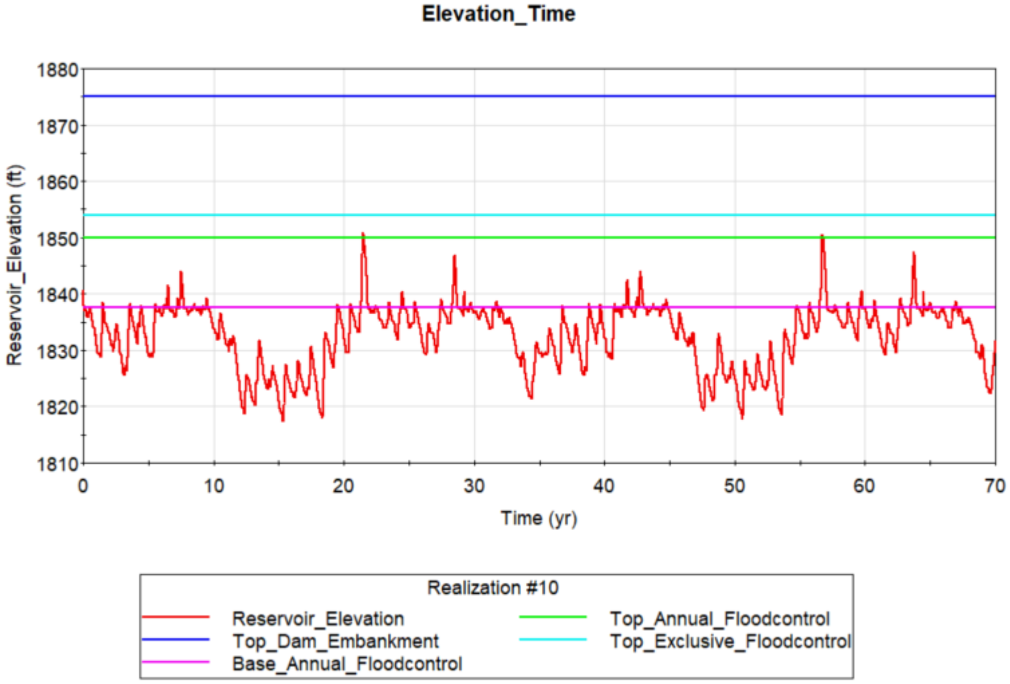


Figure 20: Reservoir elevation change results during the 70-year simulation (Garrison)

The results of the simulation of reservoir elevation at every point in time are shown in Figure 20. In general, the reservoir pool elevation followed the operating rule requirements. The reservoir operates to keep the elevation as close as possible to the top of the conservation pool. Obviously, the figure shows two cycles, one is from year 0 to year 36, and the other from year 36 to year 70. The two cycles are identical since our inflow data were repeated. Most of the time, the reservoir elevation fails down to normal operation zone, and this means no flood occurs. We could roughly see from our results that the reservoir pool elevation reached flood control zone several times in every 36 years. Once it happened, the system will evacuate the water to the base of this zone to provide adequate storage capacity for capturing runoff during the next season.

On the other hand, the figure indicated that in 70years, the spillways release happened twice (22nd year and 56th year) when the pool elevation exceeded the flood control level, and it is evacuated as rapidly as soon to the downstream condition limit in case other damages or incidents happen.

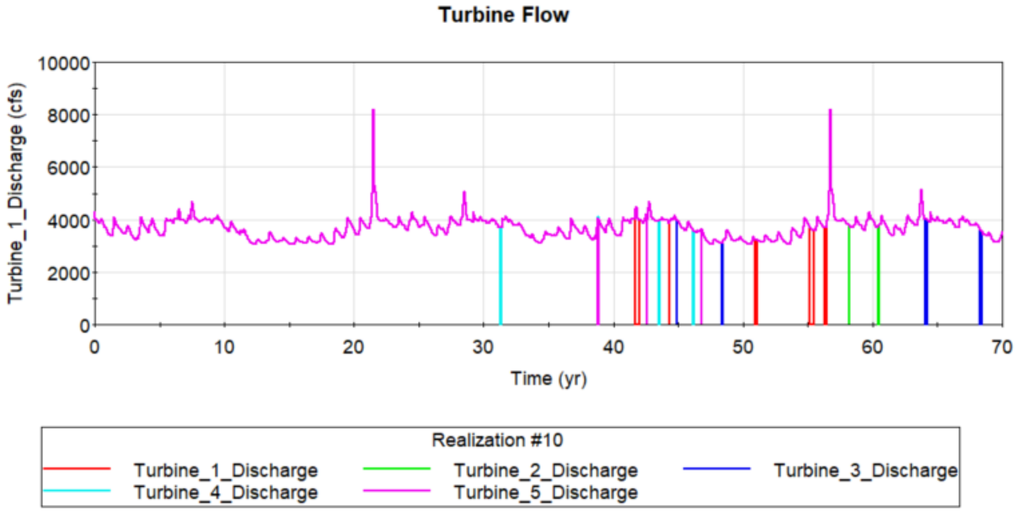


Figure 21: Turbine Flow change results during 70-year simulations (Garrison)

For the 70-year run, it is crucial to analyze the availability of turbines to ensure that it generates sufficient power. In the figure of turbines discharge (Figure 20), none of them failed in the first thirty years, but after that, they failed intensively. The main reason for this is due to the aging of the component. The consequents of turbine failed may bring catastrophes. At this point, it reminds the operator that should be ready to schedule replacement or maintenance before each time the turbine is about to fail. The failure times for each turbine could be overviewed in Table.

	Turbine 1	Turbine 2	Turbine 3	Turbine 4	Turbine 5

Failure counts	9	3	8	4	4

Table 6: Failure times overview for each dam

In GoldSim^{TM}, the status output was given in a specific number to indicate the component status. Table 5 explained it:

Output value	Component status
0	All requirements are met, the component is not failed; it is turned on and operating.
1	A preventive maintenance (that makes the component inoperable) is underway.
2	Internal requirements are not met.
3	External requirements are not met.
4	Element is not turned on.
5	The parent element is not operating.
6	An operating Resource requirement is not met.

Table 7: Component status number in GoldSim^{TM} (Source: Goldsim user's guide)

While we take a close look at the details of the turbine fails, the results of the probability of turbines status numbers (Turbine 1 as an example) are shown in Figures below.

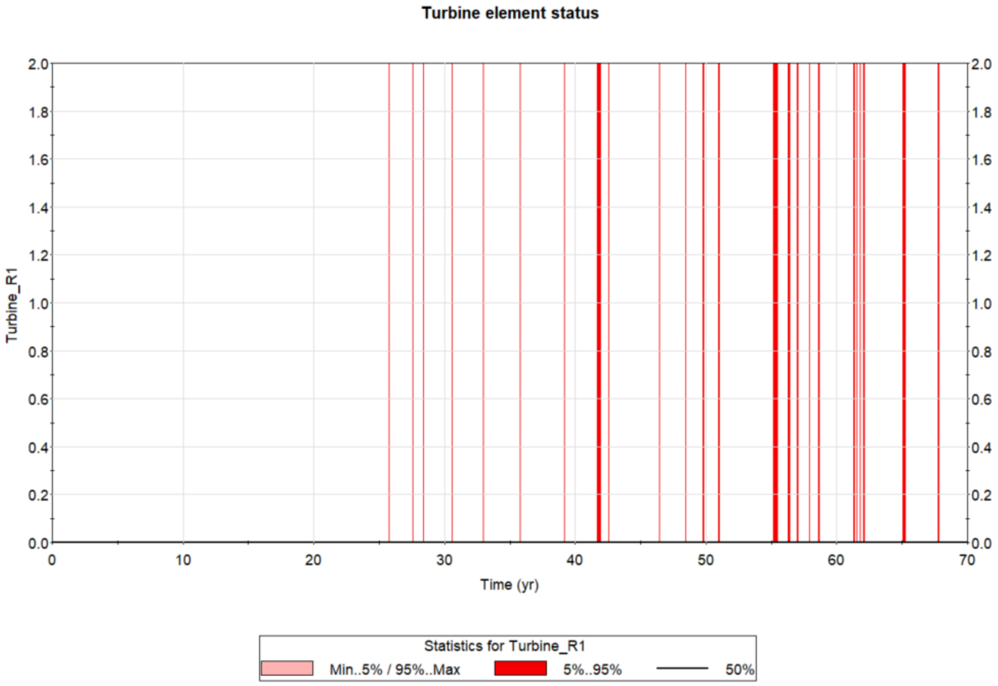


Figure 22: Probability statistics for Turbine 1 failure

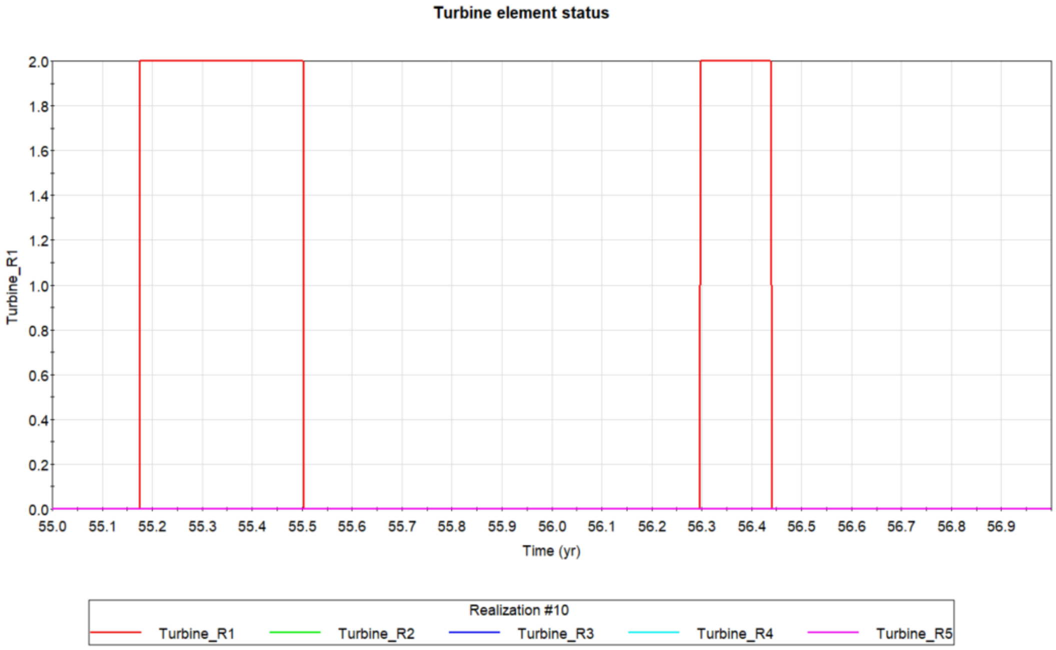


Figure 23: Turbines status zoom out in one year

Figure 22 shows a plot of the probability of turbine 1 status. To prepare for the consequences of turbine failure is important. It can infer from this plot that operators must be on standby once it has the potential likelihood of turbines failed. The operator should pay close attention to the first time when the turbine about to fail, which was approximately in year 25. Even though it not displayed in Figure 21, it has a high likelihood with a rate of 95%.

On the other hand, it is interesting to notice that in the year when the extreme flood was observed (year 56), only turbine 1 failed both before and after that. Figure 23 is the plot of the turbine's status over the two years (year 55 to year 57). It can be seen from Figure 23 that over the years, turbines worked normally expect turbine 1, which failed twice. Therefore, the management needs to ensure that turbine 1 has gone through proper maintenance before and after the flood comes.

Since the value of status (=2) indicated the failure comes from noncompliance with the internal requirements, we could observe from Figure 22 and Figure 23 that the reason for the turbine failure is mostly because of internal incidents or failures. It is suggesting to the operators that they might not need to repair the whole system of turbines but rehabilitate one single component. It also saves time on maintenance because maintaining one component is a more straightforward process than the entire system.

5.2. Statistics results – historical data

After we run the model, *GoldSim*™ automatically represented the reliability metric with high-end (95%), mean and low end (5%). Three types of availability and reliability outputs can be saved and viewed:

a. Mean operational availability: it defined the average fraction of time the component has been operating over the simulated period.
b. Mean inherent availability: it means the average fraction of time the component has been operable over the simulated period. The inherent availability is usually higher than or equal to mean operational availability.
c. Reliability: it represents the probability that the component will survive for the entire simulation.

The results of the reliability table for gates and turbines attached as Appendix 8.3. Note that the reliability may equal to 0 if the component has repeated failures and repairs during the simulation.

From our observing, each gate's components have high operational availability, which nearly 1. It indicates that the system has a strong capacity to operate and performs well. However, the existence of several failures impeded the components to be fully available. Reliability results were almost equal to 0, confirming failure existence. At meanwhile, it reminds the operators that those failures almost the repeated problem, so the operators should schedule maintenance in routine.

In this section, we are also analyzing the reliability of the components in terms of MTTF and MTTR. Both MTTF and MTTR are the indicator of the component's failure. The former one understands the time of component available, and the later one referred to the repair time they need. Studying these indicators could help us understating components failure correctly, and to manage failure in order to reduce negative impacts significantly effectively. These two indicators will be explained more in the following sections.

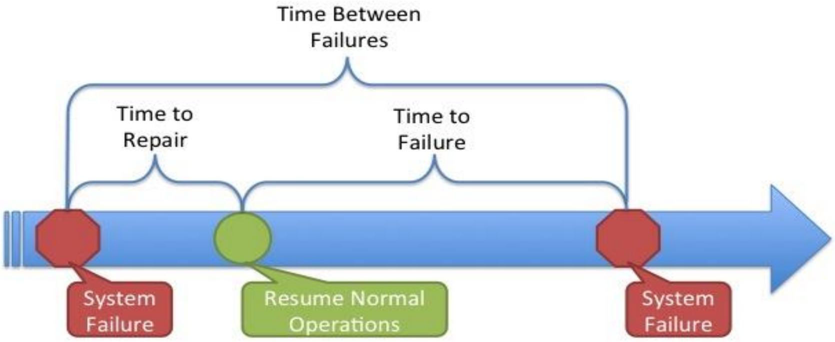


Figure 24: Differential of MTTF and MTTR ("Defining Failure," 2011)

5.2.1. Failure time statistics

The component reliability is quantified as Mean Time to Failure (MTTF) and Mean Time Between Failure (MTBF). At the same time, the MTTF measures the time interval that component has already survived before it fails (which is non-repairable). The MTBF represents the time duration between two errors (which is repairable). The mean value displayed in GoldSim 'Failure Time diagram' is represented to Mean Time to Failure. All results dispatched in Appendix 8.4.

MTTF gave a good likelihood to indicate when the components need to replace. Based on the results of failure time for each internal component, we basically have an idea that stilling basing, which installed in the spillway gate, should be replaced more frequently than others. Because its MTTF number is smaller than others, even though the sub-components of stilling basing have a longer period of MTTF. At this point, it could be noticed that even if a piece of equipment is still running and producing items, it has failed if it does not deliver the expected quantities.

Moreover, the value of MTTF for turbine 1 is 19.87 years. Combining it with our previous section, it alerts the operators should pay special attention as the turbine approaches the 20th year and ensure that the proper maintenance is provided in advance.

5.2.2. Repair times statistics

This parameter measures the time to repair the component, and the mean value represents the Mean Time to Repair (MTTR). Our system’s results shown in Appendix 8.5. Referring to MTTR, the operator could optimize time spent on maintenance that reducing MTTR as much as possible to avoid loss of productivity due to system unavailability.

Therefore, considering different maintenance schedules that adjusting the repair time (refer to MTTF) and repair period (refer to MTTR) will give us a way to determine the best maintenance strategy.

5.3. Four scenarios results- historical data

These scenarios are given to us by the Corps (the owner) because they want to know what the impact is of scheduling the maintenance in four ways. The results of elevations changed were looking like followings：

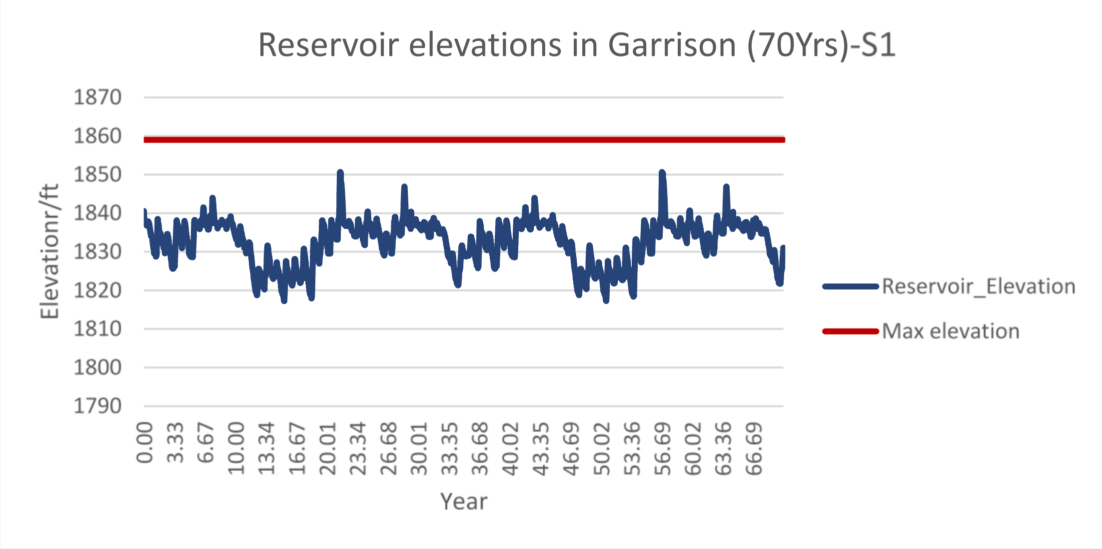


Figure 25(1) Reservoir elevation change in scenario 1.

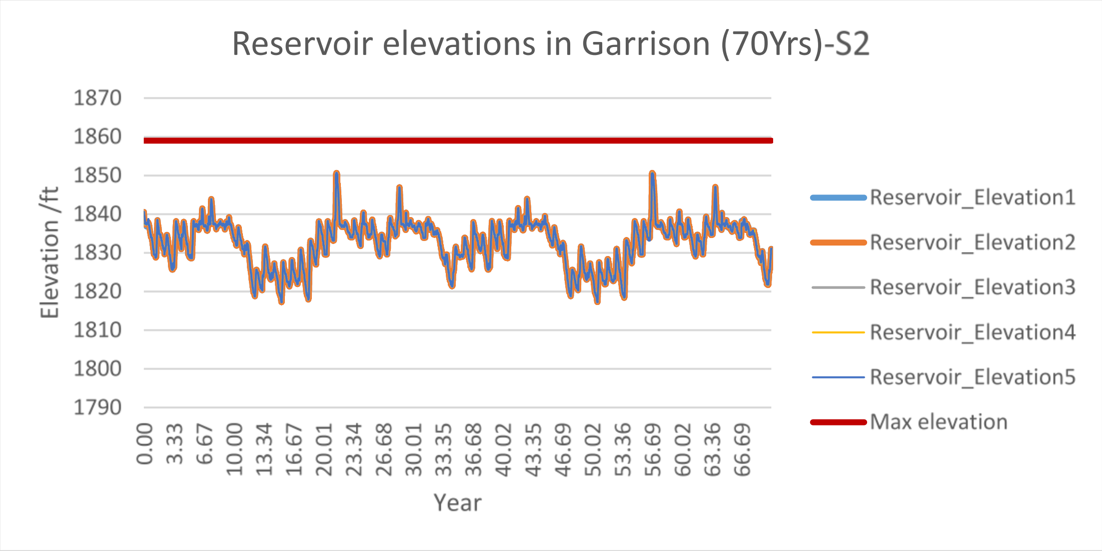


Figure 25(2) Reservoir elevation change in scenario 2.

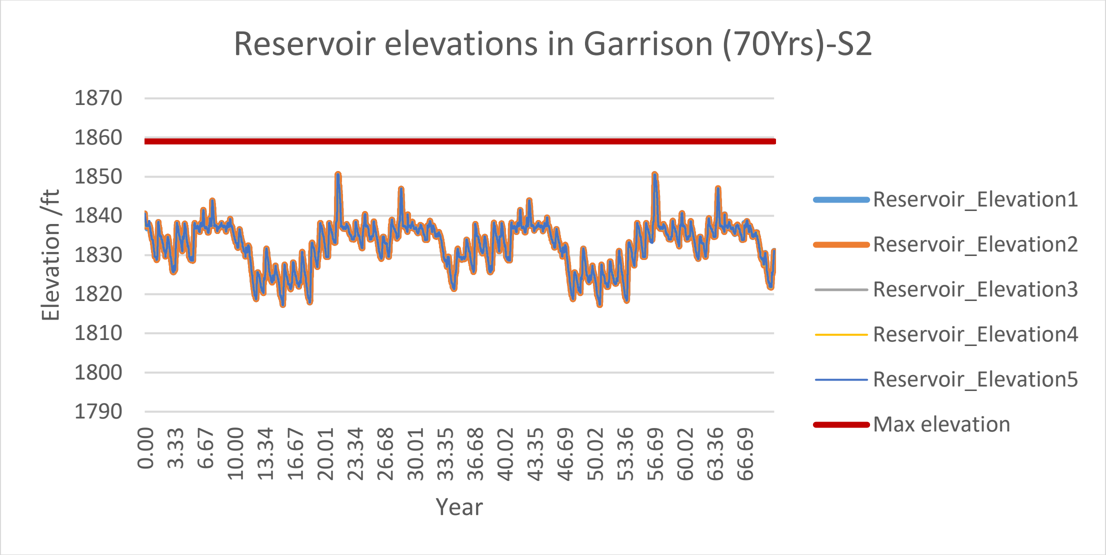


Figure 25(3) Reservoir elevation change in scenario 3.

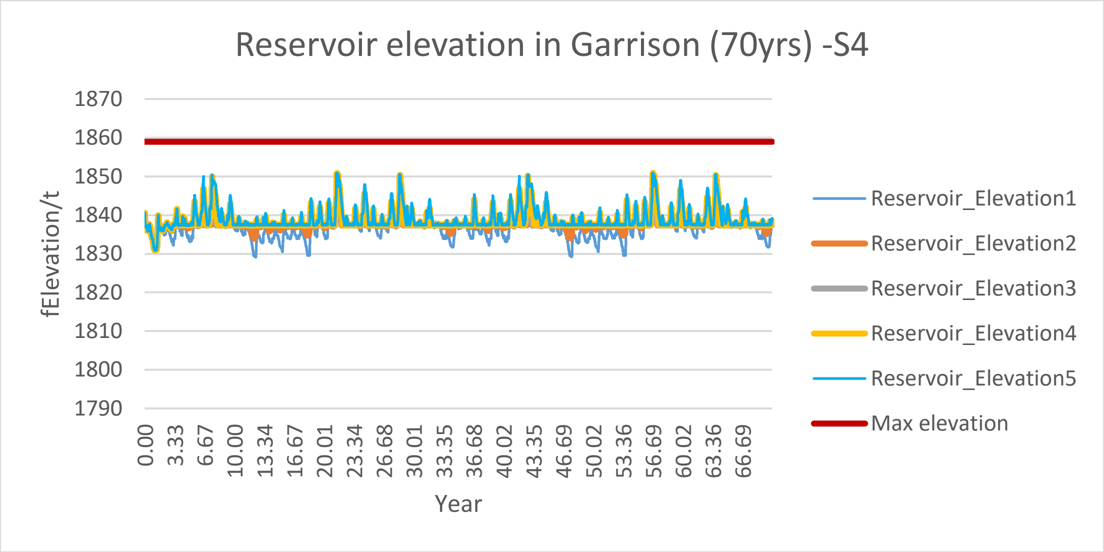


Figure 25(4) Reservoir elevation change in scenario 4.

Figure 25: Reservoir elevation change in four different scenarios

From Figure 25 above, it can observe that scenario 1, scenario 2, and scenario 3 were very similar. All of them have two cycles. However, reservoir elevations have a significant difference in scenario 4. First, the range of the elevations in scenario 4 was much shorter than the others. The other alternative scenarios have the minimum bond below 1820 ft, while scenario 4 only reaches to 1830ft. Secondly, all of these scenarios have the maximum elevation closes to 1850 ft, which is only 10ft below the top of the dam. Nevertheless, in the last scenario, the elevation goes up to the maximum bond frequently, while this happened only twice for the other three scenarios in 70 years simulations. The reason for this phenomenon happened could be explained to more power generations we take off and remove them for a long period.

5.4. Stochastic Time-series

Besides the uncertainty of the random nature of the stochastic variables in components, the uncertainty of streamflow is also vitally important. In order to investigate the effects of inflow uncertainty, streamflow forecasting provides a way to explore past behavior in the future. For many activities associated with the planning and operation of the hydrologic components, the forecast of streamflow will also be beneficial to optimize the system.

The forecasting techniques are varying. Based on time-series approaching, we have model tree (MT), artificial neutral network (ANN), autoregressive (AR), autoregressive integrated moving average (ARIMA) and autoregressive moving average (ARMA) methods to build a streamflow forecast model. Among these methods, ARIMA is the most effective approach for time series analysis because it allows the user to forecast future even if they do not have related time-series data for the streamflow(Attah & Bankole, 2011).

In our thesis, the Box-Jenkins methodology was used to build an ARIMA model in the R language for the seasonal streamflow data taken from the Garrison dam for 36 years. The steps follow in two parts:

1. Fitting the models and predictions.
2. Improving the model

To better fit our model, we divided the data into two sections of training (=30years) and test (=6years) period. After forecasting the aggregate data for six years, we tried to find the residuals between the forecasted data and the real data (test data). Based on the trends in the residuals, we improved the model to achieve the most precise prediction. Similarly, we forecasted the raw data (36 years) for the next 30 years and compared it with our training data to get better results. Our ARIMA model for Garrison's daily inflow forecasting looks like in Figure 26.

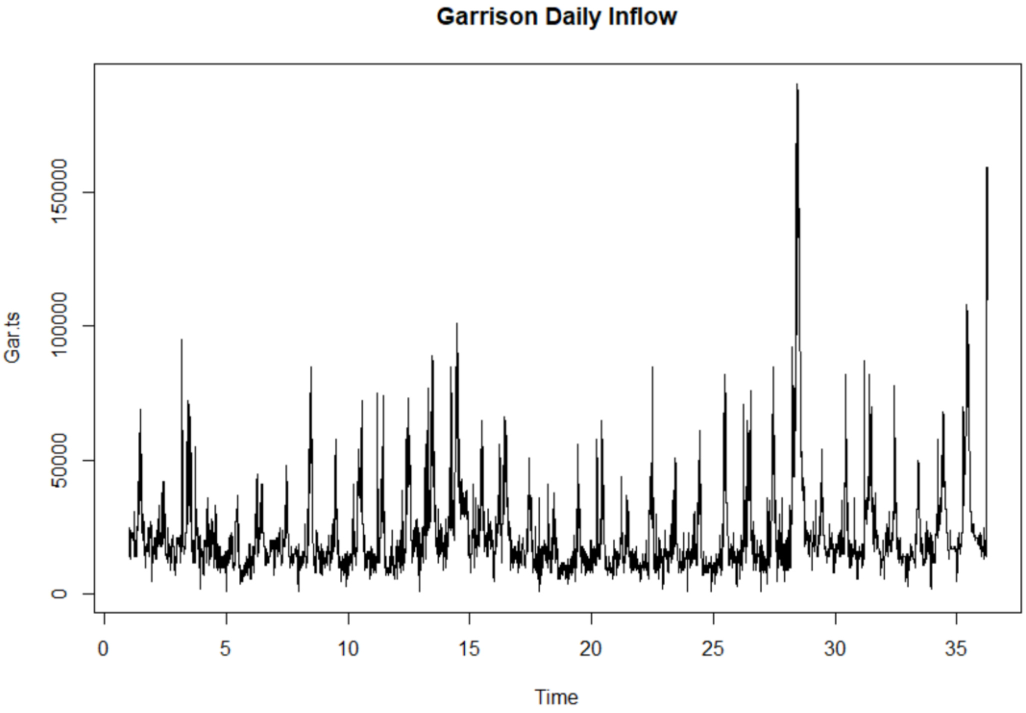


Figure 26:Forecasting model for Garrison daily inflow (Source:Afshin Fallahi)

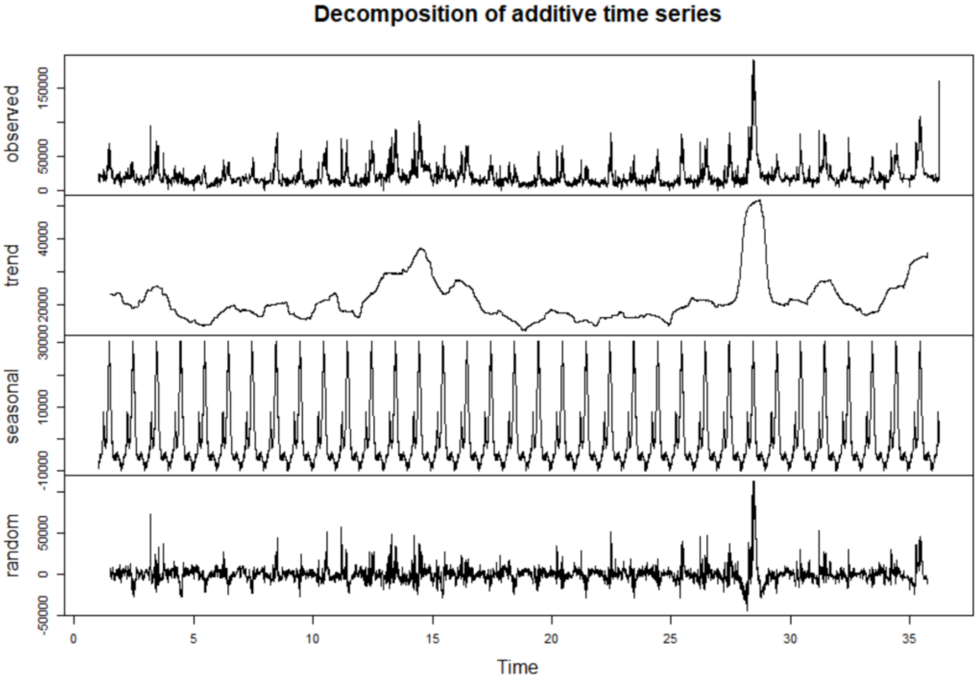


Figure 27: Decomposition of additive time series (Source:Afshin Fallahi)

On the other hand, we also took the time -series of outflows from the upstream reservoir (Fort Peck) and time-series of inflows to the next reservoir downstream (Garrison). And then we moved them in time until we get the maximum correlation. This action allows us to get the relatively reasonable ‘travel time’ of the flows between two nearby dams. The result of the correlation values shows in Figure 28.

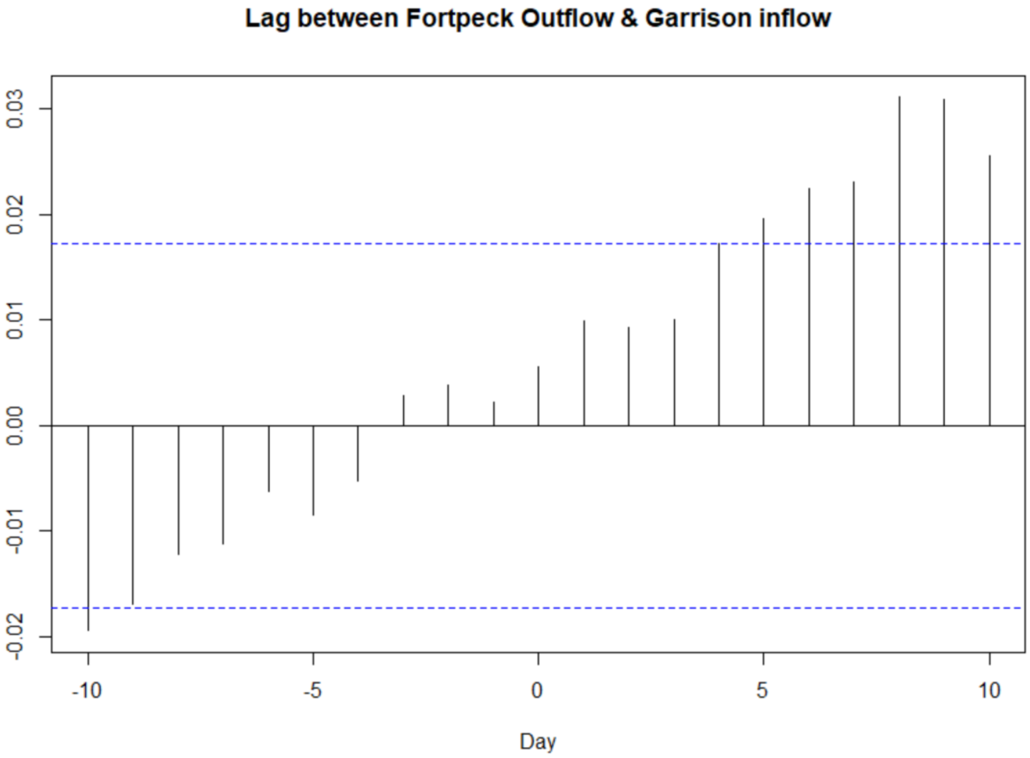


Figure 28: Correlation results

Based on Figure 28, the best value is between day (-4) and day (-3). It means that each value in the upstream dam (Fort Peck) outflow time series can be a predictor of value – 3 days later in the Garrison dam inflow time series.

Besides, replacing current historical data with our stochastic time series inflow in the Garrison Dam is another aspect we tried to analyze the performance of the system. The results of 36 years simulation ten times conducted in the following Figure 29.

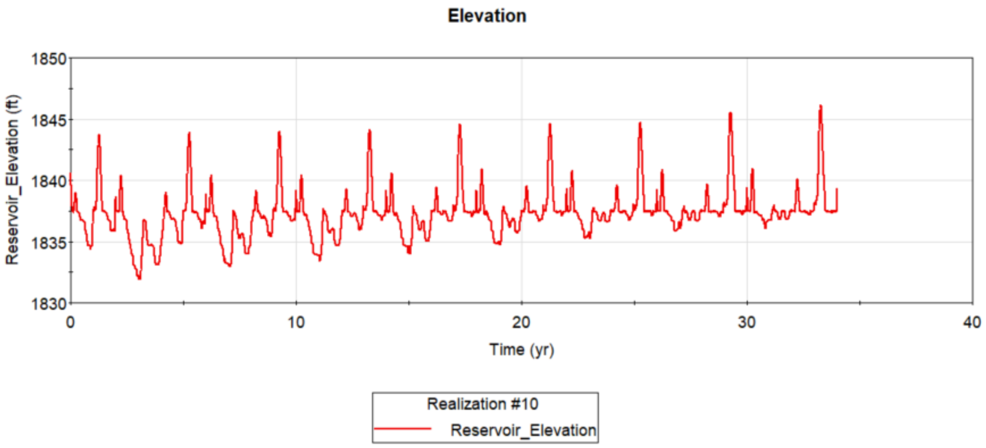


Figure 29: Time-series model results

Compared to our general model results, we find the reservoir elevation variance in the current model is much less than previously. It only goes to 1844ft and lowers down at 1832ft. It also could be noticed that the peak of the elevation slightly increases, and it might result in increasing inflow in the future. With the possibility of such a trend happening in the future, the operators must develop a maintenance schedule advance in case multiple failures occur.

Unfortunately, we have seen the results displayed a lot of cycles, which is abnormal in the real-world, and we did not find an alternative way to solve this problem within our research time. Thus, some further work that contributes to this problem is needed in the future.

6. Conclusions

There is a growing tendency to use simulation of dam systems to study dam safety on an operational basis. The risk of dam behavior is a complex problem and cannot be evaluated just by pure historical data (Rohaninejad & Zarghami, 2012). The causes of dam failure are not merely from physical damage, design error, or any other distinct reasons, but also unusual combinations of many common things. These unexpected combinations triggered by common events, but they do not follow regular operational orders. The contemporary methods usually study dam performance with separate failure modes and treat each operational event independently, which limits the evaluation of the interaction of system components. The system reliability approach addresses these weaknesses using contemporary simulation methods. It does so by treating engineered structures and human operation as a system.

This study presents the framework of how we develop an operational reliability-based model. The data outputs of the reliability module enable us to identify the reliability and availability of each component, and analysis of the failure caused roots. By tracking the structure and nature of interactions among failure mechanisms, it could be determining the states of system or subcomponent during the simulation. Additionally, referring to the distribution results of MTTF, when the components expect to fail have been known, and the distribution of MTTR given information on how often components need to repair, both parameters allow the operator to plan maintenance and repair time effectively in advance. On the other hand, our four scenarios examined the impacts of different maintenance schedule applied.

Meanwhile, we used the time-series to access the inflow leg between two nearly dams and replaced historical data with stochastic time-series inflow.

To conclude, the results of the thesis can state as follows:

1. There is no overtopping except two exclusive floods occurred, and there were two cycles for the reservoir elevations when we used the historical data from Corps engineer.
2. The turbines and spillways failed mostly consequently from internal reasons.
3. The first three scenarios came results similarly, and they do not have many impacts, but the fourth one did have significantly different effects.

7. Limitations and future work

Missouri River Mainstem Reservoir system consists of six dams and operates as a hydraulically and electrically integrated system. In our thesis, only the biggest dam (Garrison) has been studied. The daily inflows discharge influenced by the upper dam, and the outflows will affect the downstream dam. Thus, take the Garrison dam as a dependent system cannot fully understand the performance of the whole system in the Missouri River.

7.1. Limitations of the current work

Our model data based on historical records; however, in the real-life that will be more complex. Such as the failure modes for each component, we just modeling the uncertainty that has happened before or the event we are foreseeable, the probability of potential failure may inevitably omit due to lack of knowledge and experience. The external disturbance, such as earthquakes, will cause a significant incident to the system. We did not consider these natural disasters because we do not have a feasible method to accommodate these in our reliability system. Moreover, historical data obtained from physical equipment, and unfortunately, measurement errors occur commonly.

The typical problem states in our thesis are the relationship between the powerhead and turbine flow. The correlation function is hard to achieve since the points scattered located. The initial elevation, pool elevations, and daily inflow discharge were all read from historical documentation. Hence, the question about the accuracy of those data was undoubted. Even though we have an excellent polynomial function for the

Garrison dam, it still has a large number of points that did not fit this line and physical we know the line should be linear.

On the other hand, the uncertainty in measurement may also cause the spillway rating curves to have significant errors at the regular gate opening. This curve typically calculated from the discharge coefficient, flow, head, velocity, and width. Those paraments are all associate the measurement error, and their error compounds as measurements combine into equations (Haug et al., 2014). Since the rating curves are important to our gates operation and also related to energy generation, the model we developed will be inconsistent with the real system. Except for the measurement errors in the rating curve, the other data such as upstream daily inflow, reservoir elevation, etc. are all affected by the measurement precision. In further analysis, those errors will account for the reliability of the model.

Regards to those uncertainties in measurement, one suggested solution is defining how much risk in original data and then calibrate the existing rating curve. Besides, the owner of dams may take a chance to replace them with highly sensitive equipment.

7.2. Future work directions

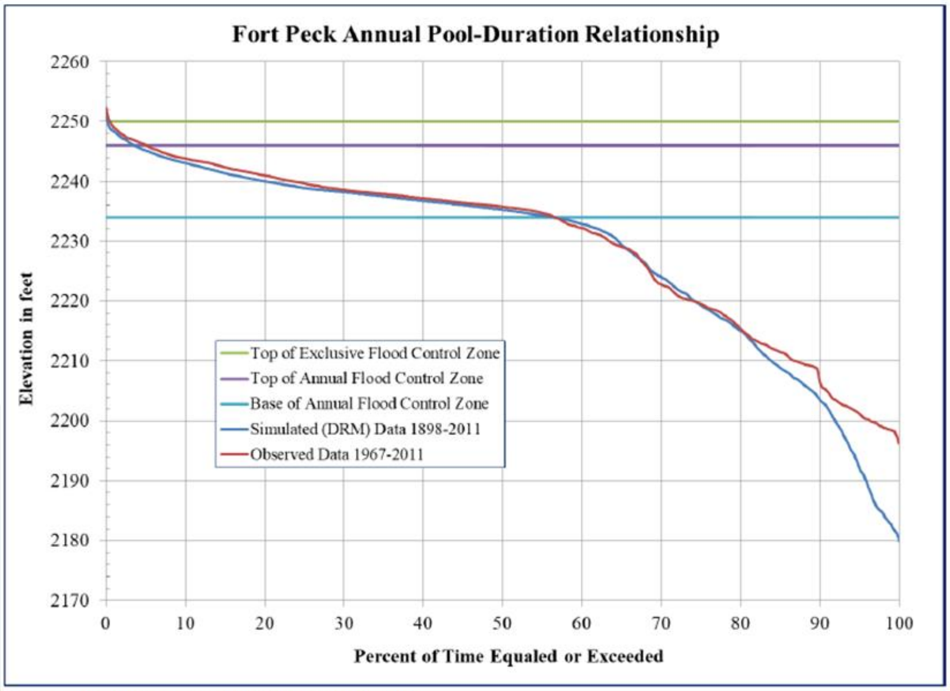
The long-term goal for our thesis is to study the performance of the multi-reservoirs in multipurpose. To integrate the six mainstem dams as one system to evaluates the performance will be our next work.

Our operational reliability-based model develops to assess and manage the risks of the dam system operational aspects. However, the risk of dam behavior is also the majority caused by external disturbance. Considering how to comply with the probabilities of those disturbances to our system's reliability assessment is one of our future work. Additionally, our limited failure modes require more further research on understanding the complexity of components of the inherent property and their interactions. In further, the measurement errors were inevitably existing, studying the percentile of these uncertainties will provide a way to improve the model system's reliability.

Moreover, reservoir operation involves a complex set of human decisions depending upon hydrologic conditions in the supply network, including watersheds, lakes, transfer tunnels, and rivers ((Karamouz & Mousavi, 2003). The uncertainty of inflow needs to consider in our reliability model framework. Even though we applied a time-series approach to forecasting the streamflow, the results did not make sense. Studying how to improve our forecast model is another challenge we should focus on in the future. Furthermore, the upper reservoir's outflow is a small portion of the inflow for the next reservoir down. Additional resources, such as rainfalls, should take into account in our forecast model. However, the way to get adequate data for those resources is extremely hard. Thus, finding a new mathematic approach that includes the most parameters that affect the uncertainty of inflows is necessary for our future research.

Appendices

1. Pool-duration relationship curve for each dam



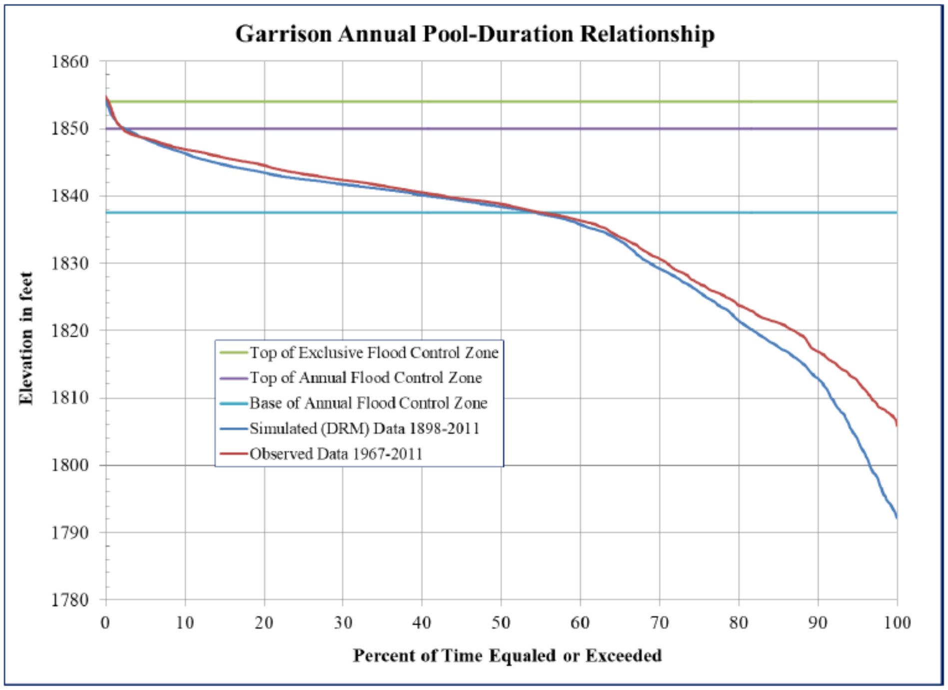
Source: Hydrologic Statistics, MRBWM, September 2013

Missouri River Basin
Mainstem Master Water Control Manual
Fort Peck Pool-Duration Relationship
U.S. Army Engineer Division, Northwestern
Corps of Engineers, Omaha, Nebraska
November 2018

Plate II-14

Missouri River Basin
Mainstem Master Water Control Manual
Garrison Pool-Duration Relationship
U.S. Army Engineer Division, Northwestern
Corps of Engineers, Omaha, Nebraska
November 2018

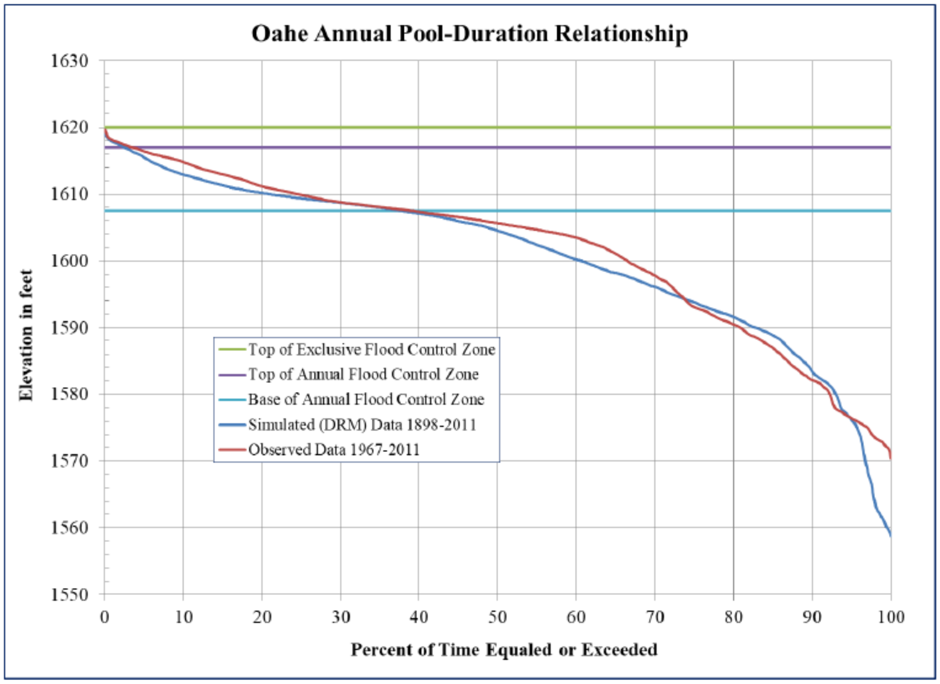
Plate II-28



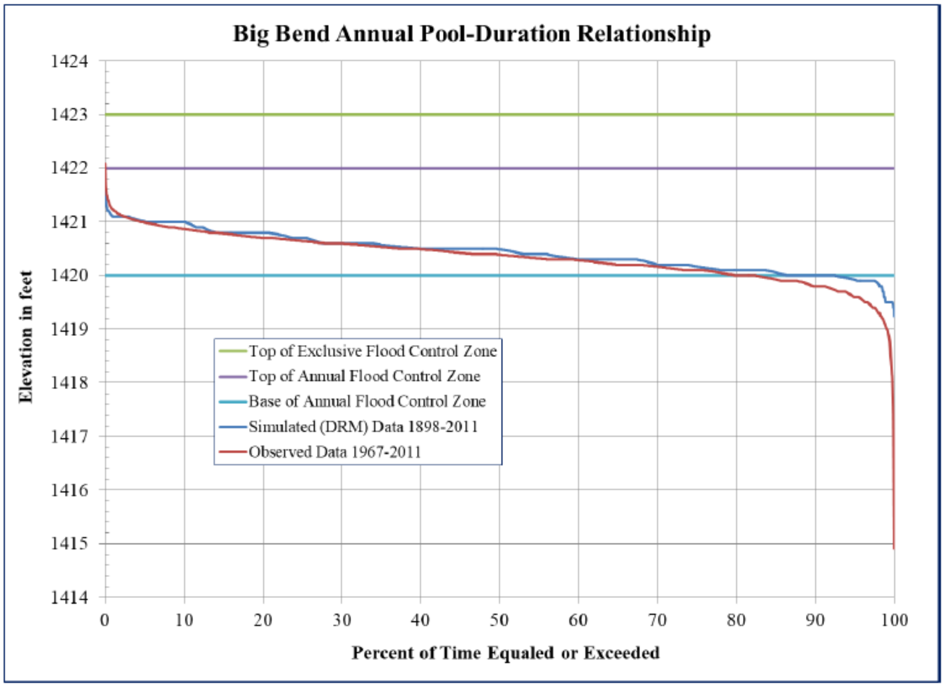
Source: Hydrologic Statistics, MRBWM, September 2013

Missouri River Basin
Mainstem Master Water Control Manual
Oahe Pool-Duration Relationship
U.S. Army Engineer Division, Northwestern
Corps of Engineers, Omaha, Nebraska
November 2018

Plate II-41



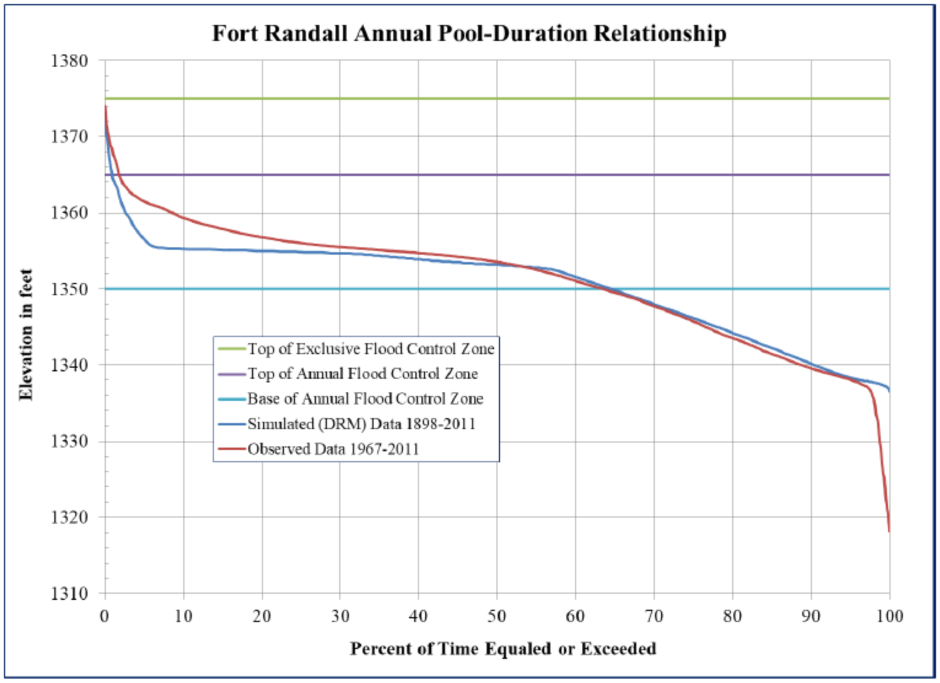
Source: Hydrologic Statistics, MRBWM, September 2013



Source: Hydrologic Statistics, MRBWM, September 2013

Missouri River Basin
Mainstem Master Water Control Manual
Big Bend Pool-Duration Relationship
U.S. Army Engineer Division, Northwestern
Corps of Engineers, Omaha, Nebraska
November 2018

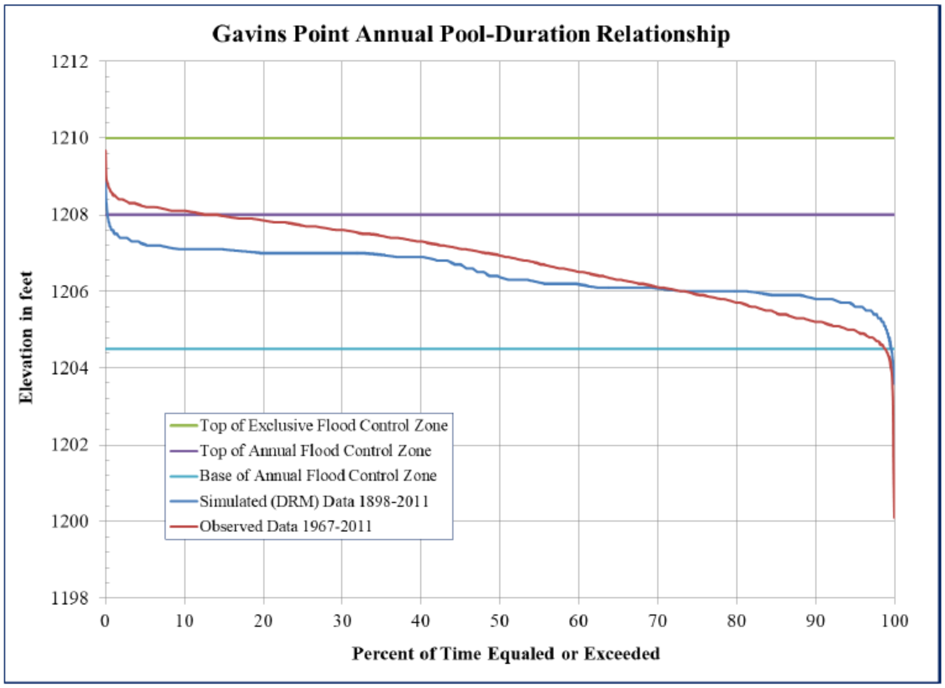
Plate II-53



Source: Hydrologic Statistics, MRBWM, September 2013

Missouri River Basin
Mainstem Master Water Control Manual
Fort Randall Pool-Duration Relationship
U.S. Army Engineer Division, Northwestern
Corps of Engineers, Omaha, Nebraska
November 2018

Plate II-66

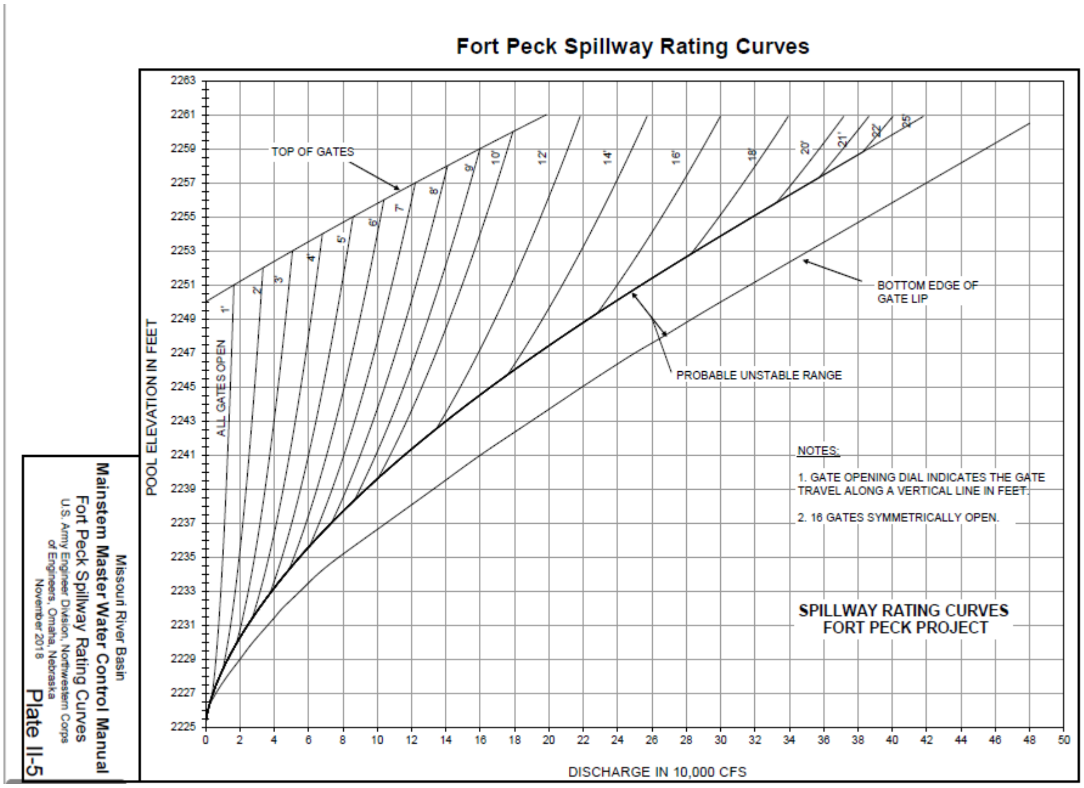


Source: Hydrologic Statistics, MRBWM, September 2013

Missouri River Basin
Mainstem Master Water Control Manual
Gavins Point Pool-Duration Relationship
U.S. Army Engineer Division, Northwestern
Corps of Engineers, Omaha, Nebraska
November 2018

Plate II-78

2. Spillway rating curve for each dam



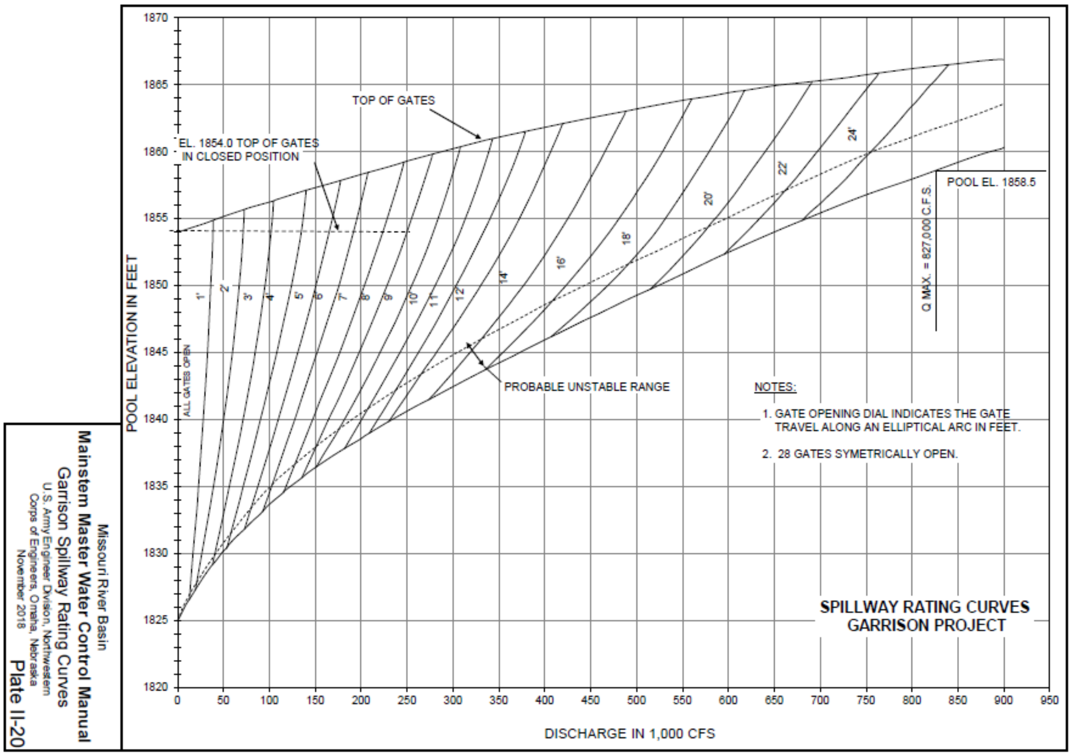
NOTES:

1. GATE OPENING DIAL INDICATES THE GATE TRAVEL ALONG A VERTICAL LINE IN FEET.

2. 16 GATES SYMMETRICALLY OPEN.

Missouri River Basin
Mainstem Master Water Control Manual
Fort Peck Spillway Rating Curves
U.S. Army Engineer Division, Northwestern Corps
of Engineers, Omaha, Nebraska
November 2018
Plate II-5

Garrison Spillway Rating Curves



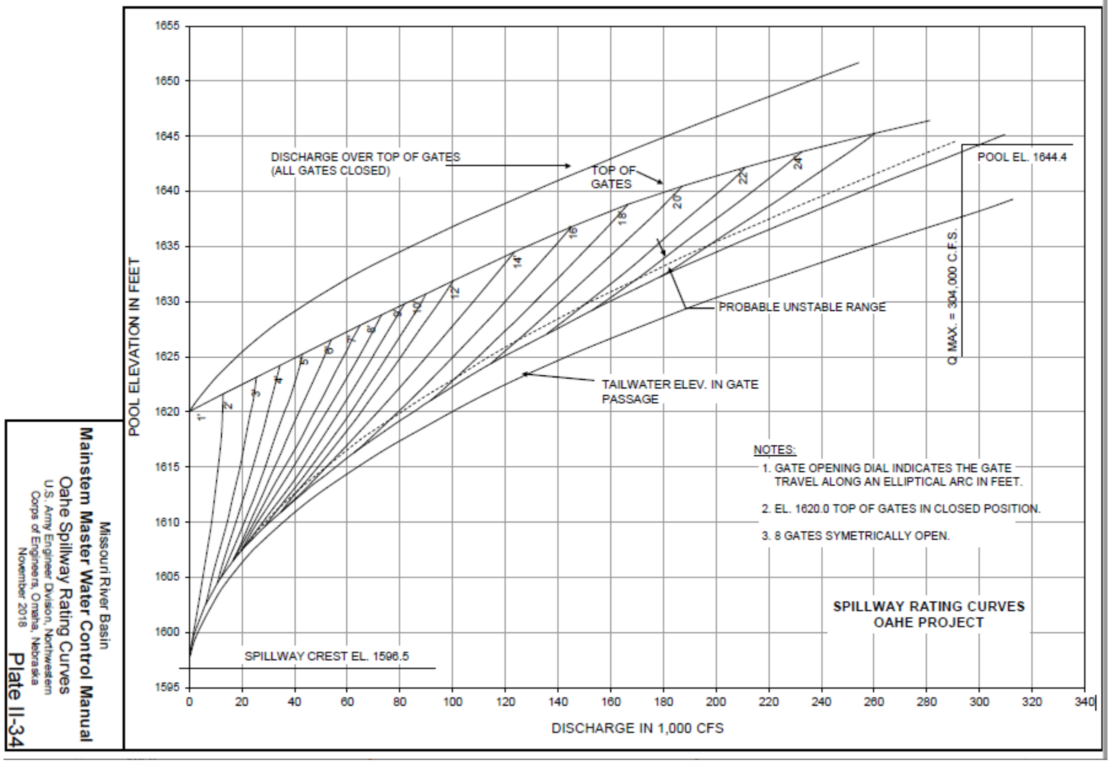
NOTES:

1. GATE OPENING DIAL INDICATES THE GATE TRAVEL ALONG AN ELLIPTICAL ARC IN FEET.
2. 28 GATES SYMETRICALLY OPEN.

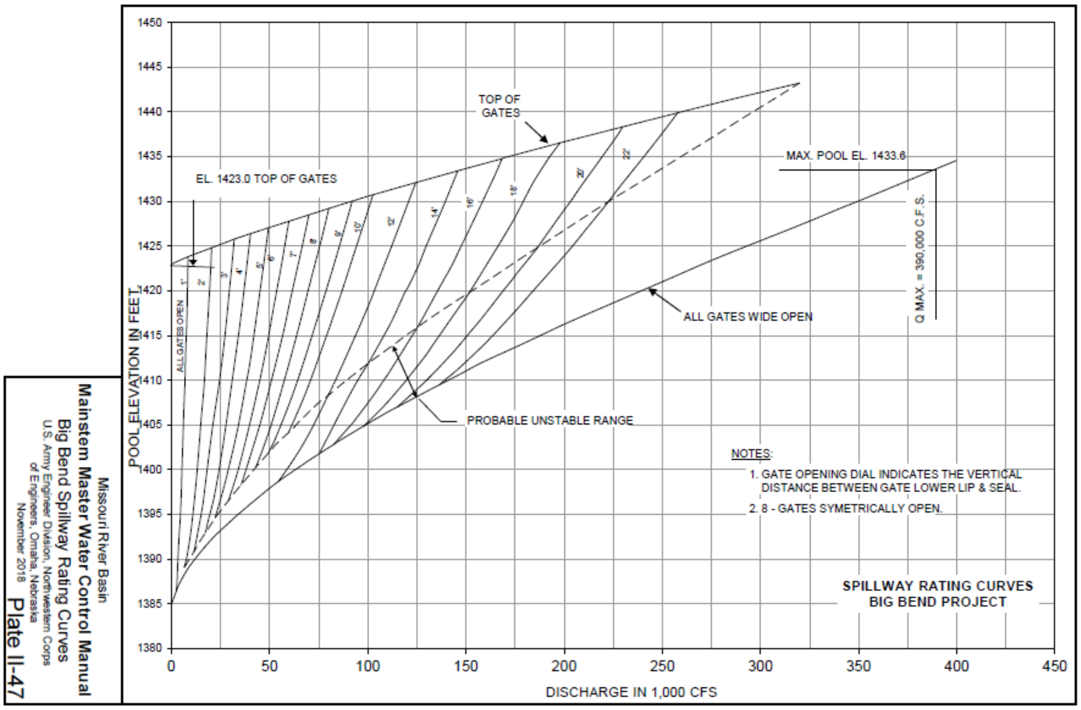
Missouri River Basin
Mainstem Master Water Control Manual
Garrison Spillway Rating Curves
U.S. Army Engineer Division, Northwestern
Corps of Engineers, Omaha, Nebraska
November 2018

Plate II-20

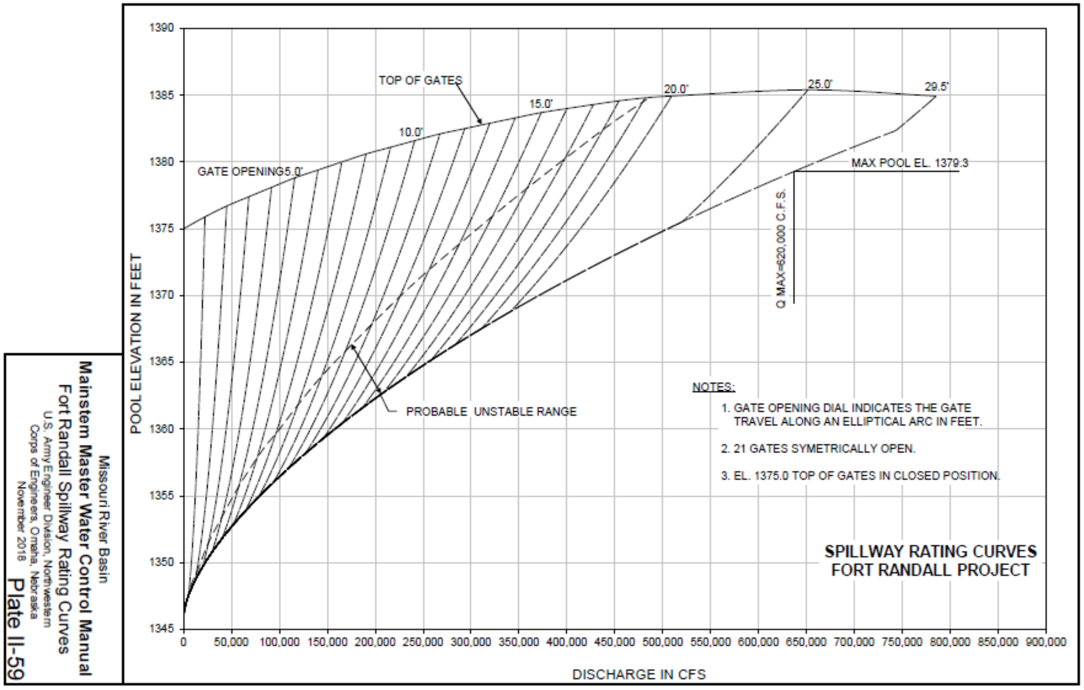
Oahe Spillway Rating Curves



Big Bend Spillway Rating Curves



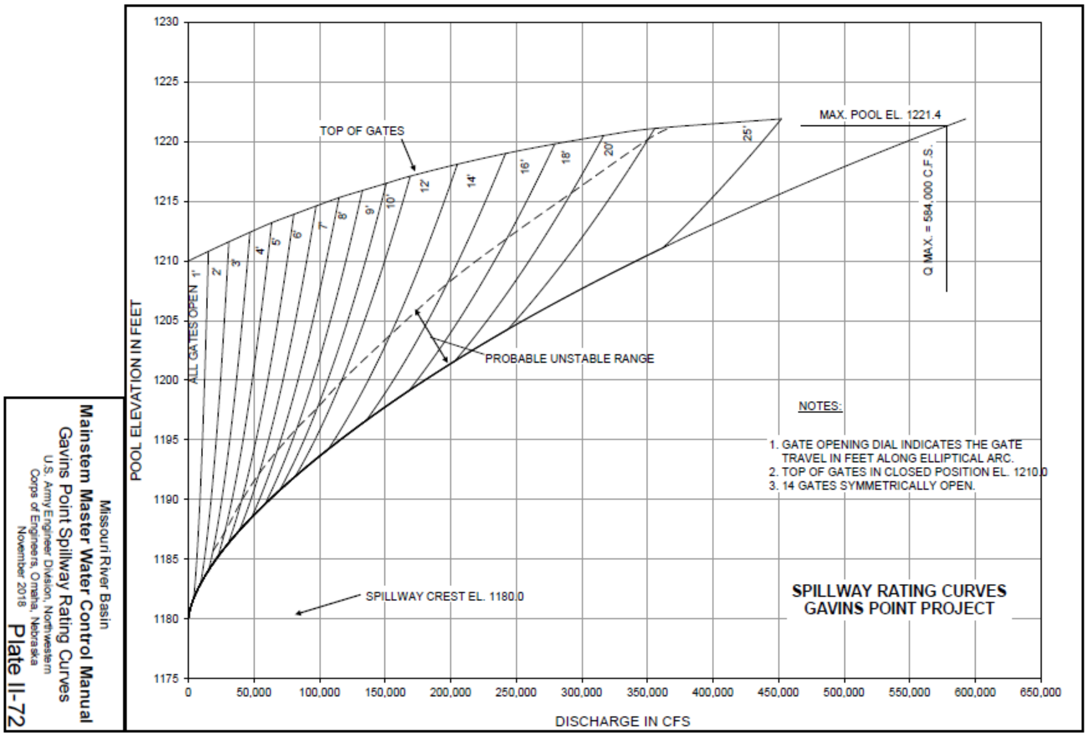
Fort Randall Spillway Rating Curves



NOTES:

1. GATE OPENING DIAL INDICATES THE GATE TRAVEL ALONG AN ELLIPTICAL ARC IN FEET.
2. 21 GATES SYMETRICALLY OPEN.
3. EL. 1375.0 TOP OF GATES IN CLOSED POSITION.

Gavins Point Spillway Rating Curves



NOTES:

1. GATE OPENING DIAL INDICATES THE GATE TRAVEL IN FEET ALONG ELLIPTICAL ARC.
2. TOP OF GATES IN CLOSED POSITION EL. 1210.0
3. 14 GATES SYMMETRICALLY OPEN.

3. Reliability and availability results summary

Gates results:

Measure	Confidence Bounds		
	5%	mean	95%
Operational Availability	0.96-0.97	0.97	0.97-0.98
Inherent Availability	0.96-0.97	0.97	0.97-0.98
Reliability	0.00	0.00	0.00

Turbine 1 results:

Measure	Confidence Bounds		
	5%	mean	95%
Operational Availability	0.99	1	1
Inherent Availability	0.99	1	1
Reliability	0.01	0.10	0.28

Turbine 2 results:

Measure	Confidence Bounds		
	5%	mean	95%
Operational Availability	1	1	1
Inherent Availability	1	1	1
Reliability	0	0	0

Turbine 3 results:

Measure	Confidence Bounds		
	5%	mean	95%
Operational Availability	0.99	1	1
Inherent Availability	0.99	1	1

Reliability	0	0	0

Turbine 4 results:

Measure	Confidence Bounds		
	5%	mean	95%
Operational Availability	1	1	1
Inherent Availability	1	1	1
Reliability	0	0	0

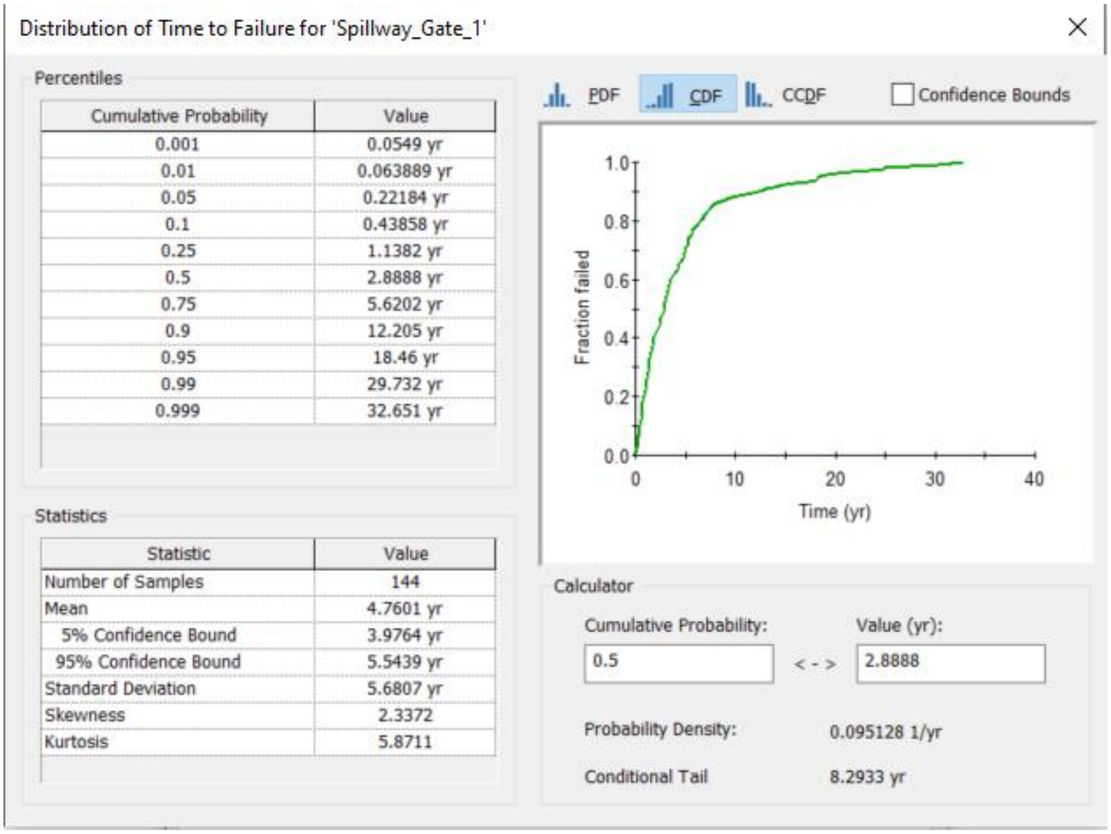
Turbine 5 results:

Measure	Confidence Bounds		
	5%	mean	95%
Operational Availability	1	1	1

Inherent Availability	1	1	1
Reliability	0	0	0

4. Failure Time results for Garrison dam

Typical spillway gate (Gate 1 was selected):



Distribution of Time to Failure for 'Spillway_Gate_1'

Percentiles

Cumulative Probability	Value
0.001	0.0549 yr
0.01	0.063889 yr
0.05	0.22184 yr
0.1	0.43858 yr
0.25	1.1382 yr
0.5	2.8888 yr
0.75	5.6202 yr
0.9	12.205 yr
0.95	18.46 yr
0.99	29.732 yr
0.999	32.651 yr

Statistics

Statistic	Value
Number of Samples	144
Mean	4.7601 yr
5% Confidence Bound	3.9764 yr
95% Confidence Bound	5.5439 yr
Standard Deviation	5.6807 yr
Skewness	2.3372
Kurtosis	5.8711

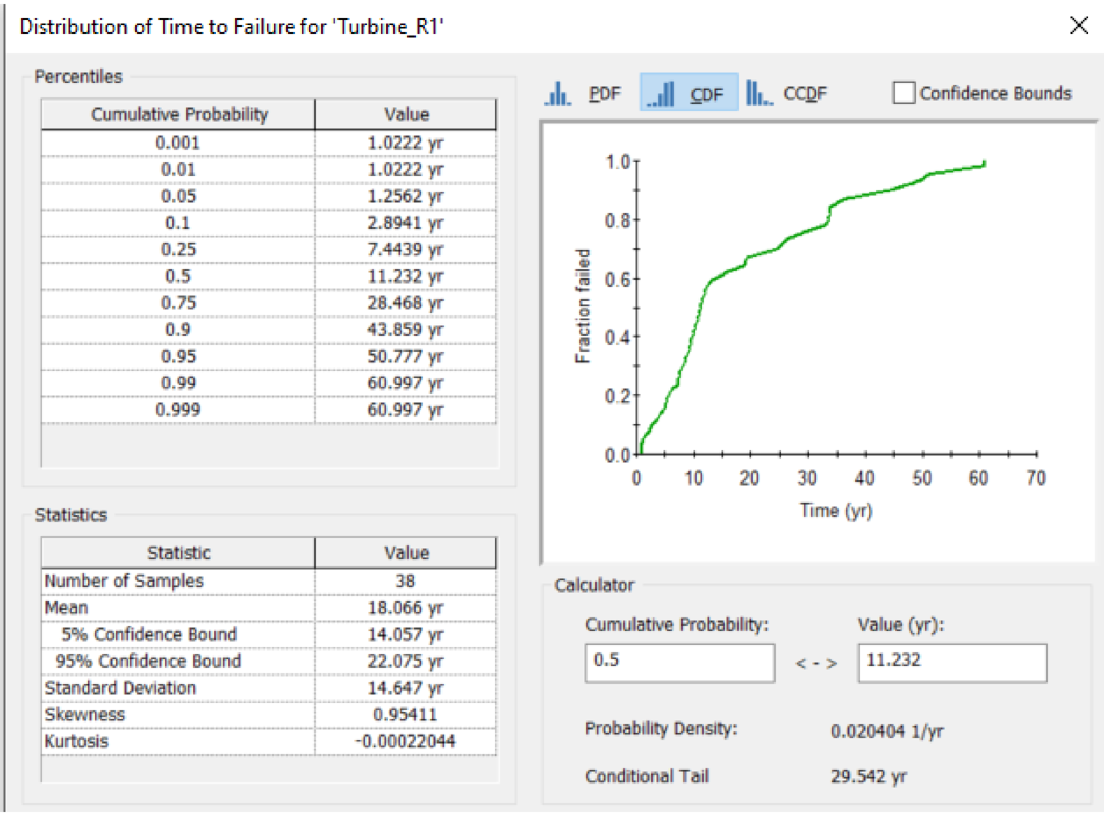
Calculator

Cumulative Probability: 0.5 < - > Value (yr): 2.8888

Probability Density: 0.095128 1/yr

Conditional Tail 8.2933 yr

Typical turbines results (turbine 1 was selected):



Percentiles

Cumulative Probability	Value
0.001	1.0222 yr
0.01	1.0222 yr
0.05	1.2562 yr
0.1	2.8941 yr
0.25	7.4439 yr
0.5	11.232 yr
0.75	28.468 yr
0.9	43.859 yr
0.95	50.777 yr
0.99	60.997 yr
0.999	60.997 yr

Statistics

Statistic	Value
Number of Samples	38
Mean	18.066 yr
5% Confidence Bound	14.057 yr
95% Confidence Bound	22.075 yr
Standard Deviation	14.647 yr
Skewness	0.95411
Kurtosis	-0.00022044

Calculator

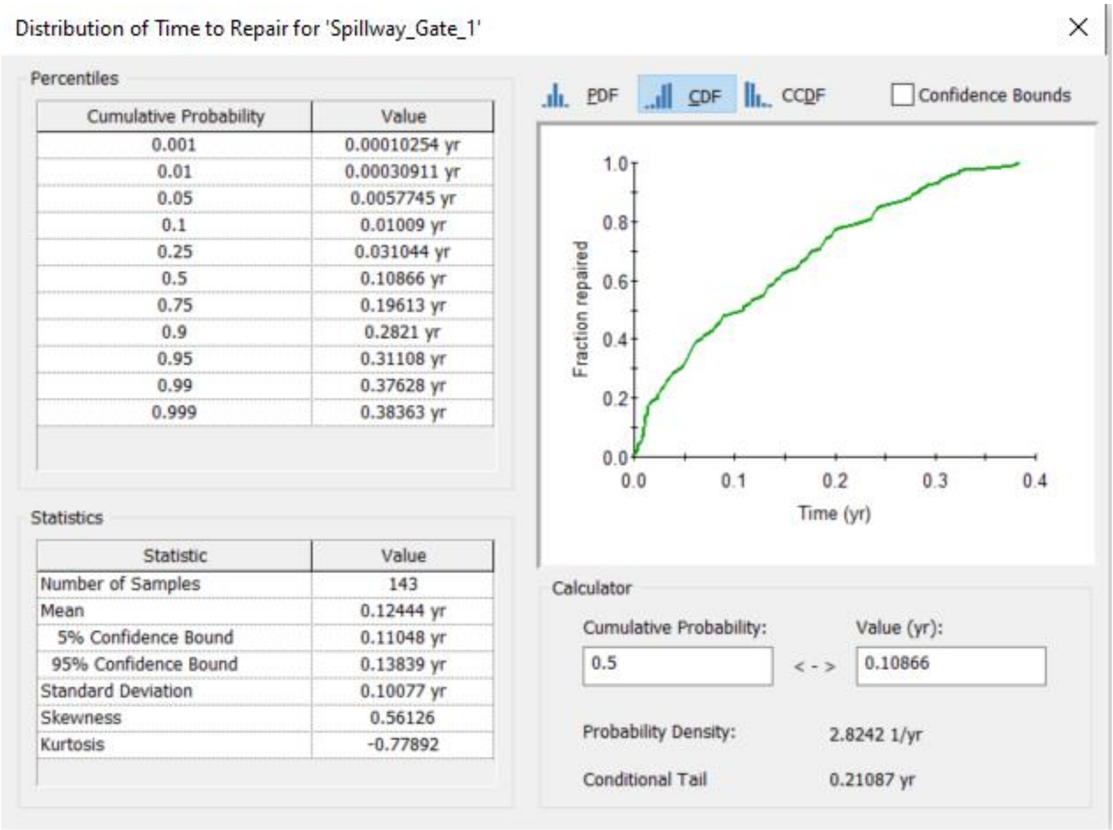
Cumulative Probability: 0.5 < - > Value (yr): 11.232

Probability Density: 0.020404 1/yr

Conditional Tail 29.542 yr

5. Repair Time results for Garrison dam

Typical spillway gate (Gate 1 was selected):



Distribution of Time to Repair for 'Spillway_Gate_1'

Percentiles

Cumulative Probability	Value
0.001	0.00010254 yr
0.01	0.00030911 yr
0.05	0.0057745 yr
0.1	0.01009 yr
0.25	0.031044 yr
0.5	0.10866 yr
0.75	0.19613 yr
0.9	0.2821 yr
0.95	0.31108 yr
0.99	0.37628 yr
0.999	0.38363 yr

Statistics

Statistic	Value
Number of Samples	143
Mean	0.12444 yr
5% Confidence Bound	0.11048 yr
95% Confidence Bound	0.13839 yr
Standard Deviation	0.10077 yr
Skewness	0.56126
Kurtosis	-0.77892

Calculator

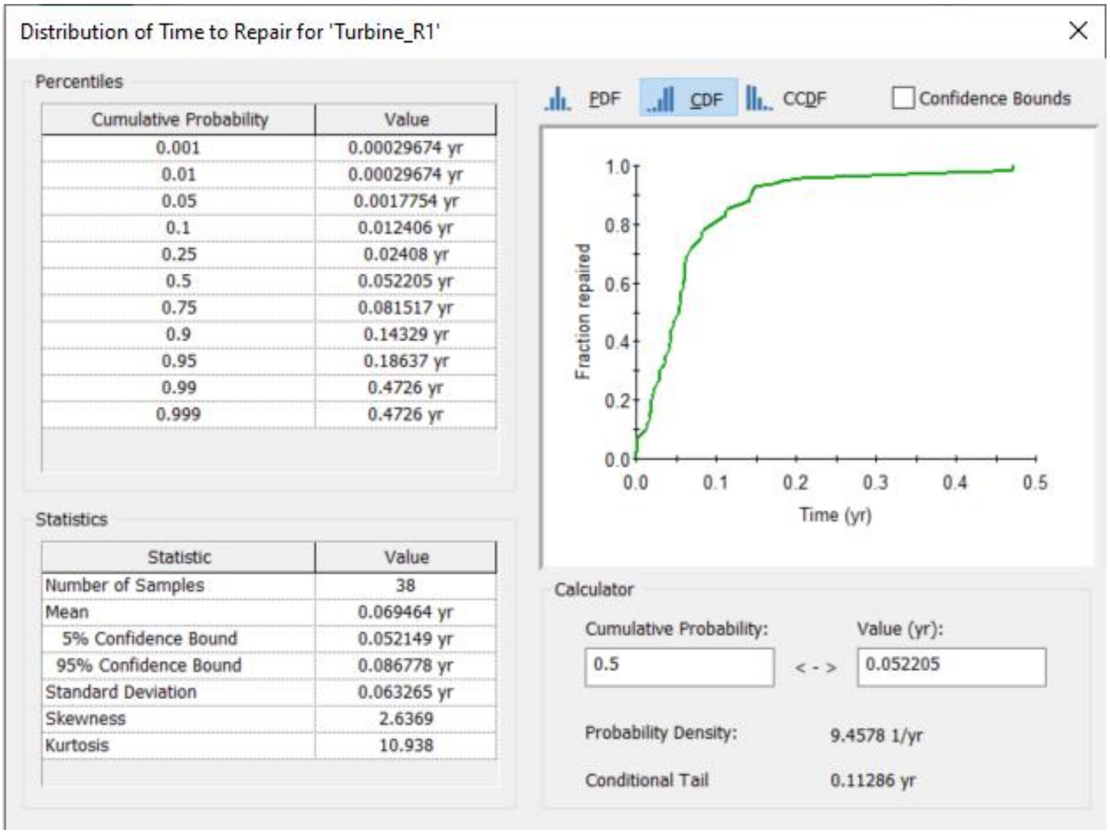
Cumulative Probability: 0.5

Value (yr): 0.10866

Probability Density: 2.8242 1/yr

Conditional Tail 0.21087 yr

Typical turbines results (Turbine 1 was selected):



Distribution of Time to Repair for 'Turbine_R1'

Percentiles

Cumulative Probability	Value
0.001	0.00029674 yr
0.01	0.00029674 yr
0.05	0.0017754 yr
0.1	0.012406 yr
0.25	0.02408 yr
0.5	0.052205 yr
0.75	0.081517 yr
0.9	0.14329 yr
0.95	0.18637 yr
0.99	0.4726 yr
0.999	0.4726 yr

Statistics

Statistic	Value
Number of Samples	38
Mean	0.069464 yr
5% Confidence Bound	0.052149 yr
95% Confidence Bound	0.086778 yr
Standard Deviation	0.063265 yr
Skewness	2.6369
Kurtosis	10.938

Calculator

Cumulative Probability: 0.5 < - > Value (yr): 0.052205

Probability Density: 9.4578 1/yr

Conditional Tail 0.11286 yr

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