# ABSTRACT

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Since the beginning of the industrial revolution in the late 18th century, the cause of many serious accidents in hydrosystems engineering has shifted from natural causes to human and technology related causes as these systems get more complex. While natural disasters still account for a significant amount of human and material losses, man-made disasters are responsible for an increasingly large portion of the toll, especially in the safety critical domain such as Dam and Levee systems. The reliable performance of hydraulic flow-control systems such as dams, reservoirs, levees etc. depends on the time-varying demands placed upon it by hydrology, operating rules, the interactions among subsystem components, the vagaries of operator interventions and natural disturbances. In the past, engineers have concerned themselves with understanding how the component parts of dam systems operate individually and not how the components interact with one another. Contemporary engineering practices do not address many common causes of accidents and failures, which are unforeseen combinations of usual conditions. In recent decades, the most likely causes of failures associated with dams have more often had to do with sensor and control systems, human agency, and inadequate maintenance than with extreme loads such as floods and earthquakes.

This thesis presents a new approach, which combines simulation, engineering reliability modeling, and systems engineering. The new approach seeks to explore the possibilities inherent in taking a systems perspective to modeling the reliability of flow-control functions in hydrosystems engineering. Thus, taking into account the interconnections and dependencies between different components of the system, changes over time in their state as well as the influence upon the system of organizational limitations, human errors and external disturbances. The proposed framework attempts to consider all the physical and functional interrelationships between the parts of the dam and reservoir, and to combine the analysis of the parts in their functional and spatial interrelationships in a unified structure. The method attempts to bring together the systems aspects of engineering and operational concerns in a way that emphasizes their interactions.

The argument made in this thesis is that systems reliability approach to analyzing operational risks—precisely because it treats systems interactions—cannot be based on the decomposition, linear methods of contemporary practice. These methods cannot logically capture the interactions and feedback of complex systems. The proposed systems approach relies on understanding and accurately characterizing the complex interrelationships among different elements within an engineered system. The modeling framework allows for analysis of how structural changes in one part of a system might affect the behavior of the system as a whole, or how the system responds to emergent geophysical processes. The implementation of the proposed approach is presented in the context of two case studies of US and Canadian water projects: Wolf Creek Dam in Kentucky and the Lower Mattagami River Project in Northern Ontario.

# A SYSTEMS RELIABILITY APPROACH TO MODELING OPERATIONAL RISKS IN COMPLEX ENGINEERED SYSTEMS

By

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# CHAPTER 1: INTRODUCTION

## *1.1. Research Motivation*

Failures of complex engineered systems always raise public concern on the safety and reliability of engineering infrastructure. Failures of hydrosystems infrastructure (e.g., dams, levees etc.) pose a significant threat to public safety and can lead to enormous damage to infrastructure and the environment. In recent decades, the cause of many serious accidents in hydrosystems has shifted from natural causes to human and technology-related causes as these systems get more complex. In a review of the performance of spillway gates and associated operating equipment reported to the National Performance of Dams Program, McCann (2013) reports that exclusive of the failure of spillway structures themselves, the performance of hydraulic systems is important even during normal operations. These systems are affected by mal-operation, control system errors, and a host of interactions among factors.

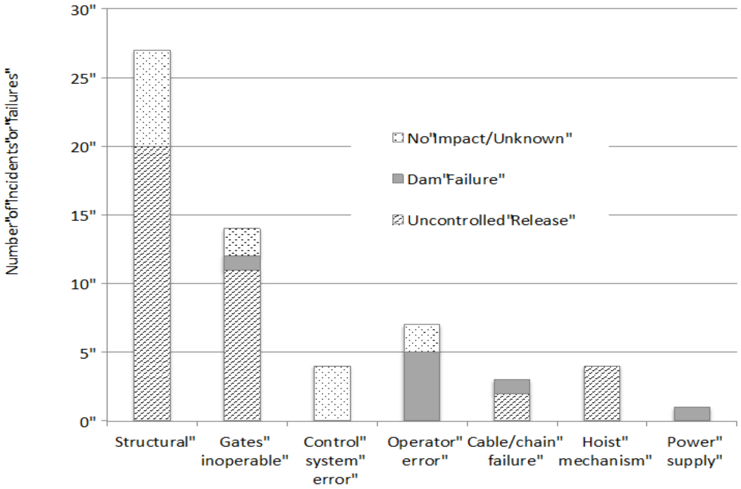


*Figure 1.1 Dam gate system events and the consequences that resulted (McCann, 2012)*

Figure 1.1 summarizes 65 flow-control accidents identified in the NPDP database, which occurred before 1995 at US dams, and grouped by apparent cause. In each case, a causal chain of contributing factors leads to each apparent final cause and thus to the subsequent accident. Further examination of dam failures and safety related incidents shows that most were not caused by a single, easily analyzed, component failure but rather by interactions between various components, operational considerations, and lack of appropriate organizational response (Bruce, 2012). It is imperative to reduce the risk associated with a dam to a level that is as low as reasonably practicable. The optimum must be done within the associated operating constraints and within the limits of current knowledge and understanding, to recognize potential failure modes before they begin to develop and to monitor those failure modes over time. To achieve this goal, dam owners must find an effective way to integrate operations, engineering, and dam safety performance monitoring into a comprehensive dam safety program. Performance monitoring and record keeping are essential to making well-informed decisions regarding the condition of the dam. As the systems that control dams get more complex and more automated, and more are remotely operated, opportunities increase for undetected incidents that can lead to dam failure. Understanding factors relating to dam safety, such as owner risk awareness, management responsibility, personnel training, and system and sub-system interactions, are become increasingly important.

### *1.2. Research Objectives and Scope*

The reliable performance of a hydraulic flow-control system such as dams, reservoirs, levees etc. depends on the time-varying demands placed upon it by hydrology, operating rules, the interactions among a cascade of reservoirs, the vagaries of operator interventions and natural disturbances. In the past, engineers have concerned themselves with understanding how the component parts of dam systems operate individually and not how the components interact with one another. They behave in complex ways that are not amenable to such simple decompositional analysis, and thus need to be understood in a systems engineering context.

This thesis examines the operational risks in hydrosystems (such as Hydropower Dams and Levees) and proposes a holistic systems reliability framework to incorporate the physical and functional interrelationships among the parts of the dam system, and to combine the analysis of the parts in their functional and spatial interrelationships in a unified structure. In order to achieve this objective, it is necessary to identify and model the dynamic feedback processes that may cause risk to increase over time into the overall model. This dissertation introduces a systems framework to model some critical aspects of safety and power generation in dam systems. The modeling approach holistically integrates river basin hydrology, the routing of reservoir inflows through the reservoir system, operating rules and human factors of operating the spillway and other waterways, out flow systems, the hydraulics of outflow, the discharge to the downstream river channel and the fragility of the structural, mechanical and electrical components of the dam system. Emphasis is placed on the interactions of this set of components and how unforeseen combinations of varying conditions may lead to failure of dam system.

### *1.3. The dynamic nature of flow control in Hydrosystems*

Hydropower plant as an integrated system is comprised of physical and organizational (human) sub-systems. The physical sub-system is made of components, which can be in different operational status, i.e., normal, to certain hazardous state, faulty or out of operation for maintenance or replacement. The organizational sub-system consists of humans organized into operational units and social groups performing different tasks for control and operation of the system. A large number of physical components being in diverse operational system states controlled by individuals usually organized in hierarchical groups makes the whole enterprise into a complex dynamic socio-technical system. The complexity becomes even more challenging due to the fact that hydropower schemes are operated in a natural environment with the random inputs and stresses in form of external disturbances. More and more electronic components are involved in hydropower operations, control and monitoring schemes. This kind of system involves a time-dependent management of numerous technical and organizational parameters and issues.

### 10.1.1. Objectives of the study and modelling framework

The objective of this study was to understand systems interactions in hydropower dam systems, and the potential for accidents or failures caused by the interactions. The approach was the following:

- Propose a systems reliability modeling approach (framework) to quantifying operational risks in dam systems that considers all the physical and functional interrelationships between the parts of the system, and to combine the analysis of these parts in a unified structure.
- Formulate and construct a systems model that accurately characterizes and holistically integrates the physics of hydrodynamics (dynamics of transport, storage

and power generation), the operating rules and human factors operating the spillway, and the dam component fragilities.

- Balance the main aspects of dam operation, performance and reliability in one integrated whole, consisting of the natural siting of the dam, including its hydrology and geology, the physics of water containment and the control of discharges and power generation, and the monitoring and control of operations.
- Utilize dynamic fault tree analysis to model the various states of a repaired component during/after maintenance and to accommodate the incorporation of dependencies among various subcomponents of a system thus allowing for the specification of resource dependencies for component repairs.
- Apply the systems modeling framework to USACE's Wolf Creek and OPG's Lower Mattagami River Hydroelectric project to better understand the systems interactions and to quantify the inherent operational risks.

Risk and reliability principles are used to evaluate the performance of mechanical, electrical, controls, and sensing equipment for scenarios such as loading range (flood, earthquake), equipment failure, project staffing with inclusion of human factors including training, management practices, *etc*. to see if the outcomes cause disturbances that affect safety. The task addresses systems reliability of operational aspects of hydropower dams operated by USACE, using Wolf Creek Dam and Lower Mattagami River Project as test cases. The reliability of flow-control systems is a broad topic that covers structural, mechanical, electrical, control systems and subsystems reliability, as well as human interactions, organization issues, policies and procedures. A systems reliability approach is developed for grappling with these varied influences.

Overall, this study would result in two major contributions. From one perspective, the establishment of a systems Reliability Framework to be used as a guidance for future Quantitative risk assessments (QRA) in hydrosystems engineering. Additionally, the proposed Systems Reliability Framework will enable the fusion of models of across different technological and human systems by offering an overall framework to combine all of the sources of uncertainty.

### *1.4. Thesis Outline*

Based on the proposed research objectives and scope, this dissertation consists of nine chapters. Details of Chapters 2-9 are summarized as follows:

**Chapter 2** provides background and the motivation for a systems approach to hydrosystems and flow control. The need for a new holistic approach for analysis of hydrosystems, what requirements should they fulfil, how they are configured, how they function and fail as well as the use and limitations of contemporary methods of risk analysis for dams are presented.

**Chapter 3** discusses Monte Carlo simulation approaches to modelling and analysing dam systems, with emphasis on flow control, and describes how these approaches allow the analyst better to understand the interactions among components, operating procedures and disturbances. Additionally, the foundations of systems thinking about hydrosystems, operation of such systems and the natural disturbances that influence the systems is also presented.

**Chapter 4** addresses hydrology and reservoir management and sets up the fundamental dam-reservoir systems model for simulation modeling and analysis. Also addressed are the hydraulics of waterways, such as spillways, turbines, and conduits.

**Chapter 5** addresses the loading conditions on flow control components of hydrosystems. Mathematical foundations are laid for the characterization of load-resistance performance parameters and reliability concepts are also presented.

**Chapter 6** reviews maintenance policies applicable to hydrosystems modeling and lays the foundation for estimation of reliability parameters. Simulation based maintenance optimization literature is also reviewed and as a final step a virtual age-based, Preventive Maintenance model is presented to be incorporated into the systems model.

**Chapter 7 and 8** presents the two supporting case studies for the application of the proposed Systems reliability modeling to analyzing operational risks in hydrosystems. More specifically, Chapter 7 & 8 takes on the Systems reliability modeling approach to dam safety performance analysis by applying the systems proposed framework to Ontario Power Generation’s cascade of four dams in the Lower Mattagami Basin (Northern Ontario, Canada) and the Wolf Creek dam—located in Kentucky.

**Chapter 9** concludes the work. Contributions and future efforts are summarized.

## CHAPTER 2: LITERATURE REVIEW

Most dam safety accidents and failures occur not because an extreme event happens (*e.g.*, a flood or earthquake); but because a series of more common things occurs, which in their unfortunate and unexpected combination leads to an accident or failure. Such combinations of unforeseen yet unfortunate events cannot be predicted easily ahead of time—or maybe at all. They are what systems engineers call *emergent* behaviours (Leveson, 2012).

This unfortunate combination may be of unusual events. Accidents and failures often occur due to a combination of events that individually are in the range of the design events. In a review of the performance of spillway gates and associated operating equipment reported to the National Performance of Dams Program, McCann (2013) reports that exclusive of the failure of spillway structures themselves, the performance of hydraulic systems is important even during normal operations. These systems are affected by mal-operation, control system errors, and a host of interactions among factors. McCann (2013), summarizes 65 flow-control accidents, which occurred before 1995 at US dams, and grouped by apparent cause. In each case, a causal chain of contributing factors lead to an apparent final cause and thus to the subsequent accident. Although the final cause may be identified as the root cause, it need not be.

The observation that most accidents and failures occur not from extreme loads but through more common, yet unforeseen sequences of events is now widely recognized. Perrow (1999) argues that ever increasing complexity in technological systems makes these failures inevitable. He argues that complex rather than linear interactions among components lead to systems performance that is difficult to understand. Flow-control in dam systems displays both sorts of interactions. Perrow (2006) also argues that tight *vs*. loose coupling among components increases the chance of accidents. Tightly coupled systems are rigid. They provide little slack between what happens at one component and at another. Loose systems provide more buffer and opportunity for intervention. Tight coupling increases the likelihood that operator intervention will make things worse rather than better, since the nature of an emerging situation may well not be understood immediately.

Many dams may be considered to be tightly coupled systems because they have little flexibility and have time-dependent operational needs. That is, a dam cannot usually wait while disturbances are attended to in an orderly way. Delays in operations may not be tolerable. Water flows into the reservoir and it must be dealt with now, not at some more convenient time in the future. Characteristics of tightly coupled systems are that delays in processing are not possible; production sequences are invariant; little slack exists in methods, equipment, or personnel; and substitutions of supplies, equipment, or personnel are limited. All of these things increase the likelihood of accidents. In tightly coupled systems, expediencies cannot be used to save a situation: Rigbey (2013) recommends that, redundancy, segregation, diversity, and defence in depth must be designed into the system from the start.

Rasmussen *et al.*, (1990) and Leveson (Leveson, 2012) argue that the chain of causality leading to an accident is often opaque. The causal path to an accident will be "prepared by resident conditions that are latent effects of earlier events or acts." Thus, the length of the causal path depends to a large extent on the stopping-rule for seeking contributing causes:

Do the causes stop with technical faults, or with operator “errors”, or do they extend back to management and design decisions? Regan (2010) makes this argument but with specific reference to dams:

> […] chain-of-event models, such as a typically defined failure mode or risk assessment event tree, oversimplify the causes of incidents and exclude many systemic factors and non-linear interactions. The failures of Teton, Silver Lake and Taum Sauk all had contributions from systemic factors and non-linear interactions that were unrecognized prior to the failure. Our current dam safety programs are, in essence, trying to determine the safety of the dam by examining a few components of the dam, one component at a time. […].

Analysing individual components against a prescribed standard is insufficient to assure the safety of dams. Reducing the risk associated with dams to a level that is as low as reasonably practicable requires evaluating the dam as a complex system with interactions of sub-systems that may be difficult to recognize.

### *2.1. Current State of The Practice*

Contemporary dam safety decision-making generally falls into one or more of the following categories:

- Standards-based decision making,
- Risk-informed decision making, or
- Probabilistic risk analysis.

Decisions based on these respective premises require an ascending order of sophistication from standards- to values dominated decisions regarding information, analyses, corporate-level decisions and regulatory environment. Many complex and important dam safety decisions involve portions of all three processes at different stages. A decision-making framework, which explicitly incorporates and elaborates on these processes, allows engineers, owners, regulators and stakeholders to determine the appropriate actions and tools to implement and sustain dam safety decisions given a wide variety of situations. These approaches to dam safety decisions are discussed at greater length in Hartford and Baecher (2004).

### 2.1.1. Standards-Based Decision-Making

Standards-based decisions have been the most commonly used in the analysis of flow-control systems at dams, although spillway configuration and dimensioning was one of the earliest dam safety problems to be addressed by risk analysis. Standards-based decisions are essentially decisions based on engineering principles and norms that employ a form of design checking against stated criteria. While historically such criteria were mostly associated with structural analysis, today similar engineering criteria have evolved for the consideration of hydrology and hydraulics, foundations, abutments and other components of the dam system (ICOLD, 1988). These engineering criteria have also evolved in parallel with advances in dam engineering and the development of advanced analytical modelling. The common design check against deterministic engineering standards is the factor of safety (FS). This is the ratio of the capacity (strength) of the dam or its components to the demands (loads) placed upon it:

$$FS = \frac{Capacity}{Demand}$$

Intuitively, a factor of safety less than 1.0 suggests that the dam will not be able to perform its intended function under the demand of the loads placed upon it. Alternatively, a factor of safety of 1.0 or higher suggests the dam is sufficiently strong to withstand the specified demand. The typical rule in dam design is to make the factor of safety sufficiently larger than one to account for uncertainties in both the specified demand and calculated capacity. The factor of safety, although a calculated construct, is related to the physical properties of a dam, in that the larger the factor of safety, the greater the capacity of the dam to withstand the applied loads.

Quantitative engineering standards are usually promulgated by regulatory authorities, even though they are typically taken from industry practices, by standards-setting professional organizations approved by the government and by the industry; or more indirectly in terms of guidance provided by non-governmental organizations such as the national member bodies of ICOLD (Hartford and Baecher, 2004). Current dam safety practice is usually predicated on the rare occurrences of extreme loads, such as unlikely but possible reservoir inflows or powerful seismic events.

Engineering standards-based decision making has evolved over the years but its focus still remains on the physical structure, not on operations, data collection, communications or operations. Loading scenarios are assessed separately, meaning the capacity of spillways and other waterways is considered to the extent that they are large enough and stable enough to accommodate specified discharges; the mechanical and electrical performance of gates and valves are considered to the extent of their availability on demand. Analytical criteria for the internal erosion of embankment dams have improved somewhat since that era, but still today, operational factors, SCADA (Supervisory control and data acquisition) system errors, and human factors have little place in engineering standards-based assessment of dam safety.

### 2.1.2. Risk-informed decision making

Risk-informed dam safety programs provide many benefits. However, according to Baecher et al, "Risk-informed decision making is different from engineering standards-based decision making in that the focus is on the level of protection to the public from the hazardous dam and reservoir." In contrast, in standards-based decision making, the hazards are the natural and other conditions that threaten the dam. What generally passes for a risk-informed approach might more accurately be described as traditional standards-based rationale with a probabilistic outlook.

Risk-informed decision-making implies taking into consideration a probabilistic description of the natural and other hazards imposed on, and the fragility of, the dam system, as well as the quantitative consequences of accidents or failures, in making decisions about dam safety, in a way that is focused on the totality of the level of protection to the public. Within this context, risk is taken to be the expected consequences of accidents or failures, that is, the product of the probability of an accident or failure, and the resultant consequences of that accident or failure. Risk-informed decision making involves balancing the expected economic, social, and environmental costs of a dam safety risk against the costs of risk reduction, at least in a qualitative way.

The shortcoming of this approach is its inability to assess non-linear failure modes and interactions between apparently unrelated components and subsystems. This hinders the identification of opportunities to prevent failures before they progress to the point where a typical risk analysis would begin (Regan, 2010). This linear nature of typical risk assessment approaches, combined with the fact that the majority of dam safety professionals are civil engineers, results in a rather narrow focus on failure modes that affect the civil structures and a neglect of the contributions to those failure modes from electrical, mechanical and control systems or human decision-making.

### 2.1.3. Bow-tie model

The bow-tie representation attempts to show the link between preventive actions, hazards, and mitigation responses in a qualitative way that allows for interactions to be identified and rational decisions to be made. To construct the bow-tie model, it is necessary to create a model of how the system works. This typically requires sub-models, such as schematic diagrams, influence diagrams, engineering drawings, plans and so on. Upstream of the bow-tie, to the left-hand side, is the traditional risk matrix of potentially adverse events. To the downstream side, to the right-hand side, is the organizational risk management scheme. So, one reason why this representation of risk informed decision-making has been successful is because it integrates threat assessment with risk management. It also meshes with the UK Health and Safety Executive (HSE) risk management paradigm (HSE 2001). Yet, the representation is qualitative.

### 2.1.4. Failure modes and effects analysis

Failure modes and effects analysis (FMEA) is a form of risk-informed analysis that is used to map out the consequences of specific events that can occur during the operation of an engineered system, and to use this information to identify and prioritize necessary actions. FMEA can be applied in several forms and for a number of purposes. In its simplest application it can be a free-standing technique to give a structured understanding of the failure modes applicable to the components of an engineered system, or it can be an integral part of a more comprehensive probabilistic analysis of the risks associated with multiple integrated systems.

FMEA was developed originally for design purposes, but now finds application in the analysis of potential for failure of existing systems. It also finds application as part of a wider asset management process that deals with the ongoing satisfactory output of the system under consideration. The use of FMEA is no longer restricted to engineered systems and is now used in a diverse range of societal activities, healthcare management being an example.

### 2.1.5. Probabilistic Risk Analysis (PRA)

Probabilistic risk assessment (PRA) provides practical techniques for predicting and managing risks (i.e., frequencies and severities of adverse consequences) in many complex engineered systems.

Risk-based decision making differs from risk-informed decision making in that it relies on the quantitative evaluation of the probabilities of accidents and failures, and of their corresponding consequences, in order to calculate quantitative risk. In the literature of techno-logical risk management, risk-based decision making is often referred to as probabilistic risk analysis (PRA). The principal methodologies of PRA are fault-tree and event-tree analysis. The former is more common in nuclear and chemical plant safety. The latter is more common in dam safety and civil infrastructure risk analysis.

Fault tree analysis (FTA) is a technique whose mathematical foundation is well-developed and that has been applied extensively in reliability and safety assessments for a wide range of engineered systems such as missile launch systems, chemical process facilities, nuclear power plants, dams, control systems and computers. In addition, the software and the databases available for conducting a FTA are sophisticated and add significantly to the efficiency of performing a risk analysis. The fault tree is a graphical construct that shows the logical interaction among the elements of a system whose failure individually or in combination could contribute to the occurrence of a defined undesired event such as a system failure. Fault trees offer the analyst the capability to construct a logic model of a system that is visual and therefore is easy to view and read, and that provides a qualitative and quantitative insight to the system's operations and reliability.

It is important to note at the outset that FTA is one of many tools available to the risk analysis team. In a risk analysis for a dam system, various methods will generally be used to build a logic structure to analyze the expected future performance. As such, FTA will simply be one of the methods used. In the course of the risk assessment it is important to co-ordinate how a FTA for a system fits into the overall risk analysis model. This theme is critical to the risk analysis in general and to the FTA in particular.

Event tree analysis (ETA) is one of the techniques available to the engineer conducting a reliability or safety analysis for a dam. It is an apparently straightforward endeavor that finds widespread application in many industries and businesses. It is an inductive type of analysis that, unlike fault tree analysis, is not supported by an extensive theoretical basis. ETA is the most widely used form of analysis in risk analysis for dam safety, although the lack of theoretical basis means that the correctness of these constructs may be difficult to determine.

An ETA is an analysis process whose essential component is the event tree. The event tree is a graphical construct that shows the logical sequence of the occurrence of events that is visual and therefore is easy to view and read, and that provides a qualitative and quantitative insight to the system's operations and reliability.

Current dam safety practice, both in the traditional deterministic form and in the more modern probabilistic risk analysis (PRA) form using fault trees and event trees, is still usually based on the rare occurrences of extreme loads, such as unlikely but possible reservoir inflows or powerful seismic events. Adding PRA to the evaluation changes this situation not at all. As an example, the Canadian Dam Association (CDA) guidelines for dam safety risk analysis presume extreme floods and earthquakes to be probabilistically independent events. Each has some probability of occurring in any given year, and each has some probability of leading to an accident or failure. This is the same whether in standards-based evaluation or in PRA. Indeed, from a geophysical view, these natural phenomena likely are probabilistically independent. The occurrence of one does nothing to change the probability of occurrence of the other.

From an operational and safety view, however, earthquakes and floods are not independent. If an earthquake occurs and causes serious damage to a dam system, it may take a year or more for repairs to be completed.

### 2.1.6. Alternative Approaches

A dam is not a single independent entity but rather its system comprising of the dam body and the waterways past the dam, usually with accompanying mechanical and electrical equipment for on-site operational control. A dam may also be considered to include the reservoir, communication links, and the organization responsible for operation of the system, including on-site operators, dispatch center and company policy makers. This system is made up of several subsystems for instance the spillway subsystem will include the gates and its complete hoist and control system, the spillway chute and the stilling basin. Thus the dam system would include all the subsystems that we normally associate with a dam: i.e., the foundation, abutments, reservoir, and reservoir rim, the operating organization and may also include a powerhouse and all its associated subsystems.

The state and nature of these components and sub components will not remain constant during the lifetime of a dam system for reasons such as wear and aging and maintenance activities as well as changes to the surrounding infra-structure and society. On a larger scale, a dam might be a subsystem within a larger system that could be a watershed with projects owned by one or more entities or an entire regional electrical grid.

### 2.1.7. Normal Accident Theory

This concept was developed by Charles Perrow in his book Normal Accidents (1984), in which he uses the term normal accidents in part as a synonym for “inevitable accidents.”

This categorization is based on a combination of features of such systems: interactive complexity and tight coupling. Normal accidents in a particular system may be common or rare, but the system's characteristics make it inherently vulnerable to such accidents, hence their description as “normal”.

NAT suggests that high risk systems have some special characteristics including complex interactions, dependencies and performance conditions that make it essentially impossible to foresee all possible failures, especially when one “minor” failure interacts with one or more other “minor” failures in an unforeseen manner. Since the failure of some parts is unavoidable, some failures must be expected and should be considered “Normal”. Perrow advocates a focus on the overall system rather than individual components. Failure in just one part (material, sub-system, human, or organization) may coincide with the failure of an entirely different part, revealing hidden connections, neutralized redundancies, random occurrences etc., for which no engineer or manager could reasonably plan.

Historically dams were operated by dam operators residing near the dam and working almost exclusively to assure the safe and reliable operation of the dam. Economic and Socio-political pressures, brought about in large part by deregulation of the electric industry, have resulted in the conversion of dam operations from a local dam tender to a remote operations control center (Regan, 2010). Thus, human operators on site have been consequently replaced with SCADA (Supervision, Control and Data Acquisition) which is composed of but not limited to river gauges upstream of the reservoir, gauges within the reservoir and gauges at the spillway. At the control center one or more operators (no longer dam tenders) make decisions on dam operations based on information obtained from

SCADA systems without directly seeing the structure. In addition, an operator's principal responsibilities are often primarily related to operation of one or more powerhouses with dam safety as an additional responsibility (Regan, 2010).

Likewise, spillway gates are now rarely operated by a dam operator on site. Presently, a remote operator may click a virtual button on a computer screen. In the first case, the dam tender gets immediate visual feedback that the proper gate is indeed moving or not. In the second case, the remote operator gets a signal that the gate is moving from some form of position sensor. If the sensor is giving erroneous data, the operator has no real knowledge if the gate is moving or how far it is moving (Regan, 2010).

When we bring the causes of technological accidents up to closer scrutiny in a bid to understand them the inherent causes, it's often very difficult to pinpoint what exactly went wrong. The reason for this is that technologies are intrinsically complex and depend on many things working closely together: Materials and components of different quality are structured into tightly engineered sub-systems, which are operated by error-prone humans in not always optimal organizational structures, which in turn are subject to production pressures and all kinds of managerial maneuvering.

Normal Accidents was first published in 1984, prior to the deregulation of the electric industry and prior to the large-scale introduction of remote operation of dams. These two factors have greatly increased the complexity of dam operation and have introduced opportunities for unforeseen interactions that did not previously exist. Perrow (1984), came to the conclusion that "some technologies, such as nuclear power, should simply be abandoned because they are not worth the risk." This political statement has made NAT highly controversial, and the main body of research has since then concentrated on how to make organizations and high-risk technologies more reliable, i.e. “disaster proof”, so that the political and democratically important discussion of allowing or not allowing specific technologies need not be taken.

### 2.1.8. High Reliability Organizations

Subsequent researchers challenged Perrow’s (1984) theory, and in particular his conclusions regarding the inevitability of accidents. Another school of thought, High Reliability Organizations (HRO), argues that four key organizational characteristics: 1) prioritization of safety and performance and achieving a consensus on the goals throughout the organization; 2) promoting a culture of reliability; 3) organizational learning to learn from accidents and safety related incidents; and 4) use of redundancy. Advocates of HRO suggest that by improving the reliability of components, system safety can be improved. Critics of the HRO theory point out that simultaneously promoting safety and performance, i.e. dam safety and powerhouse generation, creates conflicting priorities. HRO describes a subset of hazardous organizations that enjoy a high level of safety over long periods of time. What distinguishes types of high-risk systems is the source of risk, whether it is the technical or social factors that the system must control or whether the environment, itself, constantly changes. Promoting reliability is often taken to mean training all employees on exactly the steps to take in a safety related incident. Unfortunately, this can mean, at times, that the employees do exactly what they’ve been trained to do but the specific incident was outside the understanding of those who prepared the training and the response actually hastens the incident due to unforeseen interactions. Learning from the past clearly has its place in any dam safety program but this is due mainly to the fact that the industry has historically evolved at a relatively slow rate. The recent development of SCADA systems that allow remote operation of dams is a radical departure from the historical developments in dam design and operation. However, there is little to no history to help  understand the risks inherent to the remote operation of dams. It is notable that many of the recent experiences with uncontrolled releases of water are due to unintended operation of outlet works by glitches in SCADA systems, an area where the dam safety community has relatively little history. The last concern with HRO is its emphasis on redundancy, a fact that may increase complexity and thereby reduce safety, especially if operations become complacent because redundancy is designed in.

# CHAPTER 3: RISK & RELIABILITY IN HYDRO SYSTEMS ENGINEERING

The reliable performance of hydro systems infrastructure depends on the time-varying demands placed upon it by hydrology, operating rules, the interactions of its components, the vagaries of operator interventions and natural disturbances. Most of these factors, if not all, are subject to various types of uncertainty (Figure 3.1). Uncertainties in systems analysis can be classified into two forms; aleatory uncertainties associated with the natural variability in the world and epistemic uncertainties arising from knowledge deficiency about the system or processes being modeled. The overall risk in an engineering system is the result of the combined effect of these two types of uncertainties. As shown in Figure 3.1, other forms uncertainties fall under these 2 classifications. In general, the uncertainty due to geophysical processes cannot be eliminated. On the other hand, uncertainties associated with the knowledge deficiency about processes, models, parameters etc., can be reduced through improvements in data collection and analysis techniques, research, etc. The task of modeling operational risks in hydro systems engineering—specifically Dam and levee Systems—necessitates the need to capture the day to day operational activities of these systems against the backdrop of the natural processes in which the systems are embedded. Tung *et al.* (2005), broke down the uncertainties and variabilities inherent in these natural processes into 5 sub categories: structural, geophysical, operational, trans-missional and economic.

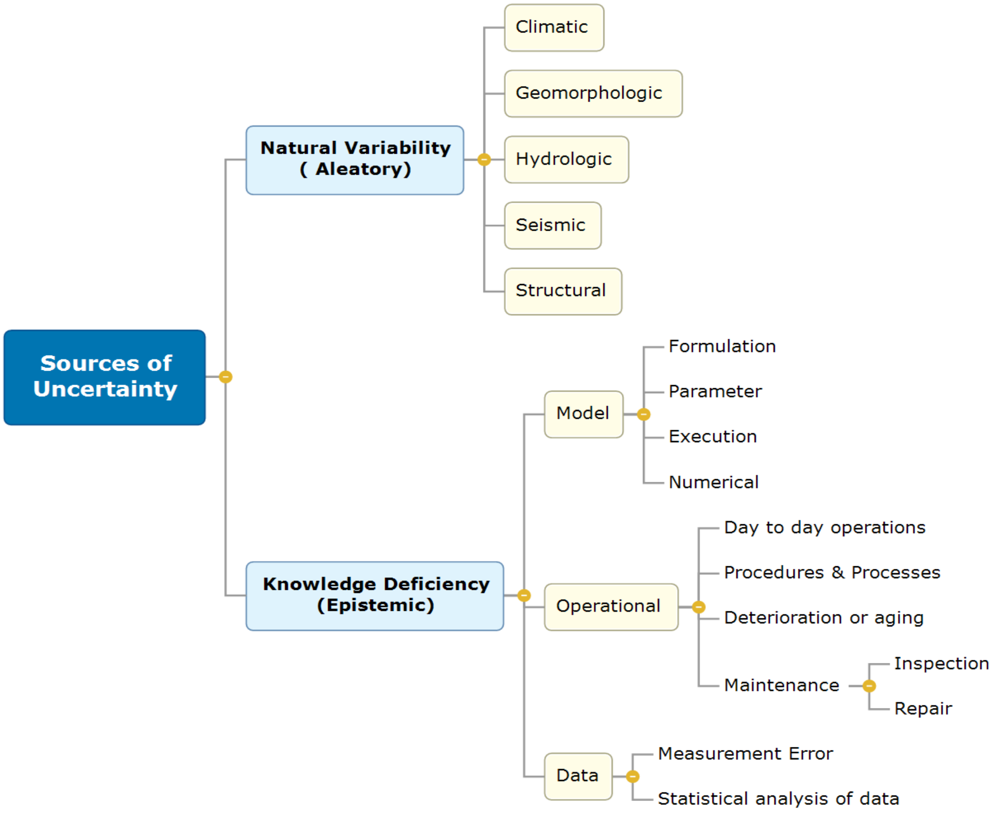


*Figure 3.1: Sources of uncertainty (Adapted from Tung and Yen, 2005.)*

Operational risks arise not only from the day-day operations of the system but also from any disturbance in its operational processes ((HKIB), 2013). In the case of dam systems, the disruption may come from a one-off event, ranging from simple human error activities such as operator push button error, to cascading failures triggered by natural occurrences such as a 50-year storm event, or from a systems breakdown due to sabotage. Physical failure of structures in hydrosystems can be caused by many things such as system overloading or structural collapse. Economic uncertainty can arise from uncertainties in construction costs, damage costs, projected revenue, operation and maintenance cost, inflation, project life, and other intangible benefit and cost items (Mays, 1999). Yen *et al.*

(1986) classified various sources of uncertainty in the analyses and designs of hydraulic engineering systems including natural variability, model uncertainties, parameter uncertainties, data uncertainties, and operational uncertainties that are equally relevant for other civil engineering infrastructural systems. Natural variability is associated with the inherent randomness of natural geo-physical processes such as the occurrence of precipitation, floods, and earthquakes. The occurrence of geophysical events often displays variations in time and space. Among the uncertainties due to knowledge deficiency, the most important are those of model, operation, and data. Detailed elaboration of uncertainties in dam and Levee systems engineering and their analysis are presented in the uncertainty task.

### *3.1. Systems Modeling Approach*

The systems modeling approach (framework) attempts to consider all the physical and functional interrelationships between the parts of the dam and reservoir, and to combine the analysis of the parts in their functional and spatial interrelationships in a unified structure. The approach relies on understanding and accurately characterizing the complex interrelationships among different elements within a system. The modeling framework allows for analysis of how structural changes in one part of a system might affect the behavior of the system as a whole or how the system responds to emergent geophysical processes. Perturbing the system under probable but unlikely scenarios makes it possible to test how the system will respond under varying sets of rare event scenarios. The systems approach also gives consideration to the influence of disturbances internal to the system. The possibility of one or more combinations of both external and internal disturbances, ranging from those that occur essentially simultaneously to those that occur at different times but in ways that the effects of the disturbances combine.

Rather than separating the analysis into physical parts, analyzing the performance of each part separately and then recombining the results to provide an overall statement of expected performance; the systems approach attempts to address the interactions of these physical and operational parts. The framework attempts to capture the dynamics of dam functions and dam safety philosophies in a more thorough way than is allowed by decompositional analysis. The intention to treat all conditions relevant to safety and performance analysis involves an expansion of the traditional design-check concept. The approach includes internal factors that pertain to the management, operation and maintenance of the dam, in addition to design loadings, which in themselves result in changes in the required functional performance of the dam.

The approach affords us a platform to incorporate into the model, feedback of operating procedures and human reliability in systems function and the ability to fuse models across different technological and human systems. Operational procedures and human decision intervention strongly affect system operations, accidents, and failures. These have not usually been accounted for in dam safety risk analysis. The proposed systems reliability approach intends to account for these systems interactions and feedback loops that are generally unaccounted for in the contemporary methods. Viewed in this way, systems-focused dam safety involves a much broader, structured and tractable view of all factors that contribute to the safe functioning of dams than does the traditional load-resistance philosophy of the traditional design-check approach.

### 3.1.1. Practicalities of a systems approach for dams

The question that arises from systems thinking is how does one identify and define all operational and physical conditions? Central to the approach presented herein is the premise that dynamic modelling and simulation of systems provides an operational basis to resolve this question.

The philosophy of systems engineering as a whole has two essential attributes:

- Structural performance and resilience; and
- Functional performance and resilience.

Structural performance and resilience pertain to the ability of the dam to withstand the forces that are applied to it and to maintain the structural support and integrity required for the functions of the dam and reservoir. Functional performance and resilience pertain to processes, products and services that the dam is intended to provide. Specifically, the dam is intended to retain the stored volume and to pass all flows through and around the dam in a controlled manner.

### 3.1.2. Systems Reliability Modelling Framework

Modelling the system's reliability of flow-control functions in a modern dam involves: (1) characterizing the performance of a spectrum of systems components, (2) following the dynamic interaction of these components over time, and (3) tracking the possible occurrence of external disturbances to the system that may perturb component performance. The modelling framework for appraising the systems reliability of flow-control involves four parts:

1) *Simulation* by which stochastic reservoir inflows are randomly generated through time using a Monte Carlo approach propagated through the reservoir-spillway-outflow system generating demand functions on all system components;
2) *Engineering modelling* to infer the impact of spillway heads and discharges (demand functions) on the hydraulic structures accommodating the outflows;
3) *Component reliability analysis* to ascertain the performance of individual components of the outflow works relative to defined failure modes and metrics; and
4) *Systems reliability assessment* through which demands on and performance of flow-control systems components are convolved into annual exceedance probabilities of adverse performance and fault and failure sequences identified.

The modelling framework is accommodating with respect to the simulation approach. The river basin may include other dams or facilities modelled as separate systems or just be the (natural) environment of the modelled dam. The catchment area provides the input driving the flow-control system. The modelling framework conceives of the flow-control system as a number of components. The outputs of each component generally form the input to the next component in the system logic. At each component, the upstream demand function is applied to the operation of the component. Engineering reliability modelling is used to evaluate the performance of that component in relation to the demand function. The performance of the component is characterized stochastically, expressing the component's probabilistic behavior as a function of the demand placed upon it. The reliability models for each component will generally describe performances of more than one type, and may be of more than one analytical structure. For example, the performance of a lift-gate may be analyzed using fault tree analysis of structural loadings and response.

#### *3.1.2.1 Context Diagram: Systems Reliability Analysis of Operational Risks*

The context diagram (figure 3.2) of the proposed systems reliability approach shows how the external entities interact with the hydrosystem against a backdrop of certain constraints and environmental factors at a higher level of abstraction. It explains the boundary conditions, required inputs, outputs, constraints and enablers for the systems reliability analysis framework.

The clear definition of the boundary is important because those elements within the boundary are presumably under the direct control of the engineers and operators, and become elements of a systems model. Modeling the systems reliability of flow-control functions in a modern dam involves (1) characterizing the performance of a spectrum of systems components, (2) following the dynamic interaction of these components through time, and (3) tracking the possible occurrence of external disturbances to the system that may perturb component performance. The constraints include factors at the management or policy level, government regulations and technical constraints of system components.

The inflows include a random time series of reservoir inflows from which the performance of the flow-control system can be modelled, reliability data for assessing how certain components react to varying load demands, statistical data required for a complete reliability analysis of components and the physical parameters of the dam system. The outputs are the statistical data generated from the simulation which can be data mined and analysed to aid in decision making. They include outflow graphs, elevation graphs, reliability data plots etc. Reliability Data comprises all system performance related data that can be used to estimate reliability parameters such as Mean Time to Failure (Mean Time to Failure), Failure Rates, Mean Down time, Mean time to Repair etc.

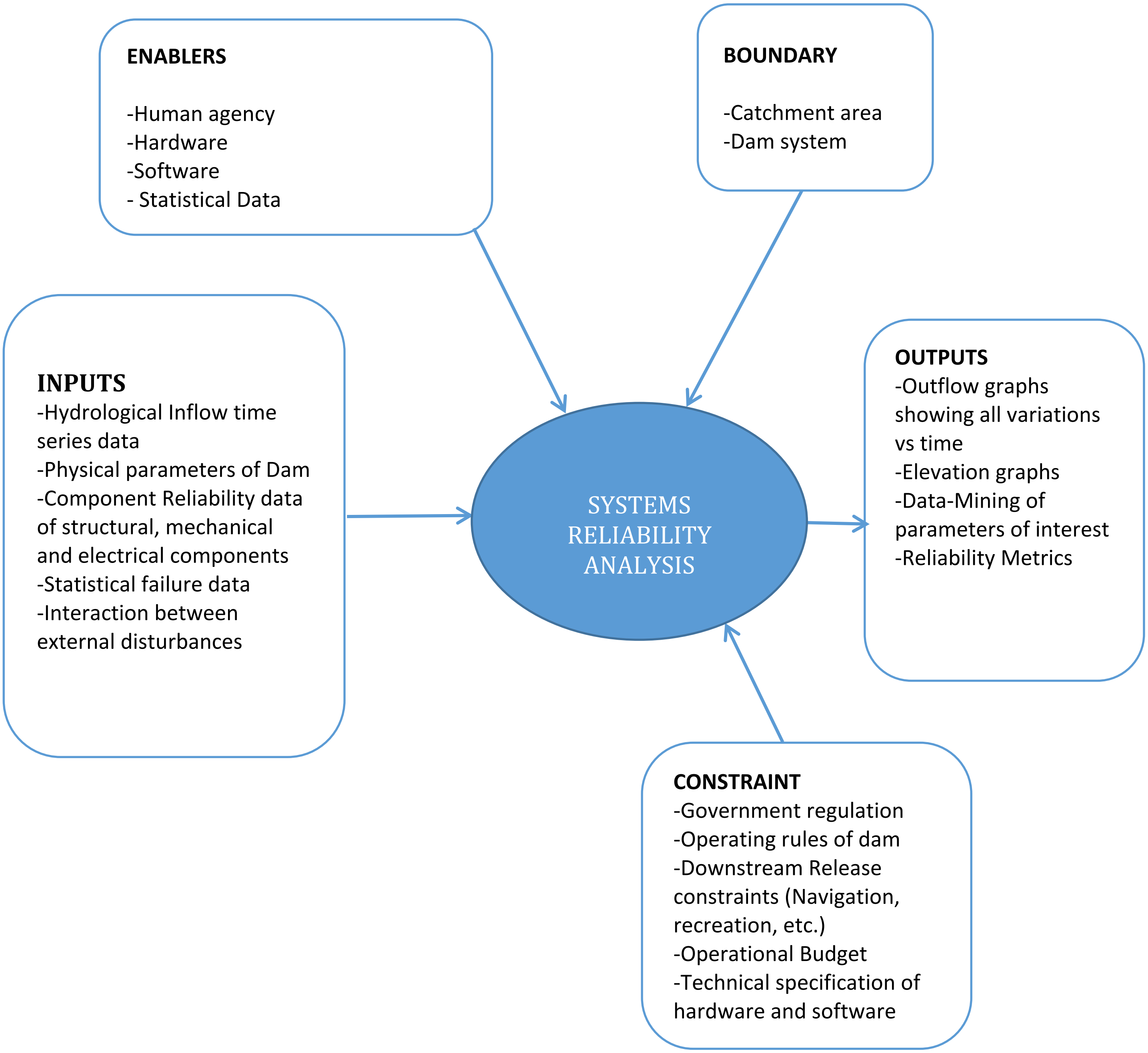

ENABLERS
-Human agency
-Hardware
-Software
- Statistical Data
BOUNDARY
-Catchment area
-Dam system
INPUTS
-Hydrological Inflow time series data
-Physical parameters of Dam
-Component Reliability data of structural, mechanical and electrical components
-Statistical failure data
-Interaction between external disturbances
SYSTEMS RELIABILITY ANALYSIS
OUTPUTS
-Outflow graphs showing all variations vs time
-Elevation graphs
-Data-Mining of parameters of interest
-Reliability Metrics
CONSTRAINT
-Government regulation
-Operating rules of dam
-Downstream Release constraints (Navigation, recreation, etc.)
-Operational Budget
-Technical specification of hardware and software

*Figure 3.2: Context Diagram for Proposed framework*

### 3.1.3. Reliability Analysis

Goodarzi (2013), defined reliability as the probability of non-failure and the complement of risk. The fundamental notion of reliability engineering is to determine the failure probability of an engineering system, from which the safety of the system can be assessed. Reliability and risk have an inverse relation in which the probability of increasing failure results in decreasing system reliability. In engineering, reliability signifies the ability of a set of components to carry out its required functions under some definite conditions over a specific time interval. One of the main objectives of risk and reliability analysis is to calculate the probability of failure or non-failure regarding potential loads and resistance.

There are two major steps in reliability analysis: (1) to identify and analyze the uncertainties of each contributing factor and (2) to combine the uncertainties of the stochastic factors to determine the overall reliability of the structure. The second step, in turn, also may proceed in two different ways: (1) directly combining the uncertainties of all factors and (2) separately combining the uncertainties of the factors belonging to different components or subsystems to evaluate first the respective subsystem reliability and then combining the reliabilities of the different components or subsystems to yield the overall reliability of the structure. The first approach applies to very simple structures, whereas the second approach is more suitable to complicated systems. As dam systems are complex systems, an evaluation of the reliability of a dam system will comprise the hydrologic, hydraulic, geotechnical, structural, and other disciplinary reliabilities. These could be evaluated separately first and then combined to yield the overall dam reliability. Or the component reliabilities could be evaluated first according to the different failure modes and then combined. Analysis tools described in Chap. 8, such as fault tree and fragility analysis, are useful to divide the system into component evaluation and combination.

### *3.1.3.1 Assessment of Reliability Function*

In the previous section, the reliability of systems was introduced in probabilistic terms and a general relationship with risk analysis was established. However, performing reliability analysis requires finding the reliability function of a real component or system. There are two different approaches to this problem. Either the reliability function can be estimated from curve-fitting failure data obtained from extensive historic failure records (non-parametric methods) or it may be hypothesized to be a certain parameterized function (parametric methods) with the parameters estimated via statistical sampling techniques (Simonović, 2009).

### *3.1.3.2 Parametric Reliability Function Assessment*

The parametric methods make an assumption about the functional form/shape of the reliability function f. For example in a linear regression analysis the relationship between the predictor X and the response Y is assumed to be linear; thus f is linear. This greatly simplifies the analysis. Linear regression is very useful in many applications but has its limitations as things in the real world don't always follow a linear pattern and in such scenarios a simple linear regression function will increase the reducible error and not lead to accurate predictions. The general form of the response function of a simple linear regression is

$$Y \approx \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p \tag{3.1}$$

The linear assumption here means that the task of estimating the function *f* boils down to estimating the set of parameters ($\beta_0$,$\beta_1$,$\beta_2$... $\beta_p$). The higher the flexibility of the parametric model, the more parameters we need to account for in our model.

Of course, linear models are the most basic form of parametric modeling. In fact a family of parametric models have been developed. This measure depends upon the amount of data available and/or the results observed. The data are normally governed by some parametric probability distribution. This means that the data can be interpreted by one or other mathematical formula representing a specific statistical probability distribution that belongs to a family of distributions differing from one another only in the values of their parameters.

Such a family of distributions may be grouped accordingly:

- Beta distribution
- Binomial distribution
- Lognormal distribution
- Exponential (Poisson) distribution
- Weibull distribution.

Estimation techniques for determining the level of confidence related to an assessment of reliability based on these probability distributions are the methods of maximum likelihood, and Bayesian estimation (Stapelberg, 2009). Most of these distributions are adopted throughout the systems modeling process.

### *3.1.3.3 Non-Parametric Reliability Function Assessment*

Non-parametric methods, unlike parametric methods make no assumptions about the shape/functional form of *f*. Instead the approach is to estimate *f* that gets us as close to the data points as possible without capturing too much of the noise in the system (James et al., 2013). With parametric methods, it is possible that the functional form used to estimate the underlying function *f* (i.e. $f_o$) is substantially different from the true underlying f; leading to a model which does not accurately fit the data. In contrast, non-parametric methods do not suffer from this issue since they essentially make no assumption about the underlying function *f*. However, non-parametric methods do suffer from high variance since they do not curtail the number of parameters used to make the fit.

Any parametric models are at best only an approximation to the true stochastic dynamics that generates a given data set. Meaning, parametric methods are plagued with the issues of models biases. According to Fan et al. (2003), “Many data in applications exhibit nonlinear features such as non-normality, asymmetric cycles, bimodality, nonlinearity between lagged variables, and heteroscedasticity.” They require nonlinear models to describe the law that generates the data. A natural alternative is to use nonparametric methods. Non-parametric methods are better at reducing the possible modeling biases that plague their parametric counterparts. This paper explores non-parametric models in the assessment of reliability functions (Non-parametric failure analysis) of certain flow control components and also in the hydrological time series analysis models constructed in chapter 10.

### 3.1.4. Systems Reliability Models

The systems reliability modeling approach aims to combine techniques from engineering risk analysis, system safety engineering, system theory, reliability theory, and system dynamics.

The systems reliability approach will involve some or all of the following components:

**System representation** (Cox, 2009) : An engineered system is often represented mathematically in one of the following forms:

(a) A "blackbox" statistical model: In this setting, the model used to estimate the system can be treated as a "black box" statistical model (see Figure 3.3) since the mathematical form of the model function is of little concern to us provided it is accurate in characterizing the system and predicting its performance.

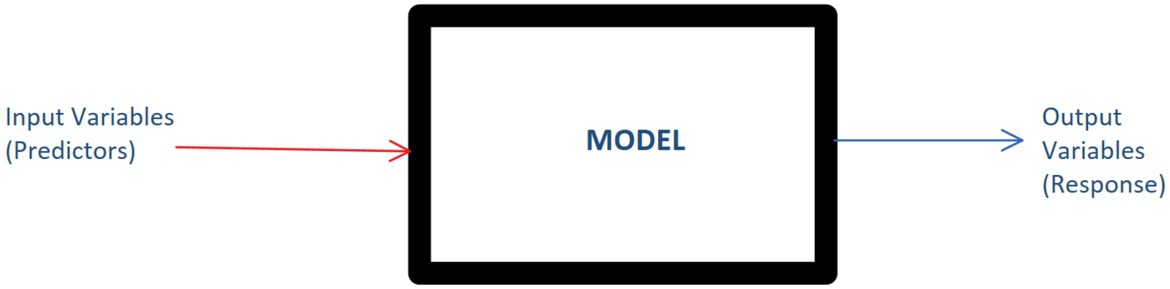


*Figure 3.3: Schematic of Blackbox statistical Model Concept*

(b) Component failure rates combined via a coherent structure function (such as a fault tree or an event tree) mapping the states of system components to the states of the system;

(c) A stochastic state-transition model (e.g., transition models representing component failure and repair rates);

(d) A combination of both discrete-event and continuous simulation model (Smith, 2005).

**Environment representation**: Like a system model, a model of the environment may be a statistical black-box model (e.g., a function describing the frequency and intensity of stresses to the system's components), a stochastic process, or a simulation model. The model of the environment is incorporated directly into the systems model.

**Operating-rules representation:** The operational rules for managing an engineered system maps observed information about the system into a resulting action or intervention. For example, a component may be replaced based on the observed history of failures and repairs for its components.

### 3.1.5. Data in Systems Reliability Modeling

The reliability data required in systems reliability modeling are the parameters of component performance (failure under demand loads) models. These parameters are generally extrapolated from historical performance statistics, although expert opinion on individual equipment assessments may also be used in some cases. Collecting suitable data is at least as essential as developing risk evaluation methods. The data must be sufficiently comprehensive to ensure that an evaluation method can be applied, but restrictive enough to ensure that unnecessary data are not collected (Li, 2005). Fundamentally, the data relates to the two main processes of component behavior, namely, the failure process and the restoration process (e.g. Mean Time to Failure (MTTF) and Mean Time to Repair (MTTR) of a gate mechanical hoist system).

The quality of data is imperative to data collection. The common analogy “garbage in and garbage out” applies here. If the quality of the data cannot be guaranteed, the subsequent reliability model built with such data will also not be accurate. In some cases, data preprocessing may be necessary to filter out bad data. The adoption of a parameter estimation procedure to pre-process the data and extract the input parameters of the systems reliability evaluation is imperative. This requires the suitable design of statistical data modeling.

### 3.1.6. Stochastic Simulation

A simulation typically consists of three parts:

1. Sub-system components such as reservoir inflow channels, spillway gates, hydraulic conveyances, and data acquisition and control systems. These can be interfaced to model a particular reservoir system.

2. Data acquisition components which track the progress of a simulation. These aggregate the data from the simulation runs and create summaries.

3. User interface and dashboard ( *i.e.,* visualization) components, which allow the data from the simulations to be portrayed to the user.

The modelled system comprises a large number of inter-related sub-system components. Modules can be developed to be free standing, and to ‘snap’ together as appropriate to form a particular reservoir and flow-control system. The sub-systems are designed to be free-standing, and may be redundant in the sense that duplicative types of sub-components might be developed for different purpose. For example, two or more sub-components might be developed for reservoir inflow. One might be a simple flood-frequency statistical model using a stochastic time series of river discharges. Another might be a spatially distributed rainfall-runoff model. These two could be swapped for one another depending on the needs of a particular analysis.

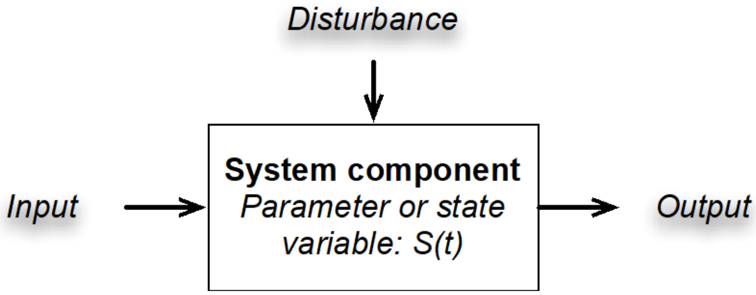


*Figure 3.4: Schematic system component.*

Each sub-system component is abstracted in mathematical expressions that describe the behavior of the component for a given input and a given set of disturbances, and specifies the output interactions of the component with other components (Figure 3.4). This set of system components forms a large network of interactions, as illustrated in Figure 3.5.

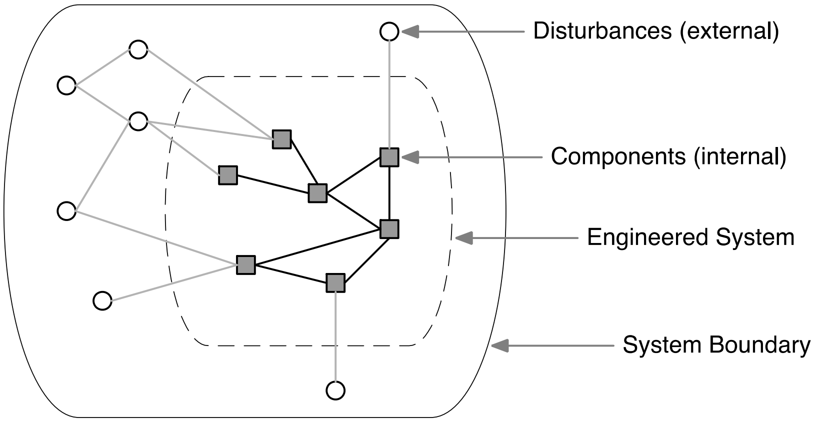


*Figure 3.5: System boundary and interactions.*

The mathematical expressions that describe the system component contain parameters, the realized values of which are the system states at any one moment in time. Some of these parameters are fixed and unchanging; others change under the influence of the history of inputs and disturbances up to that moment. At the end of any one cycle in the simulation the totality of parameter values at all of the systems components define the system state at that moment.

The total number of system state parameter values at any cycle can be large, too large to track efficiently. Thus, a subset of a limited number of these is identified as select system states, for example, water levels, flow rates, pressure distribution, vibrations, temperature, etc., and the values of these are tracked and compared against performance criteria to identify important functions, hazardous states or failures.

As a general rule in modelling systems, the systems states at the respective components may change upon each simulated cycle, but components may also be added, eliminated, or their fundamental structure modified (Weck et al., 2011). In the present case of simulating spillway systems, components may be modified but they are not typically added or eliminated once a simulation in in progress.

From an operational point of view the critical issue is to develop an interface protocol among the sub-system components such that the output of one sub-system is readily accepted as the input to the next in the chain. This allows any of the sub-system modules to be replaced with a similar module using a different calculation approach (*e.g.,* stochastic reservoir inflows *vs.* rainfall-runoff generated inflows).

Within the simulation, three process flows are tracked:

- Physical flows ( *i.e.,* water, sediments, debris, *etc*.),
- Communication ( *i.e.,* information flows), and
- Control ( *i.e.,* human action flows).

The principal models along the part of the water flow start with the hydrology model which generates inflows. Next comes the reservoir module which translates inflows into pool elevations and possibly related performance variables. The reservoir model provides inputs to the hydraulic gate and valve modules which control outflows to the respective waterways ( *i.e.,* the surface spillway, powerhouse, bottom drain if any, and auxiliary spillway if any). The gate and valve modules provide input to the downstream conveyances, energy dissipation structure, and ultimately the downstream channel.

In general, the water flow modules and path are reasonably straight forward physics-based models of the type common in hydropower engineering. They take naturally occurring weather processes as input and generate hydraulic process as output.

### 3.1.7. Monte Carlo Simulation

Goodarzi *et al.* (2013) defined simulation as the imitation of a real thing or process to replicate the behavior of a system under different conditions. Simulation helps to evaluate desired strategies to manage the system in the best way and see how it will be changed in the future.  The Monte Carlo method is a numerical method based on random sampling to solve complicated integrals that is difficult or impossible to be evaluated analytically. The basic idea behind this integration technique is choosing sample points randomly over desired domain to approximate their results. In many cases, Monte Carlo Simulation is used to estimate the performance of a real system in different situations over a desired time interval before investments are made. This process determines the main properties of outcomes with regards to input and transfer functions between input and output. The transfer function plays an important role in simulation analysis and output accuracy strongly depends on its proper identification. When the transfer function is simple, analytical techniques are applied to determine outputs, while for complex transfer functions which it is not possible to derive output properties analytically, approximation methods are normally used.

Simulation resolves to a great deal of computer modelling. The relatively simple subsystems are modelled mathematically, and then their behaviors are interrelated by means of simulation. Simulation is relied upon because closed-form analytical solution of the overall complex system is usually beyond our modelling capabilities. The simulation modelling involves mathematical characterization of the sub-systems, a backbone of network theory, probabilistic cauterization and differential equations, and a good deal of numerical computation. The result is that we can approximately simulate how the complex system behaves, and we can change things in the input and formulation to see what might happen when the complex system is disturbed. The disturbance might either be by routine variations as, for example, human factors or stochastic variations, or by systemic loadings as from earthquakes or landslides.

For many applications in the natural sciences, social sciences, and industry, simulation modelling has become a required tool of analysis and understanding. The use of large-scale stochastic simulation to study complex systems is now common in many scientific disciplines, especially when exploring questions that are poorly suited to traditionally deductive, deterministic analysis. This approach has proven particularly powerful when dealing with systems involving multiple and seemingly incommensurate aspects, for example in combining together factors such as physical science, natural processes, information networks, economics, and human factors. Today, simulation approaches are used in fields as far flung as oil and gas exploration, medicine, materials science, urban planning, and aerospace (NSF, 2006). Over the past decade the US National Research Council has published more than a dozen reports on the use of simulation in engineering science, public policy, STEMS training, and other applications (NRC, 2002, 2008, 2010).

To simulate real-world conditions, the impact of a number of different physics that occur concurrently, such as the physics of hydrodynamics, storage, power generation, etc. have to be accurately characterized. Typically, effects from one physics domain also impact how a product behaves in another physics domain. For example, combined water pressure-structural effects are crucial the performance of spillway gates.

A simulation typically consists of three parts:

1. Sub-system components such as reservoir inflow channels, spillway gates, hydraulic conveyances, and data acquisition and control systems. These can be interfaced to model a particular reservoir system.

2. Data acquisition components which track the progress of a simulation. These aggregate the data from the simulation runs and create summaries.

3. User interface and dashboard ( *i.e.,* visualization) components, which allow the data from the simulations to be portrayed to the user.

The modelled system comprises a large number of inter-related sub-system components. Modules can be developed to be free standing, and to 'snap' together as appropriate to form a particular reservoir and flow-control system.

### 3.1.8. Simulating Flow Control Operations

The previous sections lay out the systems approach to understanding operational safety and reliability, how simulation modelling can be used to track operations and flow-control, and to identify malevolent chains of events is discussed herein. This section delves deeper into the concepts and mathematics of systems modelling.

The problem faced in analyzing flow-control through a reservoir (in a broad sense, including spillways and generating units) or a cascade of reservoirs is that the whole behaves as a complex engineered system the behavior of which is more than the sum of its parts.

Complex systems comprise a large number of relatively simple systems interacting together. Each of these relatively simple sub-systems can, in principle, be mathematically modelled, at least to a first-order, but their interactions within the larger system typically cannot be. It is commonly the case that the quantitative behavior of the complex system cannot be forecast with precision, yet its qualitative behavior may be structured and understood using contemporary simulation techniques. Today, stochastic simulation techniques have been used to unravel the mysteries of many engineered and natural systems which had heretofore proven opaque to analysis. Among these are the electrical power grid, communications systems, aircraft performance, nuclear power plants, climate systems, and financial markets.

Simulation resolves to a great deal of computer modelling. The relatively simple subsystems are modelled mathematically, and then their behaviors are interrelated by means of simulation. Simulation is relied upon because closed-form analytical solution of the overall complex system is usually beyond our modelling capabilities. The simulation modelling involves mathematical characterization of the sub-systems, a backbone of network theory, probabilistic cauterization and differential equations, and a good deal of numerical computation. The result is that we can approximately simulate how the complex system behaves, and we can change things in the input and formulation to see what might happen when the complex system is disturbed. The disturbance might either be by routine variations as, for example, human factors or stochastic variations, or by systemic loadings as from earthquakes or landslides.

The purpose of the simulation is to gain holistic understanding of how the complex system works by numerically mimicking its behaviors. Things will go wrong, often by a combination of not-improbable conditions whose juxtaposition threatens the stability of the system, and in ways that no one thought of beforehand. The modelling leads to an understanding of how management might anticipate or respond to things going wrong in an operation.

The use of large-scale stochastic simulation to study complex systems is now common in many scientific disciplines, especially when exploring questions that are poorly suited to traditionally deductive, deterministic analysis. This approach has proven particularly powerful when dealing with systems involving multiple and seemingly incommensurate aspects, for example in combining together factors such as physical science, natural processes, information networks, economics, and human factors. Today, simulation approaches are used in fields as far flung as oil and gas exploration, medicine, materials science, urban planning, and aerospace (NSF, 2006). Over the past decade the US National Research Council has published more than a dozen reports on the use of simulation in engineering science, public policy, STEMS training, and other applications (NRC, 2002, 2008, 2010).

### 3.1.9. System Simulation of Hydropower operations

The system of interest is flow control operations, the fundamental functions of which are to store, bypass, or divert water. These functions are treated as sub-functions of a control system. The operating objective of different kinds of dam systems might be hydropower generation, water supply, navigation control, recreation etc. or a combination of these.

Nevertheless, flow control is the critical enabling system for any of these primary operating objectives.

Here, we are mostly concerned with hydropower generation and discharge control. The natural and engineered systems typical of hydropower can be categorized using the taxonomy proposed by Simonovic (2008):

> **Natural systems** are those regularly occurring in the world, such as hydrological, geological, climatological, or biological processes. These are the settings within which engineered systems are built. Natural systems, by virtue of their evolutionary development, exhibit a high degree of interconnectedness. They typically exhibit cyclic behavior in that energy, material, and other flows have established themselves over long periods of time and are in balance, until disturbed by externally imposed change.
>
> **Engineered systems** are those designed and constructed by people. They may or may not exhibit the high degrees of interconnectedness characteristic of natural systems. A river basin with a cascade of dams is a system composed of both natural and engineered aspects, and is made more complex by the juxtaposition of these naturally occurring and man-made factors.
>
> **Conceptual systems** exist as concepts and mathematical relations but not in an instantiation in physical reality, that is, in contrast to natural and engineered systems, which do exist in the physical world. Conceptual systems are important in mathematics, computer science, logic, and may fields of study; but are

> important in the present discussion in the extent to which they may be used in an abstract, analytical capacity to mimic physical systems.

Yet another distinction among systems involves those that are **static** in contrast to those that are **dynamic**. A static system, such as a structural frame, responds to forces and other disturbances but does not change or evolve in response to external perturbations. A static system, such as the embankment of a dam, will respond to loads and perturbations, and will generate interactions among its subcomponents; but its structure or interactions will not evolve in response. A dynamic system is one whose properties do change or evolve in response to the forces or other disturbances applied to them. The riverbed downstream of a spillway and stilling basin is a dynamic system. It's properties may be changed by the loads and perturbations to which it is subjected. The boundary between static and dynamic systems may not be finely drawn.

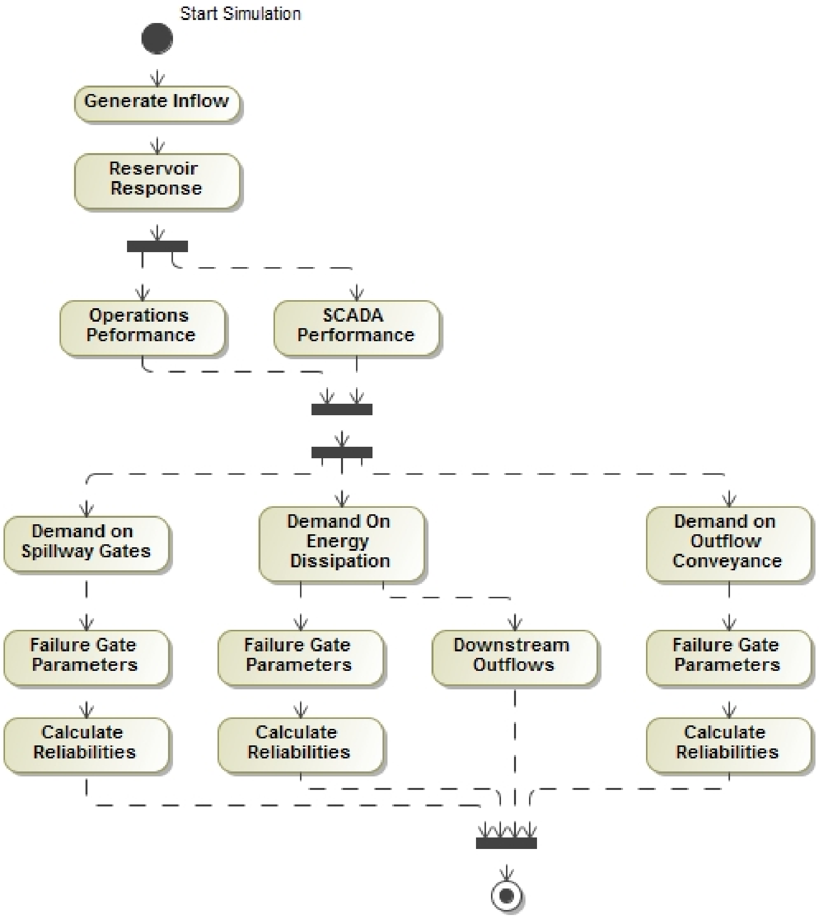


*Figure 3.6: Simulation Activity Diagram*

Within the simulation three process flows are tracked: water (i.e., the physical flows), communication (i.e., information flows), and control (i.e., human action flows). The activity diagram in Figure 3.6 shows how the simulation proceeds in a sequential manner capturing the three processes described. Once the simulation run is started, flows are generated and routed through the reservoir. The reservoir responds through changes in elevation. The operators and automated systems communicate this change in elevation to the spillway gates if its demand is needed. If its demand is needed, the spillway gates are opened either remotely, on site or by automated systems to route water out of the reservoir.

This set of events happen iteratively through time and their performance and reliabilities are computed before and provided as outputs at the end of the simulation run.

### 3.1.10. System states and process

At its core, simulation is the imitation of salient properties of one process by another. Typically, the first process is something occurring in the natural world, in our case flows of water, information, human actions, and possibly other things through a reservoir or series of reservoirs. Typically, the second process is mathematical. We say salient properties to mean those that are important, noticeable, or conspicuous to the current purpose. The natural system may have many properties that a simulation will not and need not capture, because they are irrelevant to the purpose at hand.

*System states* are the variables necessary to describe a system at a particular time and for the particular purposes of the study. In principle, there is an infinite number of potential systems states. Thus, system states need to be defined by the modeler for the particular purpose at hand and in a multitude that balances comprehensiveness with efficiency. Defining system states is simply one of the many modelling decisions that need to be made. For a hydropower dam, system states might include the reservoir inflow, the water surface elevation, the power being generated by each turbine, the open or closed condition of each gate, the discharge of water downstream, and so on.

As a simulation proceeds, the realized values of system states are tracked at each cycle of time. The values of some of the system states become inputs to other subsystems. The values of others of these *(select) system state*s may be related to, or may themselves be, output performances of the overall system. Some of these output performances may constitute adverse performance or failure of the system functions. The rate at which these adverse systems states appear in the simulated record may be taken as a statistical estimate of the probability of system failure in particular ways. For example, the rate in simulated time at which the system state, "spillway gate fails to open", can be used as a statistical estimate of gate availability. The rate in simulated time at which the system state "minimum hydraulic flow pressure on the spillway conveyance" exceeds cavitation limits, can be used to statistically estimate the probability of cavitation.

The term *process* means the sequence of system states as they evolve in time. Because these transitions among states may reflect many intellectual disciplines—hydrology and hydraulics, geotechnology, human behavior, instrumentation and control, thermodynamics—the simulation approach lends itself to multi-disciplinary analyses. The transitions within individual states or similar sets of states is modelled mathematically. From a mathematical view, the sorts of systems that we attempt to simulate have characteristic mathematical properties that are useful as a way of categorizing the types of simulations needing to be built (Table 3.1).

The simulation models used to replicate and forecast the behavior of spillway systems reliability are usually non-linear, stochastic, and spatially distributed. For example, the hydraulic pressures and cavitation damages induced in outflow conduits or stilling basins depend in highly non-linear ways on spillway discharges and thus reservoir pool elevations. Those pool elevations fluctuate as random time-series depending on the hydrological conditions creating reservoir inflows. The reservoir inflows and disturbances from events such as landslides in turn depend on spatially and possibly temporally variable basin parameters affecting runoff, debris generation, and other processes.

### 3.1.11. Why use simulation for hydropower?

Stochastic simulation approaches to modelling and understanding complex water resource system performance has become increasingly common. For example, in large-scale water and power infrastructure Tilmant et al. (2012) have applied simulation to optimizing power production in a cascade of reservoirs under variable hydrology. Von Stackelberg and Neilson (2012) apply simulation to riverine water quality. Gersonius et al. (2012) applied simulation to incorporate uncertainty and flexibility in the economic analysis of flood risk and coastal management strategies. Regan ( 2010) has suggested a simulation approach to dam safety. Billinton and Li ( 1994) applied simulation to assessing the reliability of power distribution systems. In applications to other systems safety problems Blum *et al.* (2010) applied simulation to safety analysis of airspace craft design, Leveson (2012) applies simulation to power generation systems, Hosse and Schnieder (2012) have applied simulation to highway safety, and Zio (2013) and Blom *et al.* (2006) survey many systems safety applications. Simulation methods are also now widely used in modern financial engineering analyses of risk (Glasserman 2010).

*Table 3.1. Categories of mathematical systems models*

| System property | Characteristics |
|---|---|
| Linear *vs*.<br>non-linear | In a *linear* model all the relations among input and output processes, the external constraints on the system, and the objectives for operation (if applicable) are represented by simple linear relationships. This is infrequently the case in flow control models, where these relationship, constraints, and objective functions tend to be non-linear. The behavior of non-linear models tends to be much less intuitive and predictable than for linear models due to the complexity of interactions among variables. |
| Deterministic *vs*.<br>probabilistic | For the case that each input parameter to the system model can be assigned a specific and definite value, and each computer relation or sub-model within the model translates specific and definite input parameter values to specific and definite output values, a model is *deterministic*. Those input values may themselves be uncertain, and varying those parameter values might allow sensitivity computations; but if the values and relations are specific and definite in any one running of the model, then the deterministic nature of the model still holds. The opposite of deterministic is *probabilistic*, in which input and output values are represented by probability distributions rather than specific and definite values. |
| Static *vs*.<br>dynamic | A static model is not a function of time. The forces or perturbations on the system achieve an equilibrium condition and remain such until conditions are changed or another condition is imposed. Dynamic systems respond, usually continuously, to temporal changes in environmental conditions or |

| | |
|---|---|
| | internal processes. If those conditions and the responses are probabilistic, then a dynamic system is said to be *stochastic*. |
| Lumped *vs*. Distributed parameter | Models in which parameter values are assumed constant throughout space are usually referred to as *lumped parameter* models. That is, the parameters are lumped at some average or at least defined value and are assumed to be homogeneous in space. They may change in time. *Distributed* parameter models are those that model parameter values as varying in space. The variation may be deterministic or probabilistic. In the latter case the models might be called stochastic or in special cases may be called *geo-statistical* (depending on the modelling approach). |

There are a variety of good reasons for the increasing popularity of simulation approaches to safety and risk analysis:

- Simulation allows complex systems interactions to be modelled easily when compared to closed-form analytical models.
- Computer speeds are rapidly increasing, and engineers have increasing access to high-performance computing.
- Discrete events are readily included in simulations while they often pose combinatorial problems in fault tree and event tree models.
- Simulation readily allows for the inclusion and interaction of many and differing types of system response (physics of failure, communication and control, and human reliability, for example).
- The numerical precision of simulation results are independent of the complexity of the system being modelled, and depend only on the numbers of simulation trials being performed.

Complex systems, of the type related to operational reliability, share several characteristics that make them suitable subjects for stochastic simulation approaches.

- They involve many parts (components).
- These parts have combinatorically many interactions, one-to-one and many-to-many.
- The input parameter space is large.
- The timing of events is important.
- Uncertainties in the parameters are of many types and often correlated.
- The system behaviors or outputs are also stochastic and usually unpredictable based on simple abstractions.

Finally, and perhaps most relevant, the output behaviors of these systems are *emergent*, that is, patterns of performance arise out of the diversity and number of relatively simple component interactions, and those patterns are usually not obvious ahead of time.

### 3.1.12. Tracking physical flows

The hydrology model is coupled with a reservoir routing module that takes reservoir inflows as input and returns pool elevation and possibly other states and processes as output. These reservoir outputs provide demand inputs to the various waterways (Figure 3.7). The waterway modules in turn provide outputs to the downstream channel. The physical characteristics of the water flows are instantiated in states at a set of pre-defined system states, and these system states are compared against a set of limiting state criteria to judge whether adverse performance or failures occurs at any time in the simulation.

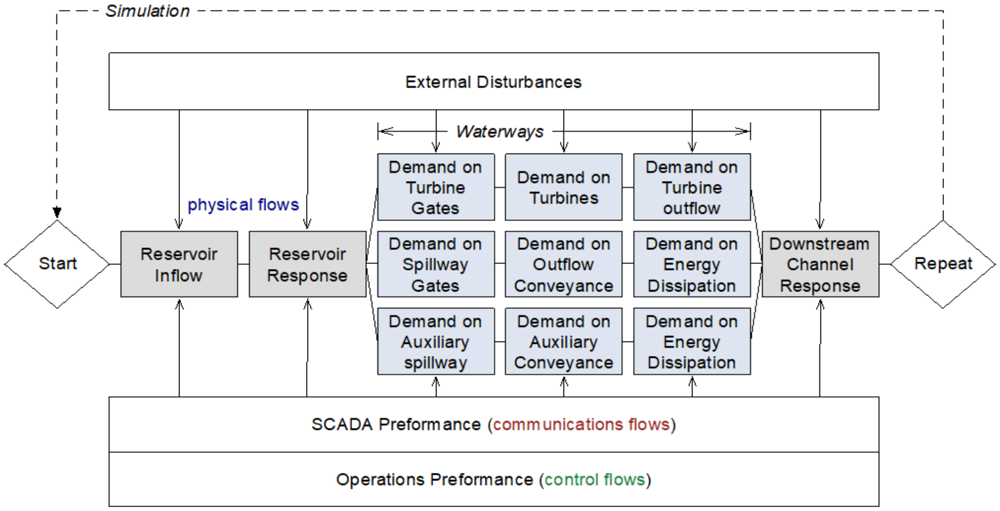

Simulation
External Disturbances
Waterways
physical flows
Start
Reservoir Inflow
Reservoir Response
Demand on Turbine Gates
Demand on Turbines
Demand on Turbine outflow
Demand on Spillway Gates
Demand on Outflow Conveyance
Demand on Energy Dissipation
Demand on Auxiliary spillway
Demand on Auxiliary Conveyance
Demand on Energy Dissipation
Downstream Channel Response
Repeat
SCADA Preformance (communications flows)
Operations Preformance (control flows)

*Figure 3.7: Simplified simulation logic. The sub-system modules are designed such that the interface protocols among the modules allow the modules to be replaced with other technologies.*

The safe operation of any industrial facility is highly dependent on the humans who operate and manage them, and who may be called upon to make decisions in the face of unexpected disruptions or other events. Over the past many decades a systematic body of theory and practice has emerged on the types, rates, and importance of human operator errors, and this insight needs to be incorporated in simulation models. The system simulations discussed so far have assumed present basin and climatological conditions: That is, how does the flow-control systems perform given the current basin configuration and environment and with its expected variations and extremes.

# CHAPTER 4: COMPONENTS OF HYDROPOWER PLANT OPERATIONS

## *4.1. The Reservoir*

The reservoir component itself is a rather complex subsystem in which a number of interacting processes takes place. The structure of a reservoir is defined by the interactions between inflow, storage, outflow and other variables specific to a particular reservoir location (Simonović, 2009). Very often reservoirs are built and operated to satisfy water quantity requirements such as irrigation or drinking water consumption, hydropower production, etc. Optimal operation of these reservoirs is vital to maximize benefits. The attributes of a reservoir can include a large number of quantities characterizing both physical properties of the reservoir as well as characteristics of the processes occurring within the component. Not all of the properties and the processes are relevant to the objectives of a particular modelling endeavor and the systems analyst has to make a decision which attributes should be included in the component model. The relevant attributes for the reservoir may include inflow, water level, discharge, chemical properties of water, storage, water temperature and many others. Regardless of the number of original or current purposes of a reservoir the storage behind the dam can be subdivided into the zones as illustrated on Figure 4.1.

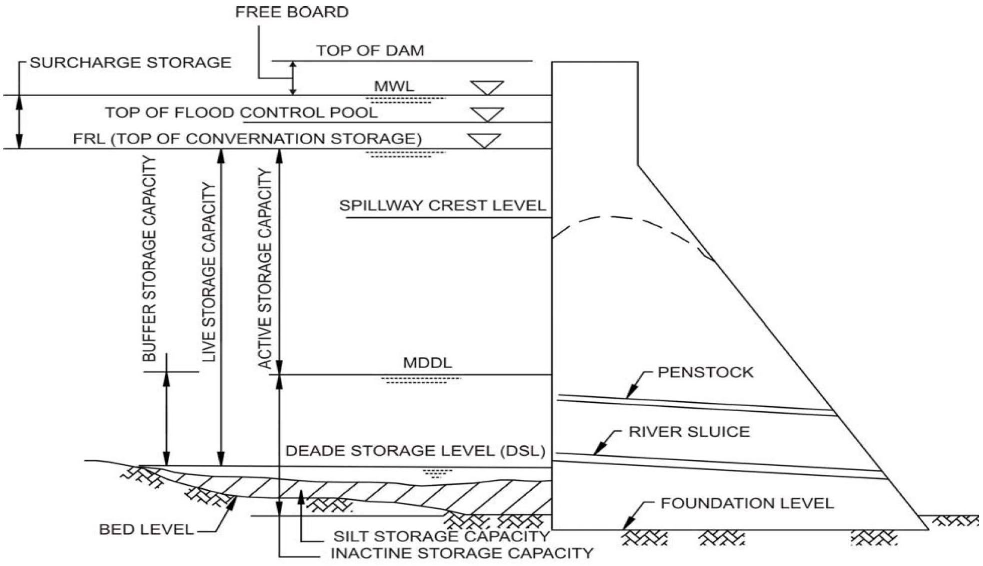


*Figure 4.1: Schematic Diagram Showing Storage Reservoir Zones*

***Full Reservoir Level (operating range maximum level)*****:** It is the level corresponding to the storage which includes both inactive and active storages and also the flood storage, if provided for. In gated reservoir systems, this is typically the highest active pool elevation before spillway flow is required.

***Minimum Drawdown Level (MDDL)*****:** It is the level below which the reservoir will not be drawn down so as to maintain a minimum head water requirement for power generation.

***Dead Storage Level (DSL)*****:** Below the level, there are no outlets to drain the water in the reservoir by gravity.

***Maximum Water Level (MWL)*****:** This is the water level that is ever likely to be attained during the passage of the design flood. This level is also called sometimes as the ***Highest Reservoir Level*** or the ***Highest Flood Level***.

***Live storage*:** This is the storage available for the intended purpose between the operating range maximum level and the Invert Level of the lowest discharge outlet. This is the reservoir operating levels usually assigned to hydropower generation.

***Dead storage*:** It is the total storage below the invert level of the lowest discharge outlet from the reservoir.

***Surcharge or Flood storage*:** This is required as a reserve between the operating range maximum level and the Maximum Water level to contain the peaks of floods that might occur when there is insufficient storage capacity for them below the operating range maximum level.

***Freeboard*:** It is the margin kept for safety between the level at which the dam would be overtopped and the maximum still water level. This is required to allow for settlement of the dam, for wave run up above still water level and for unforeseen rises in water level, because of surges resulting from landslides into the reservoir from the peripheral hills, earthquakes or unforeseen floods or operational deficiencies.

### 4.1.1. Key Parameters of Reservoir Operation

The following section describes the key parameters of reservoir modeling:

**Water Level** (denoted by *h*) can be defined is the water level measured at a specific gauge and at a specific time. Quite often in the past the measurements at hydrometric stations were carried out once daily at a specific hour.

**Inflow** (denoted by *q*) can be defined as total inflow into the reservoirs from all sources. Streamflow, like many other quantities observed in natural systems, is always continuous in time. However, the sampling of not only inflows but all other attributes usually takes place at discrete time instants. For these reason, it is convenient to build the discrete-time model in which the time parameter *t* represents the sampling or decision time instants. Following this assumption, the inflow can be now defined in more precise terms as follows and we will understand that inflow $q_{t+1}$ represents amount of water that entered the reservoir during the time interval [*t, t+1*).

**Discharge** (denoted by *d*) is the total flow released from the reservoir through all spillway facilities, turbines of the hydropower station (if present), through the navigation locks (if present) and through the lower level outlets. Similarly, as for the inflow, discharge $\mathrm{d}_{t+1}$ represents the amount of water that was released from the reservoir during the time interval [*t, t+1*).

**Storage** (denoted by s) is the volume of water stored in the reservoir.

If water level is denoted by $h_t$ then inflow within the interval [*t, t+1*) is not known at the time *t* and it can be known only when it have been realized at the end of time interval and for that reason will be denoted by $q_{t+1}$. Storage has a unique property since its value $s_{t+1}$ at time *t+1* can be calculated from its value $s_t$ at time t using the following formula:

$$s_{t+1} = s_t + q_{t+1} - d_{t+1} \qquad (4.1)$$

When a variable at any instant of time depends on its value at the previous instant, it is called a *state variable.* It describes the state, or in other words, the present condition of the component which is determined from its past history and is necessary in order to predict the future. Therefore, storage is a state variable in the reservoir model.

The water level $h_{t+1}$ at time $t+1$ can be determined from the storage $s_{t+1}$ using either stage-storage relationship or from information about the bathymetry of the reservoir and topography of its rim.

### 4.1.2. Hydrologic routing methods

Hydrologic routing techniques model the downstream conditions within the river reach in response to a given flow hydrograph at the upstream end of the reach. The modelling utilizes only the continuity equation and analytic or empirical relationships between the channel storage and the discharge at the outlet. The continuity equation for the river reach can be conceptualized as:

Continuous time

$$\frac{dS(t)}{dt} = I(t) - Q(t) \tag{4.2}$$

Discrete time

$$I - Q = \frac{\Delta S}{\Delta t} \tag{4.3}$$

Where for the discrete time formulation $I$ is the average inflow at the upstream end of the river reach during time interval $\Delta t$, $Q$ is the average discharge from the reach during time interval $\Delta t$ and $S$ is the reach storage.

The most commonly used methods applied for hydrologic routing are:

a) Linear reservoir(s)
b) Modified pulse
c) Muskingam
d) Muskingum-Cunge

The analytical methodology adopted for the systems reliability modeling will be examined in more depth in the next chapter.

### *4.2. Reservoir Outflow structures*

Reservoir outflow structures are combinations of structures used to route excess flows downstream of the reservoir and also to convey water from the reservoir to a discharge point downstream from a dam (Jansen, 2012). These can be divided into two main outflow systems; namely spillways systems and outlet systems. Outlets are frequently used for diversion during construction, and may, if highly reliable, be used to help to accommodate the design flood.

Outflow components are classified according to their function:

- Irrigation
- Municipal and/or industrial use
- Flood control
- Power production
- River outlet (for release of river flow requirements)
- Emergency drawdown

These general types have various kinds of intakes and provisions for gating and energy dissipation.

## *4.3. Spillway Gates*

Spillway is an integral part of any dam. A spillway is a method for spilling of water from dams. It is used to prevent overtopping of the dams which could result in damage or failure of dams or in some cases used to maintain prescribed water levels for energy generation. Spillways are of two types: controlled type and uncontrolled type. The uncontrolled type of spillway is one which starts releasing water when water rises above a particular level. In this type, overflow is the only way for water to reach the other side of the dam. In the case of the controlled type spillway, it is possible to regulate flow through gates provided within the dam structure that provide an opening for releasing water downstream without passing it through the turbine.

### 4.3.1. Gated Spillways

Gated spillways generally permit the use of a larger live storage than do ungated spillways, which is often economically favorable. On the other hand, gates are critically sensitive components of dam systems and gated waterways cannot be expected to always be available on demand.

The greater flexibility of operation provided by gated spillways makes it possible to regulate either the upstream water level or the water conduit discharge in a narrower band. Thus the pool elevation in a reservoir can be operated within optimal levels for power generation. The price to pay for the introduction of a movable water barrier is a significant reduction in spillway function reliability since several components and subcomponents have to come together and function on demand for the gated spillway System to work. The issue of functional reliability will be looked at in more details in chapter 7.

Operating experience with spillways for dams has revealed problems of two types: (1) inadequate capacity and (2) unsatisfactory performance for design or less-than-design discharges. Particular items that appear to be most critical in the second area are identified and categorized in the subsequent chapters.

#### *4.3.1.1 Spillway Gate Operations and Model Characterizations*

Depending on the gate operating conditions and the water elevation on either side of the spillway flow, spillways are classified into five different flow categories. More specifically those categories are (Brebbia and Carlomagno, 2007):

- Free orifice-flow (partially opened gate – i.e. gate is in the water)
- Submerged orifice-flow (partially opened gate)
- Free weir-flow (fully opened gate – i.e. gate is out of the water)
- Submerged weir-flow (fully opened gate)
- Submerged tidally-affected weir-flow (fully or partially opened gate)

Within the systems modeling framework, flows through gated spillways are generally computed from instantaneous stage and operational control information using in-house developed discharge rating tables (See Figure 4.2). The table relates discharge as a function of head water elevation. However, where such information is not available or the accuracy of discharge estimates is compromised due to certain conditions, mathematical formulations can be used. The parameters of these formulations will typically be related to flow, fluid and geometric features of the spillway gate structure. Traditionally, submerged flow is estimated as

$$Q = C_S B H_t \sqrt{2g(H - H_t)} \tag{4.4}$$

Where B is the gate width, H is the upstream head, $H_t$ is the tail-water elevation, g is the gravitational acceleration, and $C_S$ is an empirical coefficient expressed as:

$$C_S = \alpha \left(\frac{H_t}{H}\right)^{\beta} \tag{4.5}$$

where α and β are experimental constants(Tillis et al., 1998).Other basic formulas developed for the estimation of orifice and weir type of flows can also be tested to see which ones best characterizes the spillway flow being analyzed and improvisations made where necessary (Brebbia and Carlomagno, 2007).

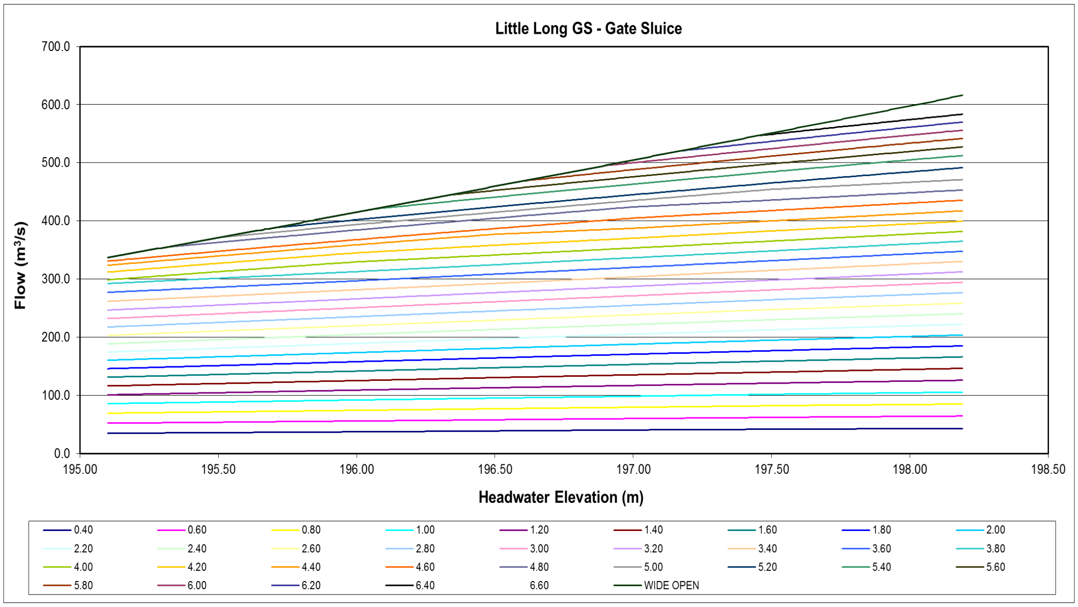


*Figure 4.2: Sluice Gate Discharge Rating Tables*

#### *4.3.1.2 Specific Deficiencies and Problems to incorporate into the model*

The outlet, spillways and gates have been traditionally viewed from the perspective of structural mechanical–electrical reliability considerations. They comprise, at a minimum, the following: structural subsystems, mechanical subsystems, electrical subsystems and controls subsystems. The controls subsystems include any SCADA technology that may be present. These systems are also those for which human factors are important. The human factors, in a broad sense, include the control room operations of people and equipment, operating rules and procedures, and the supervisory system (real-time interfaces, forecasts of reservoir inflows, etc.).

Spillway deficiencies that could compromise the safety of a dam can be broadly categorized as:

1. Inadequate spillway capacity.
2. Failure of flow surfaces due to cavitation and abrasion.
3. Structural failure because of inadequate foundation treatment and failure to prevent excessive uplift pressures.
4. Structural failure caused by dynamic loadings.
5. Failure of operating provisions, hoists, and hoist controls; gate malfunction.

### *4.4. Turbines*

The turbine can be considered as the heart of any hydropower plant. Its role is to convert the power of water into mechanical power, i.e. by rotating the shaft. The water strikes the turbine blades and turns the turbine, which is attached to a generator by a shaft.

There are two main turbine categories: “reaction” and “impulse” (International Renewable Energy Agency, 2012). Impulse turbines extract the energy from the momentum of the flowing water, as opposed to the weight of the water. Reaction turbines extract energy from the pressure of the water head. The Francis turbine-which is the most common hydropower turbine—is a reaction turbine and is the most widely used hydropower turbine in existence. Impulse turbines such as Pelton are also used in certain scenarios.

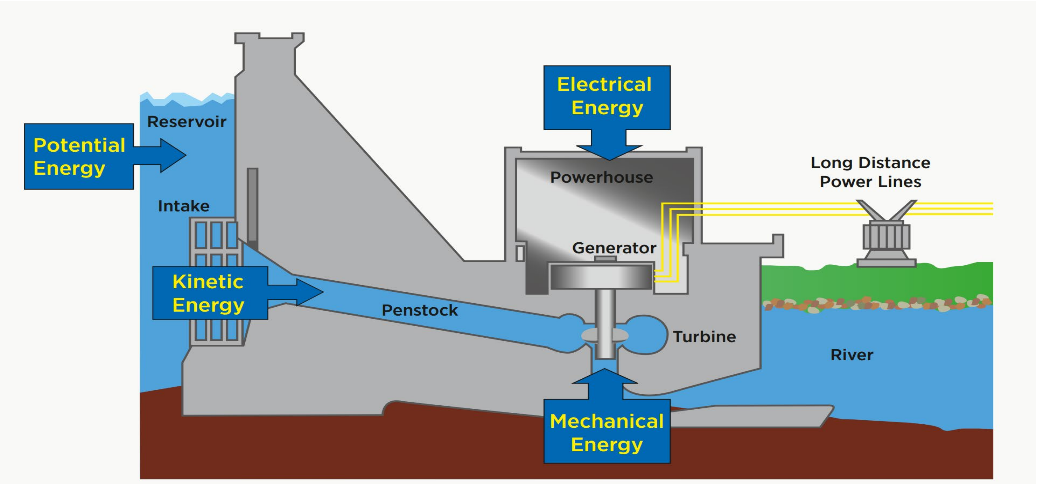


*Figure 4.3: Schematic of Dam-Reservoir-Generation Systems*

Analytically, the electric power, P, in Watts (W), of a reaction turbine can be determined by the following equation (Leon and Zhu, 2014):

$$P = \eta\gamma Q(H_g - h_L) \tag{4.6}$$

where $\gamma$ *(=* $\rho \times g$*)* is specific weight of water in $kg/(m^2 \times s^2)$*,* $Q$ is flow discharge in $m^3/s$*,* $Hg$ is gross head in m, $h_L$ is sum of head losses in m, ρ is water density in $kg/m^3$ , g is acceleration of gravity in $m/s^2$ , and $\eta$ is overall hydroelectric unit efficiency, which in turn is the product of turbine efficiency *(ηt)* and generator efficiency*(ηg).*

For an impulse turbine (see Figure 4.3), the sum of head losses can be written as

$$h_L = \frac{Q^2}{2gA_2^2}\left[f\frac{L}{D} + \sum k_{1-2} + k_N\left(\frac{A_2}{A_N}\right)^2\right] \tag{4.7}$$

where L, $D_2$ and $A_2$ are length, diameter and cross-sectional area of penstock, respectively. In addition, f is friction factor, $\sum k_{1-2}$ is the sum of local losses in penstock due to entrance, bends, penstock fittings and gates, $A_N$ is nozzle area at its exit (and $k_N$ is nozzle head loss coefficient, which is given by

$$k_N = \frac{1}{C_V^2} - 1 \tag{4.8}$$

Where CV is nozzle velocity coefficient.

Likewise, for the purpose of systems modeling, power generation as a function of turbine discharge relationships (See Figure 4.4) are usually generated in-house and the modeler may have to incorporate this data in the form of look-up tables. The table relates power generation as a function of discharge and head water elevation. However, where such information is not a not available or the accuracy of the relationship between power and discharge is inaccurate, the presented mathematical formulations can be incorporated into the model used.

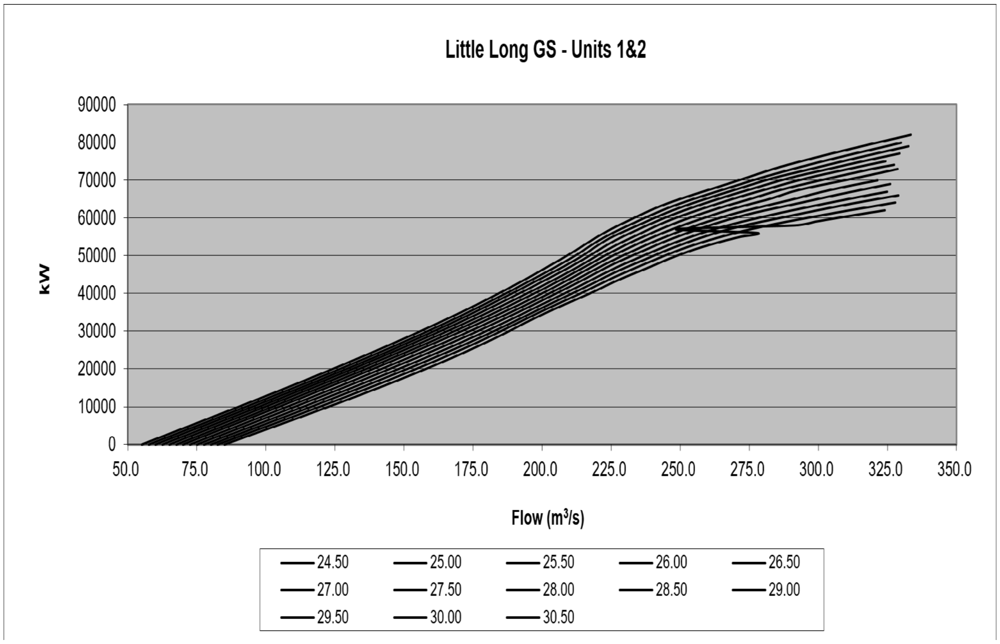


*Figure 4.4: Power Generation Rating Tables*

### 4.4.1. Operational Aspects of Turbines

The efficiency of a turbine depends on the water flow and the type of turbine. The efficiency of Pelton and Kaplan turbines is high over a wide range of water flow. Propeller and Crossflow turbines present a distinct optimum. The following features are to be noted:

- The maximum efficiency of most turbines are usually around order of 90% (Wagner and Mathur, 2011), however, this maximum efficiency is not at 100% flow (see Figure 4.6).

- The efficiency of all the turbines is low if the flow is much reduced. There must be a minimum of water flow for turbine operation.

• The shape of the efficiency curve is also dependent on the ratio of flow (Q) to design flow ($Q_o$).

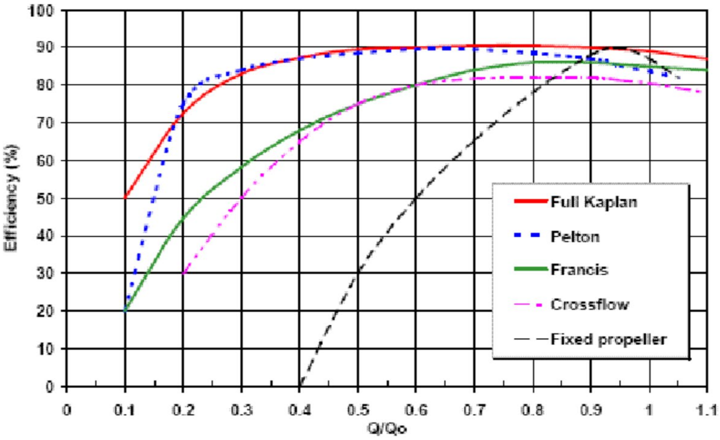
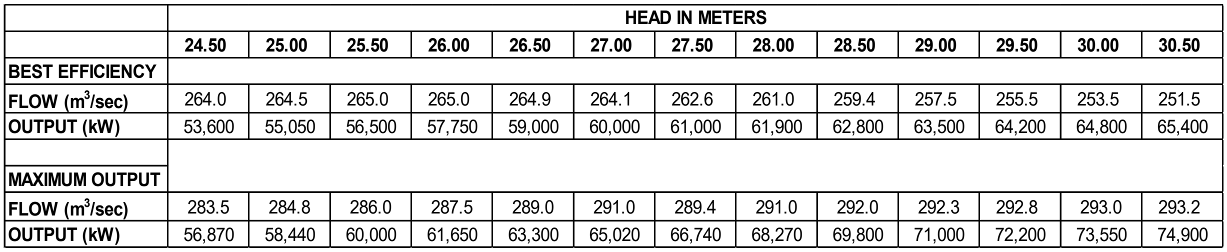


*Figure 4.5: Efficiency Curves for turbine types*



| | HEAD IN METERS | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **24.50** | **25.00** | **25.50** | **26.00** | **26.50** | **27.00** | **27.50** | **28.00** | **28.50** | **29.00** | **29.50** | **30.00** | **30.50** |
| **BEST EFFICIENCY** | | | | | | | | | | | | | |
| **FLOW ($m^3$/sec)** | 264.0 | 264.5 | 265.0 | 265.0 | 264.9 | 264.1 | 262.6 | 261.0 | 259.4 | 257.5 | 255.5 | 253.5 | 251.5 |
| **OUTPUT (kW)** | 53,600 | 55,050 | 56,500 | 57,750 | 59,000 | 60,000 | 61,000 | 61,900 | 62,800 | 63,500 | 64,200 | 64,800 | 65,400 |
| | | | | | | | | | | | | | |
| **MAXIMUM OUTPUT** | | | | | | | | | | | | | |
| **FLOW ($m^3$/sec)** | 283.5 | 284.8 | 286.0 | 287.5 | 289.0 | 291.0 | 289.4 | 291.0 | 292.0 | 292.3 | 292.8 | 293.0 | 293.2 |
| **OUTPUT (kW)** | 56,870 | 58,440 | 60,000 | 61,650 | 63,300 | 65,020 | 66,740 | 68,270 | 69,800 | 71,000 | 72,200 | 73,550 | 74,900 |

*Figure 4.6: Snapshot of Best Efficiency turbine flows vs Maximum turbine flows*

### *4.5. Control Gates*

Control gates play a very important role by regulating the amount of water flow into the turbine through the penstock. These gates are normally of the vertical lifting type and due to their heavy weight and large size, can only be lifted with the help of large motors mounted on the top portion of the dam. The major part of the control gates remains submerged in the water body. As it is constant contact with corrosive conditions, the material of the control gates of a hydropower plant is very important and critical. For the same reason the maintenance and repair of the control gates is a work-filled job related to hydropower plants.

## *4.6. Hydropower systems operation*

This chapter focusses on the broader context of hydropower systems operation and how systems reliability modeling can be employed to emulate the performance of the hydropower systems. Emulation of the salient aspects of hydropower operation is imperative to devising operating rules and maintenance schedules to optimize the performance and reliability of the system as a whole. System operation is defined as the modus operandi of the organization that owns and operates the system. It is recognized that the owner-operator model is not the only feasible organizational arrangement, but the term is used as a convenient means of conveying the notion that both ownership type and operator type decisions and actions together constitute operation of the system. The next sections talk about the constraints within the framework that organizations must develop hydropower operating rules in.

## *4.7. Operating objectives*

Together with the determination of physical parameters of a system, the operating objectives of the system are equally important in finding the best performance of the system to serve its purpose. Modeling the operational objectives of a dam system and must capture the uncertainty of the system, its components and all related phenomena of interest (Nandalal and Bogardi, 2013). From the perspective of long term operational objectives, the stochasticity, inherent both in a system and in its environment, must not be neglected in the modeling process. The operational objectives main goal is to provide an expected optimal response of the dam system under a wide range of short- and long-term scenarios. In general, the systems analysis implies two basic strategies in operational assessment: simulation and optimization approaches. These two strategies are incorporated into the systems modeling framework to emulate the real-world performance of the dam systems under consideration and to test out improvements to already established operating policies and objectives.

### 4.7.1. Optimal Reservoir Operation and Modeling

The reservoir subsystem is a complex subsystem in which interacts with other processes within the larger hydropower system. The attributes of a reservoir can include a large number of quantities characterizing both physical properties and processes occurring within the component. Not all of the properties and the processes are relevant to the objectives of a particular modelling endeavor, and the system analyst has to make a decision which attributes should be included in the component model. The relevant attributes of the reservoir may include inflow, water level, discharge, chemical properties of water, bathymetry, water temperature etc.

Reservoirs have to be best operated to achieve maximum benefits from them. The rule curves (see Figure 4.7), which define instantaneous ideal reservoir storage levels, have been the essential operational tool. Reservoir operators are expected to maintain these pre-fixed water levels as closely as possible while generally trying to satisfy various water needs downstream. If the levels of reservoir storage are above the target or desired levels, the release rates are increased. Conversely, if the levels are below the targets, the release rates are decreased. Typically, these operating rules are defined to include not only storage target levels, but also various storage allocation zones, such as conservation, flood control, spill or surcharge, buffer, and inactive or dead storage zones. These zones also may vary throughout the year and the advised release range for each zone is provided by the rules. The desired storage levels and allocation zones mentioned above are usually defined based on historical operating practice and experience while meeting Power production expectations and downstream release constraints. Having only these target levels for each reservoir, the reservoir operator has considerable responsibility in day-to-day operation with respect to the appropriate trade-off between storage levels and discharge deviations from ideal conditions. Hence, such an operation requires experienced operators with sound judgment.

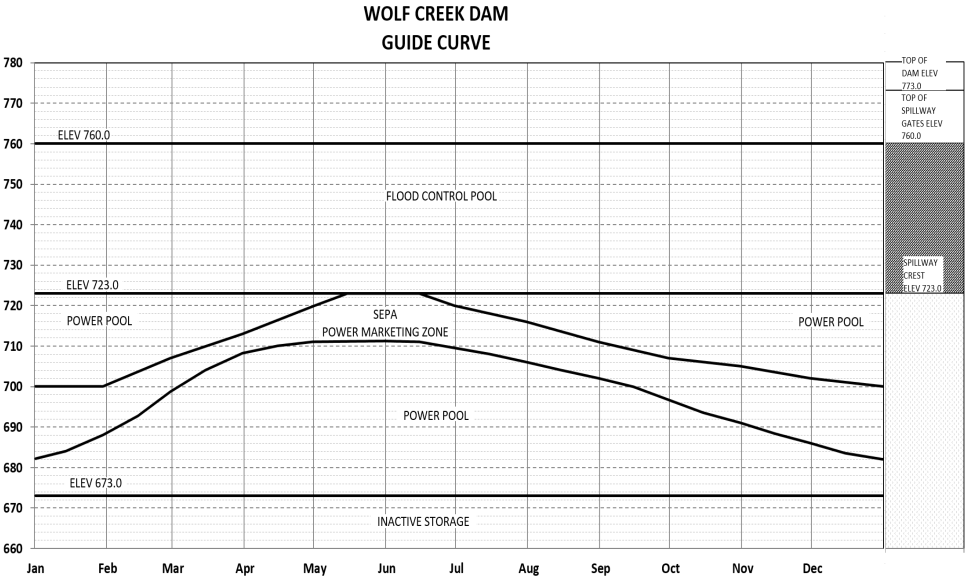


*Figure 4.7: Guide curve showing reservoir stages*

The systems modeling technique can be used to test these operating rules in a wide range of scenarios and also to test out improvements and modifications (optimizations) to the pre-existing operating rules. This is a key advantage that the systems modeling has given the fact that dam systems are dynamic systems with emergent properties that may not have been conceived at the time of the rule curves developments. In general, these techniques lead to models which can be classified into two categories: optimization models and simulation models.

To counteract the inefficiency in operating a reservoir system only by the ‘‘rule curves,’’ additional policies for operation have now been incorporated into most reservoir operation rules. These operation guidelines define precisely when conditions are not ideal (e.g., when maintenance of the ideal storage levels becomes impractical), and the decisions to be made for various combinations of hydrological and reservoir storage conditions. For some reservoir systems, this type of operation policy has already taken over the rule curves and is acting as the principal rule for reservoir operation.

Simulation models can effectively analyze the consequences of various proposed operation rules and indicate where marginal improvements in operation policy might be made. Although both optimization and simulation can be, and at times are, used independently to analyze an operational problem, they are essentially two complementary methods which will be explored in the proposed systems modeling framework.

### 4.7.2. Salient Aspects of Systems Modeling Approach To Reservoir Operations

In order to be able to accurately account for the uncertainty involved with hydropower operations, it is imperative to incorporate the reservoir optimization concepts into the Monte-Carlo simulation framework. This captures the optimal, expectation oriented, long-term operational strategy for reservoirs. The aspects of the reservoir optimization model that need to be captured within the systems simulation framework are present in the next sections.

### 4.7.3. Objective Function

From the perspective of an optimization model, the objective is to maximize the expected annual energy generation from the reservoir. If there are other objectives for the reservoir system such as releases for irrigation or for environmental deficits, these will have to be factored in as well. The assumption for this objective function is that, the sole objective is to maximize energy generation. In that case, the objective function will in the form presented below.

$$OF = Maximize\ \xi \left\{ \sum_{j=1}^{T} EP_j \right\} \tag{4.1}$$

Where,

$EP_j$ = energy generation by power plant at period j (MWh)

=$9.81 \times \eta \times Q_j \times (EL_j - TWL)/10^6$

$EL_j$ =average water surface elevation of reservoir during period j (m),

$Q_j$=release from reservoir during period j (m3/s),

$TWL$ =normal tail water level of power plant (m),

T=number of periods within annual cycle,

η =overall efficiency of power plant, and

$\xi$=denotes expectation.

### 4.7.4. Stages, State, and Decision Variables

The state of the system is described by water available in the reservoir at the beginning of any time step and inflow level at the present time period. Consecutive time steps are identified as stages. The decision variable is storage volume at the end of the time period. The optimization is subject to constraints on reservoir storage and release.

### 4.7.5. Storage Volume Constraint

The storage volume constraints are usually set in the operating rules for the reservoir operation. This is usually a pre-specified upper and lower bound limits of minimum and maximum live storage capacity:

$$S_{min} \leq S_j \leq S_{max}; \quad j = 1,2, \ldots., T$$

(4.2)

Where,

$S_j$=storage volume at beginning of period j,

$S_{min}$ = allowable minimum storage volume, and

$S_{max}$=allowable maximum storage volume.

### 4.7.6. Release Constraint

The releases from each reservoir are subject to the constraints of maximum and minimum limits. This is due to the maximum capacities of outlets and the compulsory releases such as environmental flows, if any:

$$R_{min} \leq R_j \leq R_{max}; \quad j = 1,2,\ldots.,T \quad (4.3)$$

Where,

$R_j$=reservoir release during period,

$R_{min}$ = maximum allowable release through turbines in period j, and

$R_{max}$=minimum release from reservoir during period j.

### 4.7.1. Reservoir Routing Analysis

One of the main objectives of a systems reliability analysis of dams is to performing overtopping analysis and generate analytical outputs that can be used to analyze the performance of the dam system during breach scenarios. The key parameters at play here are water height in the reservoir under various inflows and disturbance conditions (hurricanes), and comparing the result with the dam crest elevation. The change in reservoir pool elevation is simply the net of the inflows and outflows of the reservoir system. Mathematically, this can be modeled with the continuity equation with the following basic form:

$$I - Q = \frac{ds}{dt}$$

(4.4)

Where I and Q represent the reservoir inflows and outflows respectively. S is the storage and t is time. This can be implemented at each time step in the model as

$$\frac{I_t + I_{t+1}}{2} - \frac{Q_t + Q_{t+1}}{2} = \frac{S_{t+1} - S_t}{\triangle t} \qquad (4.5)$$

Where $I_t$ and $I_{t+1}$ are inflow into the reservoir $Q_t$ and $Q_{t+1}$ are outflow from the reservoir, $S_t$ and $S_{t+1}$ are reservoir storage at t and t+1 respectively and $\triangle t$ is the time interval.

The water height in the reservoir could be estimated by solving Equation 4.5 at each time step. Time interval Dt determines the length of each step in the reservoir routing and output precision will be increased with decreasing Dt.

### *4.8. Risk and Uncertainty of Overtopping*

Overtopping happens when the reservoir release outlets cannot release water fast enough and water rises above the dam and spills over. In overtopping analysis, the maximum water height in the reservoir (Hmax) and dam height (HR) can be considered load and resistance of the system, respectively.

In most cases, overtopping leads to dam breach. The consequences of this resulting breach would inundate each of the downstream dams if it’s a cascade and ultimately impact the downstream population.

In order to develop an accurate Systems Risk Model, the objective of the reservoir routing analysis is to provide the system loading (reservoir levels, inflow volumes, outflow discharges, overtopping durations, failure intervention measures etc.). In order to accomplish this, the needed data are: incoming hydrographs (inflows), starting pool elevations, spillway and outlet waterways properties (including functionality), hydraulics and hydrodynamics of power generation, reservoir physical properties and reservoir operating procedures. This leads to a parametric flood routing analysis, considering all the possible permutations of input variables. All this is done from a probabilistic point of view.

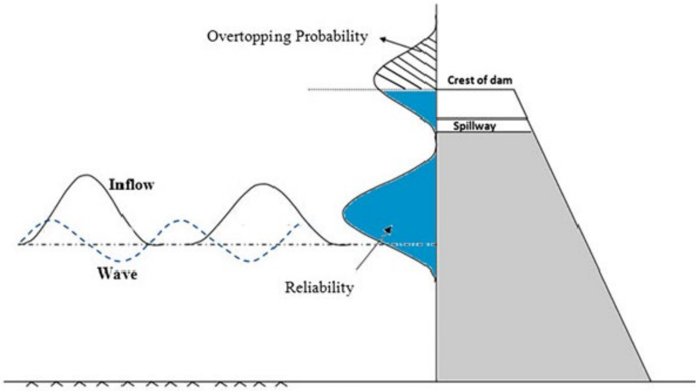


*Figure 4.8: Overtopping risk concept based on probabilistic approach*

### *4.9. Generation of synthetic streamflow data*

Accurate forecasts of the net inflows into a reservoir is essential for determining the optimal operation policy and management of the reservoir system. In practice, the reservoir net inflow is computed based upon the application of the water balance equation to the reservoir system since it is difficult to obtain direct and reliable measurements of this variable (Burton, 1998). The net inflow process has been thus found to possess a random behavior because it is related to the stochastic nature of various physical processes involved in the water balance computation (e.g., precipitation, evaporation, etc.). Therefore, the aim the adopting forecasting method should be to accurately and efficiently predict the random reservoir inflow series.

The generation of stochastic inputs to the system can be approached in several ways. The modelling framework accommodates any of these, and it is left to the user to decide which approach is most appropriate or preferred for a particular application. Accuracy of reservoir inflow forecasts is instrumental for maximizing the value of water resources and benefits gained through hydropower generation. There are two distinct approaches to modeling reservoir inflows; namely, conceptual and data-driven models (Gragne et al., 2015). Lumped conceptual hydrologic models use sets of mathematical expressions to provide a simplified generalization of the complex natural processes of the hydrologic systems in the headwater areas of reservoirs. Application of such models conventionally requires estimating the model parameters by conditioning them to observed hydrologic data. Unlike conceptual models, data-driven models establish mathematical relationship between input and output data without any explicit attempt to represent the physical processes of the hydrologic system. However, the two approaches can be reconciled and thus combining the advantages of both approaches (Todini, 2007).

The case studies presented in chapter 11 and 12 utilize data driven time series forecasting models; specifically the Auto regressive integrated moving average (ARIMA) models. The framework for the forecasting using ARIMA is provided in the next section.

### 4.9.1. Reservoir Inflow time series model building

This section is intended to present the time series concepts for transforming the available reservoir inflow time series into the stationary series, which would then be fitted to the ARIMA or seasonal ARIMA models. A three-step iterative procedure is used to build an ARIMA model. First, a tentative model of the ARIMA class is identified through analysis of historical data. Second, the unknown parameters of the model are estimated. Third, through residual analysis, diagnostic checks are performed to determine the adequacy of the model and make improvements if necessary (Montgomery et al., 2015).

#### *4.9.1.1 Model Identification*

The first step in modeling time index data is to convert the non-stationary time series to a stationary one. This is important due to the fact that a most statistical time series methods are based on the assumption of stationarity and can only be applied to stationary time series.

Simple time series plots can be used as a preliminary assessment tool to test for stationarity and seasonality in the time series data. The visual inspection of these plots is a crude way of assessing the stationarity of time series data (see Figure 4.9). Better and more methodological tests of stationarity also exist and are presented in several texts on time series analysis. Statistical software packages such as Minitab, STATA and JMP all have more mathematically rigorous methods for testing for stationarity and trends in time series data.

If nonstationarity is suspected, the time series plot of the first (or dth) difference should also be considered. The unit root test by Dickey and Fuller (1979) can also be performed to make sure that differencing is indeed needed. Once the stationarity of the time series can be presumed, the sample ACF (autocorrelation function) and PACF (partial autocorrelation function) of the time series of the original time series (or its dth difference if necessary) should be obtained (see Figure 4.10).

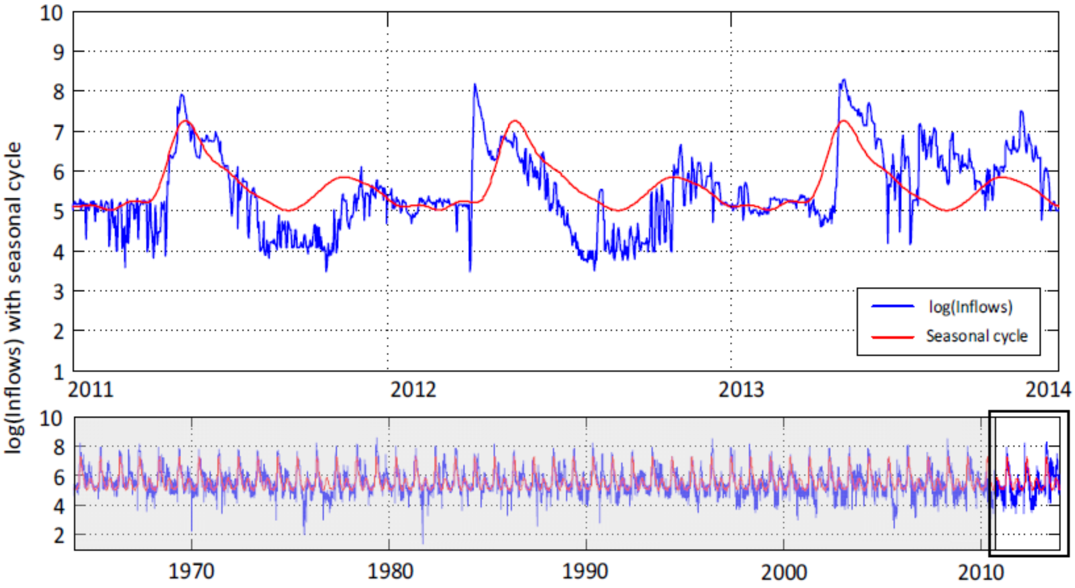


*Figure 4.9: Logarithm of inflow hydrograph showing stationarity and seasonality*

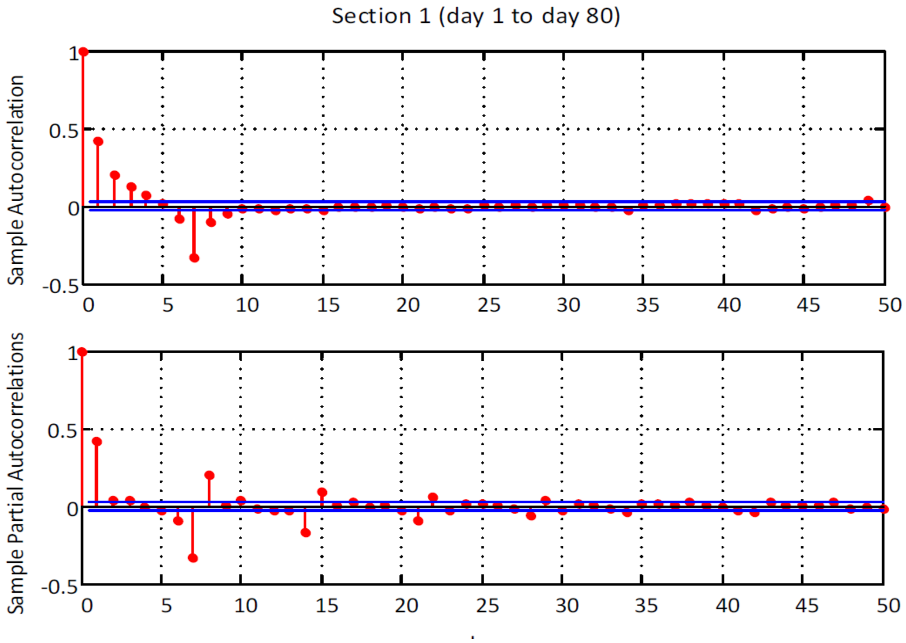


*Figure 4.10: ACF and PACF for pre-processed inflows from example*

#### *4.9.1.2 Parameter Estimation*

There are several methods such as the methods of moments, maximum likelihood, and least squares that can be employed to estimate the parameters in the tentatively identified model. However, unlike the regression models, most ARIMA models are nonlinear models and require the use of a nonlinear model fitting procedure. This is usually automatically performed by sophisticated software packages such as Minitab, JMP, and SAS. In some software packages, the user may have the choice of estimation method and can accordingly choose the most appropriate method based on the problem specifications.

#### *4.9.1.3 Diagnostic Checking*

After a tentative model has been fit to the data, the adequacy of the model must be examined and, if necessary, suggest potential improvements. This is done through residual analysis. According to Montgomery *et al*. (2015), the residuals for an ARMA (p, q) process can be obtained from

$$\hat{\varepsilon}_t = y_t - \left(\hat{\delta} + \sum_{i=1}^{p} \hat{\phi}_i y_{t-i} - \sum_{i=1}^{q} \hat{\theta}_i\, \hat{\varepsilon}_{t-i}\right) \tag{4.6}$$

If the specified model is adequate and hence the appropriate orders p and q are identified, it should transform the observations to a white noise process. Thus the residuals in Equation (4.6) should behave like white noise. Detailed analysis of the further diagnostic procedures are presented in in Box *et al.* (2008).

# CHAPTER 5: CHARACTERIZATION OF LOAD AND RESISTANCE PARAMETERS OF FLOW CONTROL SYSTEMS

In a multitude of hydrosystems engineering problems, uncertainties in data and in theory, including design and analysis procedures, warrant a probabilistic treatment of the problems. The risk associated with the potential failure of a dam system, is the result of the combined effects of inherent randomness of external loads and various uncertainties involved in the analysis, design, construction, and operational procedures. Hence, to evaluate the probability that a dam system will function as designed requires uncertainty and reliability analyses.

The basic idea of reliability engineering is to determine the failure probability of an engineering system, from which the safety of the system can be assessed, or a rational decision can be made on the design, operation, or forecasting of the system. Without exception, failures of hydrosystem infrastructure (e.g., dams, levees, and storm sewers) could potentially pose significant threats to public safety and inflict enormous damage on properties and the environment. (Tung et al., 2005).

Dams and their associated flow control are highly complex systems of engineered structures, natural processes, and human operation. They behave in complex ways that are not amenable to such simple decompositional analysis, and thus need to be understood in a systems engineering context. This chapter presents a primer on the basics of reliability analysis as it pertains to flow control systems. These reliability concepts will be built on and incorporated into the systems reliability framework.

## *5.1. <u>Basic concept of Systems Reliability Computation</u>*

Failure of an engineering system can be defined as the load L (external forces or demands) on the system exceeding the resistance R (strength or capacity) of the system. The reliability $p_s$ is defined as the probability of safe (or nonfailure) operation, in which the resistance of the structure exceeds or equals to the load, that is,

$$p_s = P(R > L) \tag{5.1}$$

in which P(·) denotes the probability. Conversely, failure probability pf can be computed as

$$p_f = P(L > R) = 1 - p_s \tag{5.2}$$

The definitions of reliability and failure probability, Eqs. (5.1) and (5.2), are equally applicable to component reliability, as well as total system reliability. In hydro systems engineering analyses, the resistance and load frequently are functions of several stochastic basic variables, that is, *L = g(XL) = g(X1, X2, . . . , Xm)* and *R = h(XR) = h(Xm+1, Xm+2, . . . , XK),* where *X1, X2, . . . , XK* are stochastic basic variables defining the load function *g(XL)* and the resistance function h(XR). Accordingly, the failure probability and reliability are functions of stochastic basic variables, that is,

$$p_s = P[g(X_L) \leq h(X_R)] \tag{5.3}$$

Evaluation of reliability or failure probability by Eqs. (5.1) through (5.3) does not consider the time-dependent nature of the load and resistance if statistical properties of the elements in $\boldsymbol{X}_L$ and $\boldsymbol{X}_R$ do not change with time. This procedure generally is applied when the performance of the system subject to a single worst-load event is considered. From the reliability computation viewpoint, this is referred to *as static reliability analysis.*

In general, a hydrosystem infrastructure is expected to serve its designated function over an expected period of time. Engineers frequently are interested in knowing the reliability of the structure over its intended service life. In such circumstances, elements of service period, randomness of load occurrences, and possible change in resistance characteristics over time must be considered. Reliability models incorporating these elements are called time-dependent reliability models (Karamouz et al., 2012).

### 5.1.1. Relationship between Load and Resistance

One of the popular ways of modeling the reliability of a component is the direct integration method. This method works very well within the probabilistic monte-carlo framework. The direct integration computation of reliability requires knowledge of the probability distributions of the load and resistance or of the component being modeled. In terms of the joint PDF of the load and resistance, can be expressed as

$$p_s$$

$$= \int_{r_1}^{r_2} \left[ \int_{l1}^{r} f_{R,L}(r,l) dl \right] dr \tag{5.4}$$

$$= \int_{l_1}^{l_2} \left[ \int_{l}^{r_2} f_{R,L}(r,l) dl \right] dl \tag{5.5}$$

in which $f_{R,L}(r,l)$ is the joint PDF of random load $L$ and resistance $R$, $r$ and $l$ are dummy arguments for the resistance and load, respectively, and ($r_1$, $r_2$) and ($l_1$, $l_2$) are the lower and upper bounds for the resistance and load, respectively. The failure probability can be computed as

$$p_f = 1 - p_s = \int_{r_1}^{r_2} \left[ \int_{l1}^{r} f_{R,L}(r,l)dl \right] dr \tag{5.6}$$

$$= \int_{l_1}^{l_2} \left[ \int_{l}^{r_2} f_{R,L}(r,l)dl \right] dl \tag{5.7}$$

This computation of reliability is commonly referred to as *load-resistance interference*. The failure probability, when the load and resistance are independent, can be expressed as

$$p_f = 1 - ps = E_R[1 - F_L(R)] = E_L[F_R(L)] \tag{5.8}$$

A schematic diagram illustrating load-resistance interference in the reliability computation, when the load and resistance are independent random variables, is shown in Figure 5.1.

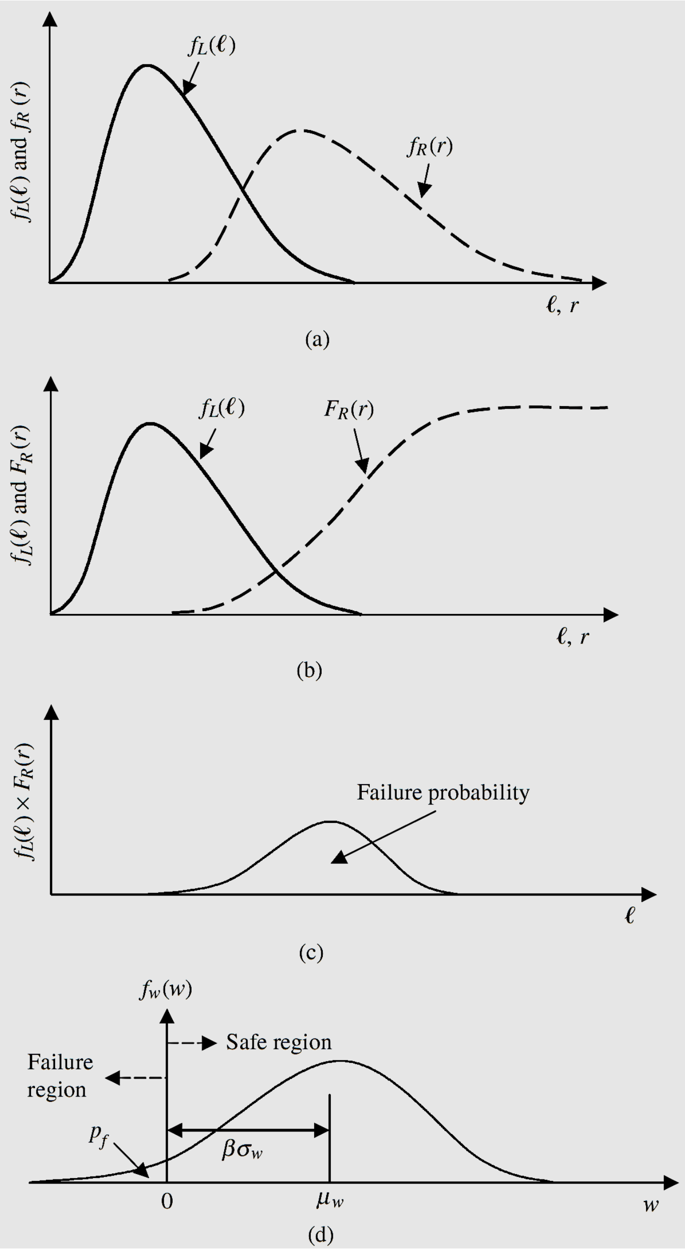


*Figure 5.1: Schematic diagram of load-resistance interference for computing failure probability: (a) marginal densities of load and resistance; (b) PDF of load and CDF of resistance; (c) compute f L(l) × FR(r) over valid range of load; the area underneath the curve is the failure probability; (d) PDF of the performance function; the area left of w = 0 is the failure probability.*

### 5.1.2. Time-Dependent Reliability Models

In preceding section, emphasis was placed on static reliability analysis, which does not consider the time dependency of the load and resistance. This section considers the time-dependent random variables in reliability analysis. As a result, the reliability is a function of time, i.e., time dependent or time variant. The objective of time-dependent reliability models is to determine the system reliability over a specified time interval in which the number of occurrences of loads is a random variable.

When both loading and resistance are functions of time, the performance function $W(t) = R(t) - L(t)$ is time-dependent. Consequently, the reliability $ps(t) = P[W(t) > 0]$ would vary with respect to time. Figure 5.1 shows schematically the key feature of the time-dependent reliability problem in which the PDFs of load and resistance change with time. In Figure 5.2, the mean of resistance has a downward trend with time, whereas that of the load increases with time. As the standard deviations of both resistance and load increase with time, the area of interference increases, and this results in an increase in the failure probability with time. The static reliability analysis described in preceding sections considers neither load nor resistance being functions of time.

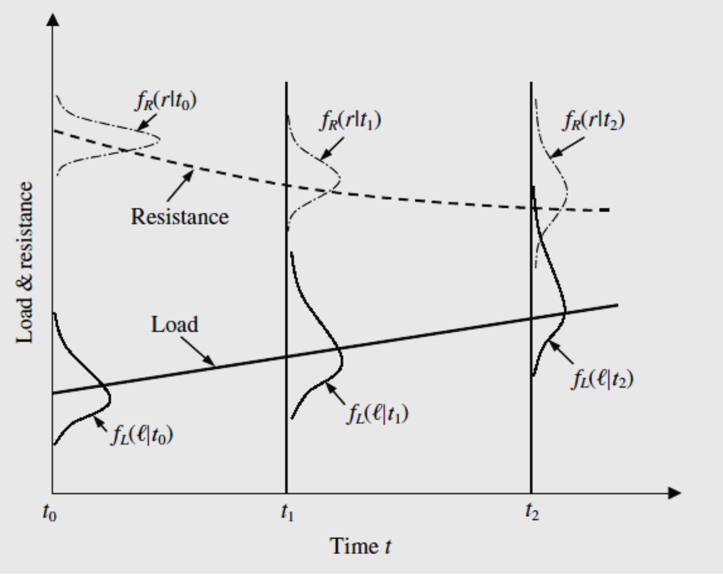


*Figure 5.2: Time Dependent Load and resistance probability distribution functions*

For a hydraulic structure placed in a natural environment over a period of time, its operational characteristics could change over time owing to deterioration, aging, fatigue, and lack of maintenance. Consequently, the structural capacity (or resistance) would vary with respect to time. Modeling time-dependent features of the resistance of a hydrosystem requires descriptions of the time-varying nature of statistical properties of the resistance.

### 5.1.3. Time-dependent load

In time-dependent reliability analysis, one is concerned with system reliability over a specified time period during which external loads can occur more than once. Therefore, not only the intensity or magnitude of load is important but also the number or frequency of load occurrences is an important parameter.

Over an anticipated service period, the characteristics of load to be imposed on the system could change. More specifically, the magnitude of floods could increase as urbanization progresses upstream, or downstream dams in a cascade could be subjected to handling larger than normal volumes of water due to operational necessities in the upstream reservoirs. Characterization of the time-varying nature of load intensity requires extensive monitoring, data collection, and engineering analysis.

### 5.1.4. Modeling intensity and occurrence of loads

A hydraulic structure placed in a natural environment over an expected service period is subject to repeated application of loads of varying intensities. The magnitude of load intensity and the number of occurrences of load are, in general, random by nature. Therefore, probabilistic models that properly describe the stochastic mechanisms of load intensity and load occurrence are essential for accurate evaluation of the time-dependent reliability of dam systems.

**Probability models for load intensity:** In the great majority of situations in dam system reliability analysis, the magnitudes of load to be imposed on the system are continuous random variables. Therefore, univariate probability distributions may be used to model the intensity of a single random load. In a case in which more than one type of load is considered in the analysis, multivariate distributions may be used.

The selection of an appropriate probability model for load intensity depends on the availability of information. In a case for which sample data about the load intensity are available, formal statistical goodness-of-fit tests can be applied to identify the best-fit distribution. On the other hand, when data on load intensity are not available, selection of the probability distribution for modeling load intensity has to rely on the analyst's logical judgment on the basis of the physical processes that produce the load.

**Probability models for load occurrence:** In time-dependent reliability analysis, the time domain is customarily divided into a number of intervals such as days, months, or years, and the random nature of the load occurrence in each time interval should be considered explicitly. The occurrences of load are discrete by nature, which can be treated as a point random process. Two popular types of discrete distributions for such characterizations are the binomial and Poisson distributions(Melchers, 1999). This section briefly summarizes two distributions in the context of modeling the load-occurrences. Other load occurrence models can be found elsewhere.

**Bernoulli process.** A Bernoulli process is characterized by three features: (1) binary outcomes in each trial, (2) constant probability of occurrence of outcome in each time interval, and (3) the outcomes are independent between trials. In the context of load-occurrence modeling, each time interval represents a trial in which the outcome is either the occurrence or nonoccurrence of the load (with a constant probability) causing failure or non-failure of the system. Hence the number of occurrences of load follows a binomial distribution, Equation (5.9), with parameters $p$ (the probability of occurrence of load in each time interval) and $n$ (the number of time intervals). It is interesting to note that the number of intervals until the first occurrence $T$ (the waiting time) in a Bernoulli process follows a *geometric distribution* with the PMF

$$g(T = t) = (1 - p)^{t-1}p \tag{5.9}$$

The expected value of waiting time *T* is 1/*p*, which is the mean occurrence period. It should be noted that the parameter *p* depends on the time interval used.

**Poisson process.** In the Bernoulli process, as the time interval shrinks to zero and the number of time intervals increases to infinity, the occurrence of events reduces to a *Poisson process*. The conditions under which a Poisson process applies are (1) the rate occurrence of an event in time is constant (stationarity) (2) the occurrences of events are independent, and (3) only one event occurs at a given time instant. The PMF describing the number of occurrences of loading in a specified time period (0, t] is given by

$$p(n|\lambda,t) = \frac{(\lambda t)^n n e^{-\lambda t}}{n!} \qquad for\, n = 0,1,\dots\dots. \tag{5.10}$$

in which λ is the average time rate of occurrence of the event of interest. The inter-arrival time between two successive occurrences is described by an exponential distribution with the PDF

$$f(t|\lambda) = \lambda e^{-\lambda t} \tag{5.11}$$

### 5.2. Fragility Analytics

In safety or risk assessment of dams, limit states or probability of failure serve as yardsticks of system performance. The fragility curve gives the conditional probability that a certain limit-state be exceeded (i.e., probability of failure) given a certain load (or demand). They can be derived from analysis, expert opinion, or case history data, or often a combination of all three (Tesfamariam and Goda, 2013) .

Fragility analysis deals with the balance of demands (loads) on a system and the capacity of the system (resistance) to withstand those demands. This relationship is used to generate a fragility curve for a particular component. The fragility curve relates the demand function on the component to the probability of adverse performance (Figure 5.3).

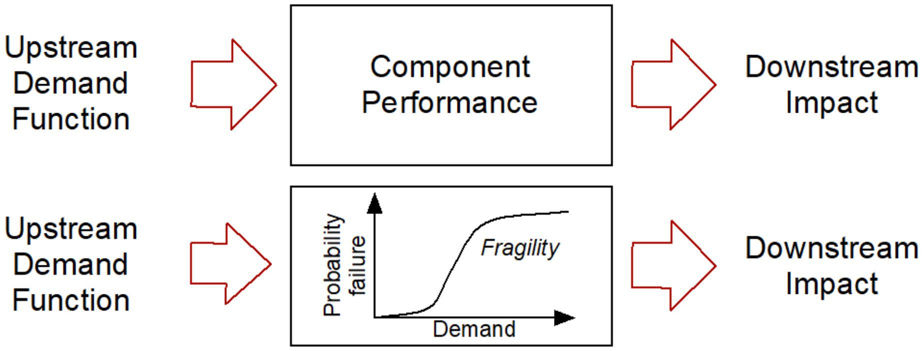


*Figure 5.3: Reliability analysis of the individual component based on upstream demand function.*

In dam safety risk analysis, the fragility curve is typically used to predict the probability of a dam component failure, given a hydraulic hazard (Ebeling et al., 2012). It is an alternative way of characterizing the relationship between load and resistance other than explicitly using probability distributions to define the inherent load and the systems performance (resistance). The fragility curve is defined by the cumulative distribution function (CDF) of the system response curve.

For example, if a dam in which the overtopping limit state, i.e., $FS_{overtopped} \leq 1.0$, is the limit state resulting in failure of the dam.

The probability of failure, $P_{failure}$, is given by the expression:

$$\mathrm{P}_{failure} = \sum_{H_{pool}} P(FS_{overtopped} \leq 1.0 \parallel Pool = H_{pool}) P(Pool = H_{pool}) \qquad (5.12)$$

In which *Pool* is a vector of random variables describing the intensity of demand (e.g. pool elevation, etc.) and other factors; *P(Pool = $H_{pool}$)* is the hazard, considering channel inflows and storm runoff from the watershed behind the dam, and is expressed in terms of annual probability; and *P($FS_{overtopped}$≤ 1.0 | Pool = $H_{pool}$ )* is the conditional probability of structural failure, given that *Pool = $H_{pool}$*, Expressing the limit state probability as in Equation 5.12 allows the overall risk to be deconstructed into its significant contributors (Chase, Sr, 2012). Figure 5.4 shows the fragility characterization of mechanical gate components where the inherent load is the height of gate opening. The higher the gate opening, the more overstressed the mechanical components of the gates become and consequently, the higher the chance of the mechanical component failing.

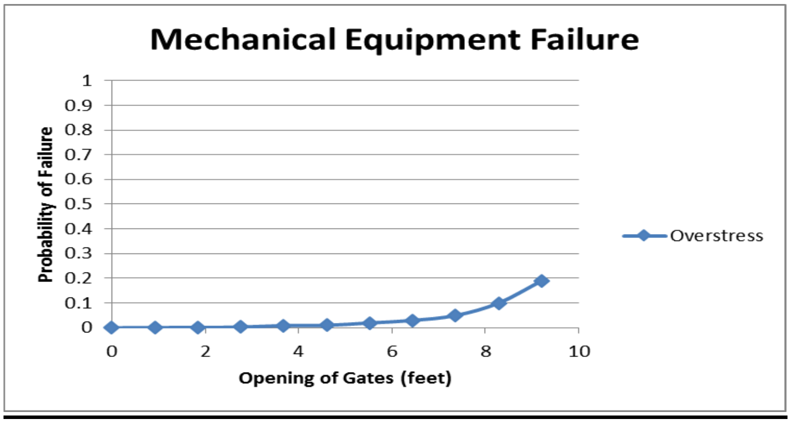


*Figure 5.4: Mechanical Equipment failure fragility curves*

The fragility equation in this instance can be written as

$$\mathrm{P}_{failure} = \sum_{H_{pool}} P(ME_{failure} \leq 1.0 \parallel Pool = H_{gate\ opening}) P\big(Pool = H_{pool}\big) \qquad (5.13)$$

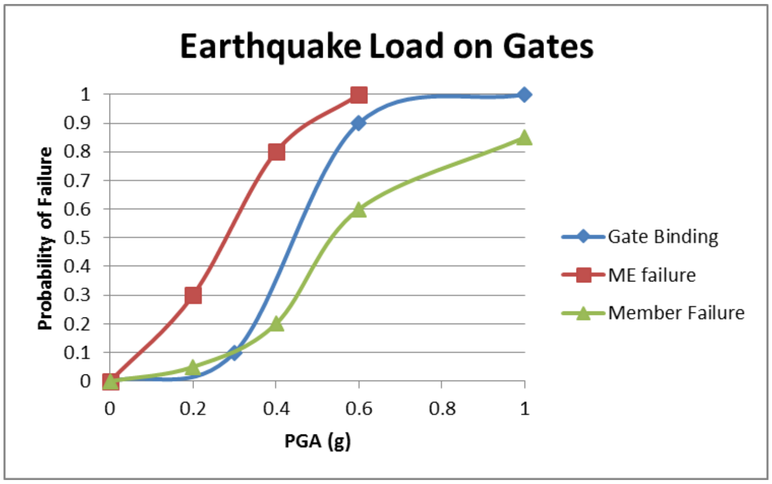


*Figure 5.5: Earthquake Load on Gates*

## 5.3. *Reliability Parameter Characterization of Repairable Systems*

For repairable components of dam systems, such as spillway gate mechanical hoists, electrical generators, and turbines, failed components within the system can be repaired or replaced so service can be restored. The time required to have the failed system repaired is uncertain, and consequently, the total time required to restore the system from its failure state to an operational state is a random variable.

### 5.3.1. Relationship between mean time to failure (MTTF), mean time between failures (MTBF), and mean time to repair (MTTR)

The mean time to failure of a system is a commonly used reliability performance measure of the expected time to failure (TTF) of the system. The MTTF can be defined mathematically as

$$MTTF = E(TTF) = \int_0^\infty p_s(t)dt \qquad (5.14)$$

By Equation (5.14), the MTTF geometrically is the area underneath the reliability function. The MTTFs can be determined from mean time between failures (MTBF) and mean time to repair (MTTR) (See Equation 5.15).

The mean time to repair (MTTR) is the expected value of the time to repair of a failed system. It measures the elapsed time required to perform the maintenance operation and is used to estimate the downtime of a system. It is also a commonly used measure for the maintainability of a system.

The MTTF is a proper measure of the mean life span of a non-repairable system. However, for a repairable system, a more representative indicator for the fail-repair cycle is the mean time between failures (MTBF) (Tung et al., 2005), which is the sum of MTTF and MTTR, that is,

$$MTBF \ = \ MTTF \ + \ MTTR \qquad (5.15)$$

The mean time between Failure (MTBF) is the expected value of the time between two consecutive repairs, and it is equal to MTBF.

### *5.4. <u>Systems concepts Applied to the Reliability of Flow control Systems</u>*

Most systems involve many subsystems and components whose performances affect the performance of the system as a whole. The reliability of the entire system is affected not only by the reliability of individual subsystem s and components but also by the interactions and configurations of the subsystems and components. Many engineering systems involve multiple failure paths or modes; that is, there are several potential paths and modes of failure in which the occurrence, either individually or in combination, would constitute system failure. As discussed in Sec. 4.1.1, engineering system failure can be structural failure such that the system can no longer function, or it can be performance failure, for which the objective is not achieved but the functioning of the system is not damaged.

## *5.5. General View of System Reliability Computation*

As mentioned previously, the reliability of a system depends on the component reliabilities and interactions and configurations of components. Consequently, computation of system reliability requires knowing what constitutes the system being in a failed or satisfactory state. Such knowledge is essential for system classification and dictates the methodology to be used for system reliability determination.

### 5.5.1. Classification of systems

From the reliability computation viewpoint, classification of the system depends primarily on how system performance is affected by its components or modes of operation. A multiple-component system called a *series system* (see Figure 5.6) requires that all its components perform satisfactorily to allow satisfactory performance of the entire system. Similarly, for a single-component system involving several modes of operation, it is also viewed as a series system if satisfactory performance of the system requires satisfactory performance of all its different modes of operation.

A second basic type of system is called a *parallel system* (see Figure 5.7). A parallel system is characterized by the property that the system would serve its intended purpose satisfactorily as long as at least one of its components or modes of operation performs satisfactorily.

For most real-life problems, system configurations are complex, in which the components are arranged as a mixture of series and parallel subsystems or in the form of a loop. In dealing with the reliability analysis of a complex system, the general approach is to reduce the system configuration, based on the arrangement of its components or modes of operation, to a simpler situation for which the reliability analysis can be performed easily. However, this goal may not always be achievable, in which case a special procedure would have to be devised.

### *5.6. Reliability of Simple Systems*

In this section the reliability of some simple systems will be discussed. In the framework of time-to-failure analysis, availability of such systems will be presented. Information such as this is essential to serve as the building blocks for determination of reliability or availability of more complex systems.

### 5.6.1. Basic probability rules for system reliability

The solution approaches to system reliability problems can be classified broadly into failure-modes approach and survival-modes approach (Bennett and Ang, 1983). The failure-modes approach is based on identification of all possible failure modes for the system, whereas the survival-modes approach is based on the all possible modes of operation under which the system will be operational.

The two approaches are complementary. Depending on the operational characteristics and configuration of the system, a proper choice of one of the two approaches often can lead to significant reduction in efforts needed for the reliability computation. Consider that a system has M components or modes of operation. Let event $F_m$ indicate that the mth component or mode of operation is in the failure state. If the system is a series system, the failure probability of the system is the probability that at least one of the M components or modes of operation fails, namely,

$$p_{f,sys} = P(F_1 \cup F_2 \cup \cdots \cup F_M) = P\left(\bigcup_{m=1}^{M} F_m\right) \tag{5.1}$$

in which pf ,sys is the failure probability of the system. On the other hand, the system reliability $p_{s,sys}$ is the probability that all its components or modes of operation perform satisfactorily, that is,

$$p_{f,sys} = P(F_1 \cap F_2 \cap \cdots \cap F_M) = \left(P \bigcap_{m=1}^{M} F'_m\right) \tag{5.2}$$

in which $F'_m$ is the complementary event of $F_m$ indicating that the mth component or mode of operation does not fail.

### 5.6.2. Series systems

A series system requires that all its components or modes of operation perform on demand to ensure a satisfactory operation of the entire system. In the context of load-resistance interference, the reliability associated with a mode of operation assuming non-repairable components can be computed as:

$$R = P[E_1 \times E_2, \ldots, E_i, \ldots, E_n] \tag{5.3}$$

Where $E_i$ is the event that component $C_i$ is operating at time t. If all the events are independent of each other, then the reliability

$$R = \prod_{i=1}^{n} P[E_i] \tag{5.4}$$

Or in other words, the reliability of the system R is calculated as a product of the reliabilities of its components Ri:

$$R = \prod_{i=1}^{n} R_i \tag{5.5}$$

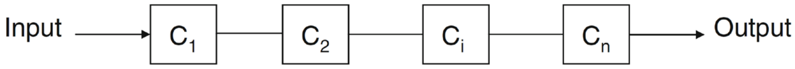


*Figure 5.6 Reliability block diagram with n components in series*

### 5.6.3. Parallel systems

For a parallel system, the entire system would perform satisfactorily if any one or more of its components or modes of operation is functioning satisfactorily; the entire system would fail only if all its components or modes of operation fail. Figure 5.7 shows a reliability block diagram of a system containing n parallel components.

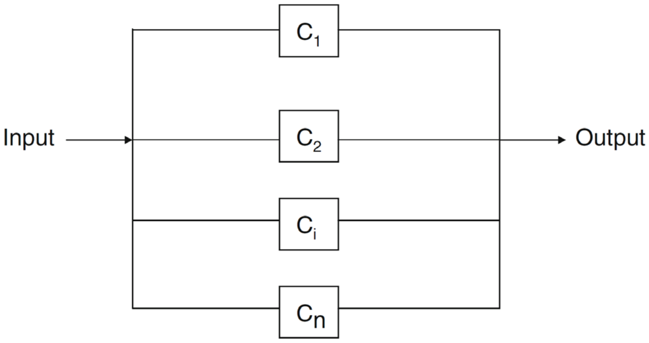


*Figure 5.7: Reliability block diagram with n parallel components*

If E is the event that component Ci is operating at time t, then the reliability of the system may be written as:

$$R = P[E_1 + E_2 +, \dots, +E_i +, \dots, +E_n] \tag{5.6}$$

If $\overline{E_\iota}$ is the complement of the event $E_i$ and represents the event that component I has failed at time t, assuming all events are independent, the reliability may be computed as

$$R = 1 - \prod_{i=1}^{n} P[E_i] \tag{5.7}$$

Or in other words, the reliability of the system is calculated from the reliabilities of its components:

$$R = \prod_{i=1}^{n} (1 - R_i) \tag{5.8}$$

Figure 5.8 shows that the system reliability increases fast with increased number of parallel components. The redundant components largely increase the reliability of the system. Figure 5.9 shows that the system reliability increases fast with increased reliability of its components.

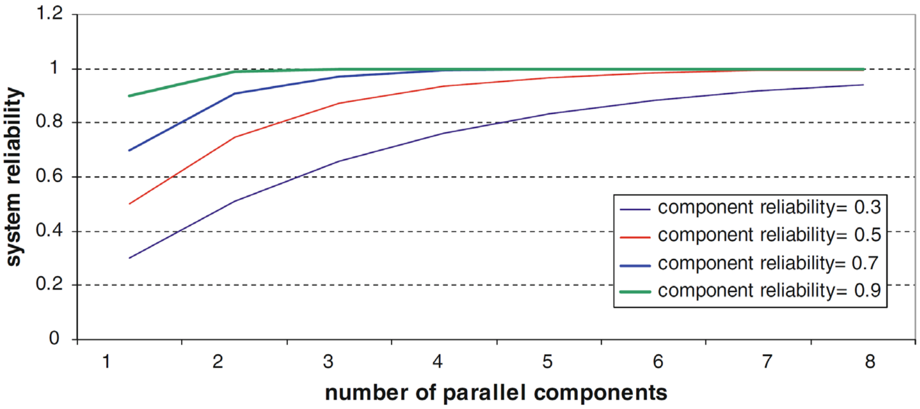


*Figure 5.8: System reliability versus number of parallel components*

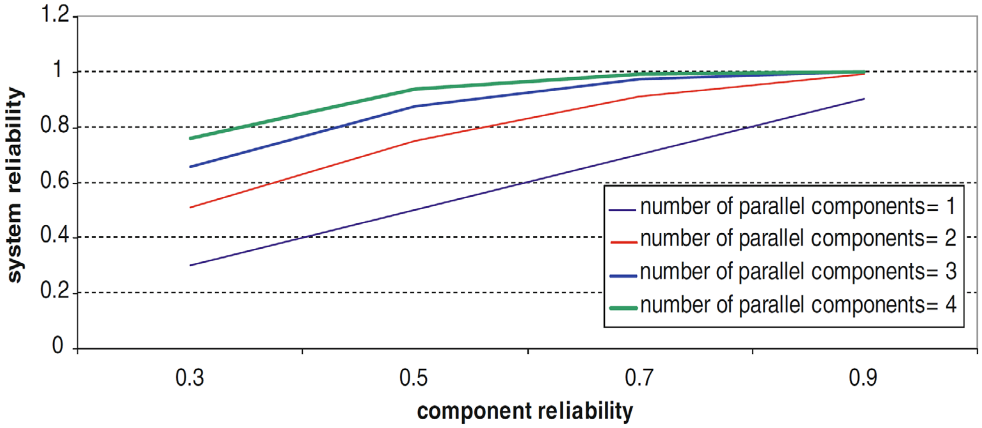


*Figure 5.9: System reliability versus number of parallel components*

## 5.6.1. Availability

If one considers both reliability and maintainability (the probability that the item is successfully restored after failure), then an additional metric is needed for the probability that the component/system is operational at a given time, (i.e., has not failed or it has been restored after failure) (Subburaj, 2015). This metric is availability. Availability is a performance criterion for repairable systems that accounts for both the reliability and maintainability properties of a component or system. It is defined as the probability that the system is operating properly when it is requested for use. That is, availability is the probability that a system is not failed or undergoing a repair action when it needs to be used.

### *5.6.1.1 Availability Classifications*

The definition of availability is somewhat flexible and is largely based on what types of downtimes one chooses to consider in the analysis. As a result, there are a number of different classifications of availability, such as:

**Instantaneous or Point Availability**

This is the probability that the system is operating at time t. The point availability is very similar to the reliability function in that it gives a probability that a system will function at the given time, t. Unlike reliability, however, the instantaneous availability measure incorporates maintainability information. At a given time, t, the system will be operational if one of the following conditions is met:

- The system functioned properly from 0 to t, i.e., it never failed by time t. The probability of this happening is R(t).

  Or,

- The system functioned properly since the last repair at time u, $0 < u < t$. The probability of this condition is:

**Average Uptime Availability (or Mean Availability)**

The mean availability is the proportion of time during a mission or time period that the system is available for use. It represents the mean value of the instantaneous availability function over the period (0, T].

**Operational Availability:**

Operational availability, which is symbolized by Ao, represents the probability that the an item—System or Entity—will operate in accordance with its specified performance requirements and prescribed Operating Environment conditions when tasked to perform its mission (Wasson, 2015). Operational availability is a measure of the average availability over a period of time and it includes all experienced sources of downtime, such as administrative downtime, logistic downtime, etc. Mathematically, a System or Entity's Operational Availability, $A_o$, is expressed:

$$A_o = \frac{Uptime}{Operating\ Cycle} = \frac{MTBM}{MTBM + MDT}$$

where:

- MDT = Mean Downtime

- MTBM = Mean Time between Maintenance (repairable items)

**Inherent Availability**

Inherent availability is the steady state availability when considering only the corrective downtime of the system. According to the FAA (2008), it is the maximum availability theoretically within the capabilities of the system or constituent piece

For a single component, this can be computed by:

$$A_o = \frac{MTBF}{MTBF + \overline{MTTR}}$$

### *5.7. <u>Methods for Computing Reliability of Complex Systems</u>*

Evaluation of the reliability of simple systems, as described in the preceding section, is generally straightforward. However, many practical hydrosystems engineering infrastructures, such as water distribution systems, have neither series nor parallel configuration. Evaluation of the reliability for such complex systems generally is difficult. For some systems, with their components arranged in a complex configuration, it is possible to combine components into groups in such a manner that it appears as in series or in parallel. For other systems, special techniques have to be developed that require a certain degree of insight and ingenuity from engineers. A great deal of work has been done on developing techniques for evaluating the reliability of complex systems. This section describes some of the potentially useful techniques for hydro systems reliability evaluation.

### 5.7.1. Fault Tree Analysis

A fault tree is a graphical logic diagram representing main system faults that shows the malfunctions and other events inside a system. It tracks the consequence of the component failures (basic or primary failures) on the system failure (top failure or top event). Basically, the main purpose of fault tree analysis is to evaluate the probability of top event failure while gaining insight on the interaction of malfunctions and other events inside a system that led to the failure. A simple fault tree is given in Figure 5.10 as an example. Two major types of combination nodes (or gates) are used in a fault tree. The AND node implies that the output event occurs only if all the input events occur simultaneously, corresponding to the intersection operation in probability theory. The OR node indicates that the output event occurs if any one or more of the input events occur, i.e., a union.

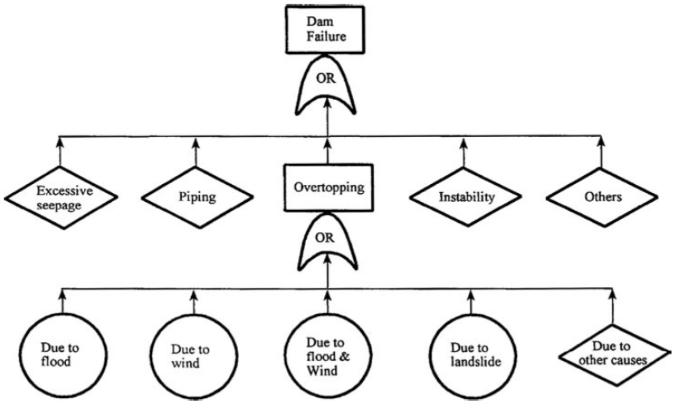


*Figure 5.10: Simple fault tree for failure of existing dam (After Cheng, 1982)*

### 5.7.2. Dynamic Monte-Carlo based Fault Tree Analysis

Fault tree and event tree analysis are static and Boolean logic based (Verma et al., 2015a).Incorporating dynamic (time-dependent) interactions into these models is essential to accurate system characterization within the monte-carlo framework. Stochastic variabilities need to be considered. For example, if actual tests on the components were not performed, the parameters describing their failure modes would be uncertain, and probability distributions can be used in order to capture this uncertainty. The subcomponents such as the electric motor in Figure 5.11 shows the basic events in the traditional fault tree nomenclature.

The behavior of components of complex systems and their interactions such as sequence- and functional-dependent failures, spares and dynamic redundancy management, and priority of failure events cannot be adequately captured by traditional FTs. The inherent variability of failures and repairs times of equipment imposes the use of probabilistic models; as such phenomena cannot be dealt with deterministic approaches. In addition to this inherent variability, there may also be uncertainty about some of the failure parameters such as Repair time and down time. Dynamic Fault trees within the monte-carlo framework make it possible to quantify such epistemic uncertainty which could be modeled as probability distributions. Dynamic simulation then allows the analyst to develop a representation of the system whose reliability is to be determined, and then observe that system's performance over a specified period of time. It also provides the ability to model the interdependencies of components, as well as the capability to define multiple independent failure modes for each component.

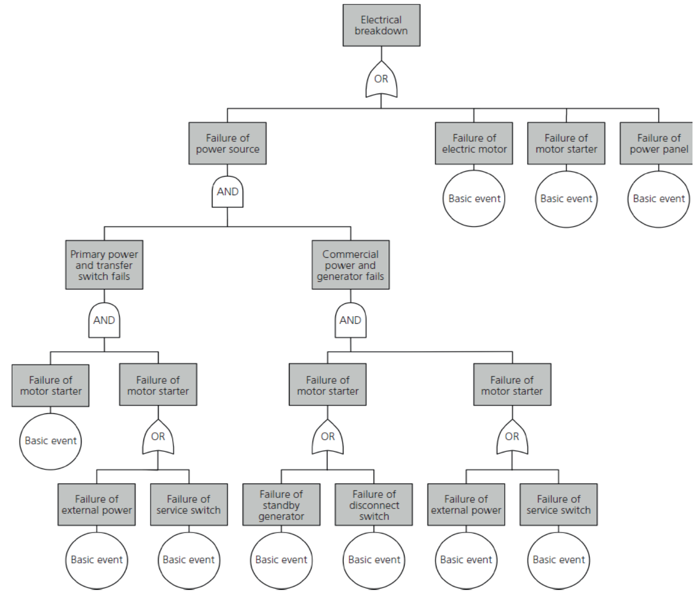


*Figure 5.11: Spillway gates fault tree analysis*

The Dynamic fault trees also enable the use of real world systems reliability metrics such as availability and Reliability. Availability is more commonly used to represent a maintainable system which is a function of reliability and maintainability. The nature of the Monte Carlo framework makes it possible to compute the average unavailability/availability of components of interest based on failure rates, repair rates and demand failure probabilities (stand by failure rate) time to failure and time to repair over a period of time.

The primary advantages of dynamic fault tree based probabilistic simulation are:

- The system can evolve into any feasible state and its properties can change suddenly or gradually as the simulation progresses.

- The system can be affected by random processes, within the system itself (internal failure) or from external an external event that may influence the system (external failure).

- If some system properties are uncertain, the significance of those uncertainties can be determined.

- The ability to incorporate repair logic means automatic repairs can be specified for each individual component failure mode using repair time distributions. Multiple failure modes can also be repaired using a Preventive Maintenance event, or the entire component can be replaced during a maintenance event.

- Each component can either act as a simple element, with its failure distribution specified by failure modes, or as a more complex system which contains models of subcomponents. This makes it possible to construct an initial model by using simple reliability elements with failure modes, and in subsequent versions of the model these are enhanced with subsystem models until an appropriate overall degree of modeling realism is achieved.

- Ability to track all the unique System and subcomponent states during the simulation (i.e., whether the component is operating, if a particular failure mode has occurred, if it is undergoing maintenance, is turned off, or its requirements- or fault tree shows the component cannot operate). These unique states also record the states of any reliability elements referenced as part fault-tree.

- Ability to perform root cause analysis if a component's fault-tree prevents it from operating.

# CHAPTER 6: MAINTENANCE OPTIMIZATION APPROACHES IN HYDROPOWER SYSTEMS

The performance of an engineered system depends not only on its design and operation, but also on its maintenance during its operational lifetime. Duffuaa and Raouf (2015), defined maintenance as the combination of activities by which equipment or a system is kept or restored to a state in which it can perform its designated function. The idea of an "optimized" maintenance program suggests that an adequate mix of maintenance actions and policies needs to be selected and fine-tuned in order to improve Equipment/System uptime, extend the total life cycle of physical assets and assure safe working conditions, while bearing in mind limiting maintenance budgets and environmental legislation.

One of the major maintenance concerns is the complex decision making problem when the availability aspect as well as the economic issue of maintenance activities is considered . The goal here is to improve the availability of equipment/systems in order to ensure given production throughputs and meet service level agreements at the lowest cost. This decision making problem concerns the allocation of the right budget to the appropriate equipment or component. The objective is to minimize the total expenditure and to maximize the effective availability of production resources. Different maintenance policies can be applied. These actions can be derived from different approaches leading to different categories of maintenance strategies: failure based maintenance, use based maintenance, detection based maintenance, condition based maintenance and design-out maintenance (Ben-Daya et al., 2009).

Engineered systems have different maintenance requirements, different levels of complexities, and make use of different maintenance policies. Understanding these differences shows clearly that maintenance is multifaceted and there are several aspects involved including technical, commercial, social, and management viewpoints (Ben-Daya et al., 2016). This implies that effective maintenance decisions need to be made in a framework that takes into account these issues from an overall business perspective. In particular, a comprehensive maintenance system is needed, combining science, engineering, technology, and management.

In this section, the incorporation of maintenance modeling and optimization of repairable systems into the systems framework is explored.

### *6.1. Maintenance Policies*

Maintenance actions can be divided into two broad categories: (i) preventive maintenance (PM) and (ii) corrective maintenance (CM). PM can be divided into predetermined PM tasks based on a clock or usage and Condition Based Maintenance (based on equipment condition). CM actions are maintenance activities that are carried out after a failure has occurred. CM must be initiated immediately to restore critical systems to their functional state or can be deferred to a more convenient timing if the failure is not critical and does not need immediate action. Maintenance improvement is possible by using maintenance data and feedback information to design out maintenance (removing the need for maintenance) or design for maintenance (ease of maintenance).

Preventive Maintenance (PM) is a key element of the performance of Maintainable Systems and plays a very vital role throughout the systems planned life-cycle. Preventive maintenance is performed in the hope of restoring the operational performance of these systems to a satisfactory level. Therefore, the objective is to attain an optimal balance between the Maintenance policies and Resource requirements (available budget, Spares etc.). Bridging the gap between theory and practice in this area requires realistic modelling of the effect of PM activities on the failure characteristics of maintainable systems.

The maintenance policy defines which type of maintenance will (normally) be performed on the various components of the system. It is determined by maintenance engineers, system producers and users to achieve high safety, reliability and availability at minimum cost. With respect to the relation of the instant of occurrence of failure and the instant of performing the maintenance task the following maintenance policies exist:

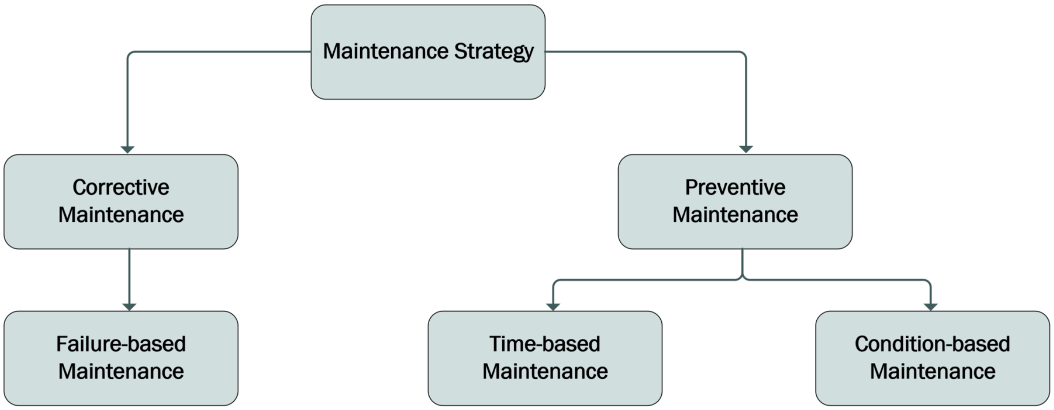


Figure 6.1: Systematics of maintenance strategies (Oelker et al., 2016)

The maintenance load denotes the volume of maintenance work anticipated over time into the future and is made up of the following two main components:

*Planned maintenance:* This includes all PM (preventive maintenance) work that has been planned and scheduled in advance.

*Unplanned maintenance:* This includes all CM (corrective maintenance) work due to unforeseen breakdowns and failures.

1. **Failure-Based maintenance policy (Corrective Maintenance)**, where corrective maintenance tasks are initiated by the occurrence of failure, i.e., loss of function or performance (Kumar et al., 2012) . Failure-Based maintenance policy, FBM, represents an approach where corrective maintenance tasks are carried out after a failure has occurred, in order to restore the functionality of the item/system considered. Consequently, this approach to maintenance is known as breakdown, post failure, firefighting, reactive, or unscheduled maintenance. According to this policy, maintenance tasks often take place in ad hoc manner in response to breakdown of an item following a report from the system user.

***Disadvantages of failure-based maintenance***

In spite of the advantages of implementing failure based maintenance policy, it has some disadvantages when not utilized in the right scenario (Kumar et al., 2012).

- The failure of an item will generally occur at an inconvenient time.
- Maintenance activities cannot be planned leading to prolonged down time of failed component.
- It demands a lot of maintenance resources and an extensive spare inventory.

- The failure of an item can cause a large amount of consequential damage to other items in the system.

2. **Time-Based maintenance policy, TBM**, where preventive maintenance tasks are performed at predetermined times during operation, at fixed length of operational life. TBM, maintenance decisions (e.g., preventive repair times/intervals) are determined based on failure time analyses. In other words, the aging (expected lifetime), T, of some equipment is estimated based on failure time data or used-based data (Kobbacy and Murthy, 2008).

   In TBM, maintenance decisions are determined based on failure time analyses. In other words, the aging (expected lifetime), T, of some equipment is estimated based on failure time data (life data analysis) or used-based data (Lee et al., 2006). TBM assumes that the failure behavior (characteristic) of the equipment is predictable.

The first process of TBM starts with failure data analysis/modelling. The basic purpose of this process is to statistically investigate the failure characteristics of the equipment based on the set of failure time data gathered. Analysis of maintenance costs have shown that a repair made after failure will normally be three to four times more expensive than the same maintenance activity when it is well planned (Mobley, 2002). One of the main advantages of this maintenance policy is the fact that preventive maintenance tasks are performed at a predetermined instant of time when all maintenance support resources could be planned and provided in advance, and potential costly outages avoided. For failures, which could have catastrophic consequences to the user/operator and environment it may be the only feasible option. Time-based maintenance has many advantages over failure-based maintenance, which are summarized in the following list:

I. Maintenance can be planned ahead and performed when it is convenient from the operational and logistics point of view.

II. The cost of lost production and of consequential damage can be reduced.

III. Downtime, the time that the system is out of service, can be minimized.

IV. Safety can be improved.

3. **Condition-Based maintenance policy, CBM,** where conditional maintenance tasks in the form of inspections are performed at fixed intervals of operation, until the performance of a preventive maintenance task is required or until a failure occurs requiring corrective maintenance. The principal difference between the above maintenance policies occurs at the time when the maintenance task is performed.

### *6.2. Maintenance of Repairable Systems*

A commonly used definition of a repairable system (Ascher and Feingold, 1984) states that this is a system which, after failing to perform one or more of its functions satisfactorily, can be restored to fully satisfactory performance by any method other than replacement of the entire system. In order to cover more realistic applications, and to cover much recent literature on the subject, we need to extend this definition to include the possibility of additional maintenance actions which aim at servicing the system for better performance. This is referred to as preventive maintenance (PM), where one may further distinguish between condition based PM and planned PM. The former type of maintenance is due when the system exhibits inferior performance while the latter is performed at predetermined points in time.

Traditionally, the literature on repairable systems is concerned with modelling of the failure times only, using point process theory. A classical reference here is Ascher and Feingold (1984). The most commonly used models for the failure process of a repairable system are renewal processes (RP), including the homogeneous Poisson processes (HPP), and nonhomogeneous Poisson processes (NHPP). While such models often are sufficient for simple reliability studies, the need for more complex models is clear. In this chapter we consider some generalizations and extensions of the basic models, with the aim to arrive at more realistic models which can be applied to maintenance optimization policies in hydrosystems maintenance optimization.

### 6.2.1. Preventive Maintenance

Preventive maintenance (PM) is a schedule of planned maintenance actions aimed at the prevention of breakdowns and failures . The primary goal of preventive maintenance is to prevent the failure of equipment before it actually occurs. It is designed to preserve and enhance equipment reliability by replacing worn components before they actually fail. Preventive maintenance activities include equipment checks, partial or complete overhauls at specified periods, oil changes, lubrication and so on. In addition, workers can record equipment deterioration so they know to replace or repair worn parts before they cause system failure. Recent technological advances in tools for inspection and diagnosis have enabled even more accurate and effective equipment maintenance. The ideal preventive maintenance program would prevent all equipment failure before it occurs.

### 6.2.2. When Does Preventive Maintenance Make Sense?

Preventive maintenance is a logical choice if, and only if, the following two conditions are met:

- Condition #1: The component in question has an increasing failure rate. In other words, the failure rate of the component increases with time, implying wear-out. Preventive maintenance of a component that is assumed to have an exponential distribution (which implies a constant failure rate) does not make sense!

- Condition #2: The overall cost of the preventive maintenance action must be less than the overall cost of a corrective action.

If both of these conditions are met, then preventive maintenance makes sense. Additionally, based on the costs ratios, an optimum time for such action can be easily computed for a single component. This is detailed in later sections.

## *6.3. Reliability Centered Maintenance*

Reliability centered maintenance (RCM) is a method for maintenance planning that was developed within the aircraft industry and later adapted to several other industries and military branches (Kobbacy and Murthy, 2008). A high number of standards and guidelines have been issued where the RCM methodology is tailored to different application areas. A major advantage of the RCM analysis process is a structured, and traceable approach to determine the optimal type of preventive maintenance (PM). This is achieved through a detailed analysis of failure modes and failure causes. Although the main objective of RCM is to determine the preventive maintenance, the results from the analysis may also be used in relation to corrective maintenance strategies, spare part optimization, and logistic consideration. In addition, RCM also has an important role in overall system safety management.

Reliability data may be derived from the operational data by statistical analysis. The reliability data is used to decide the criticality, to describe the failure process mathematically and to optimize the time between PM tasks.

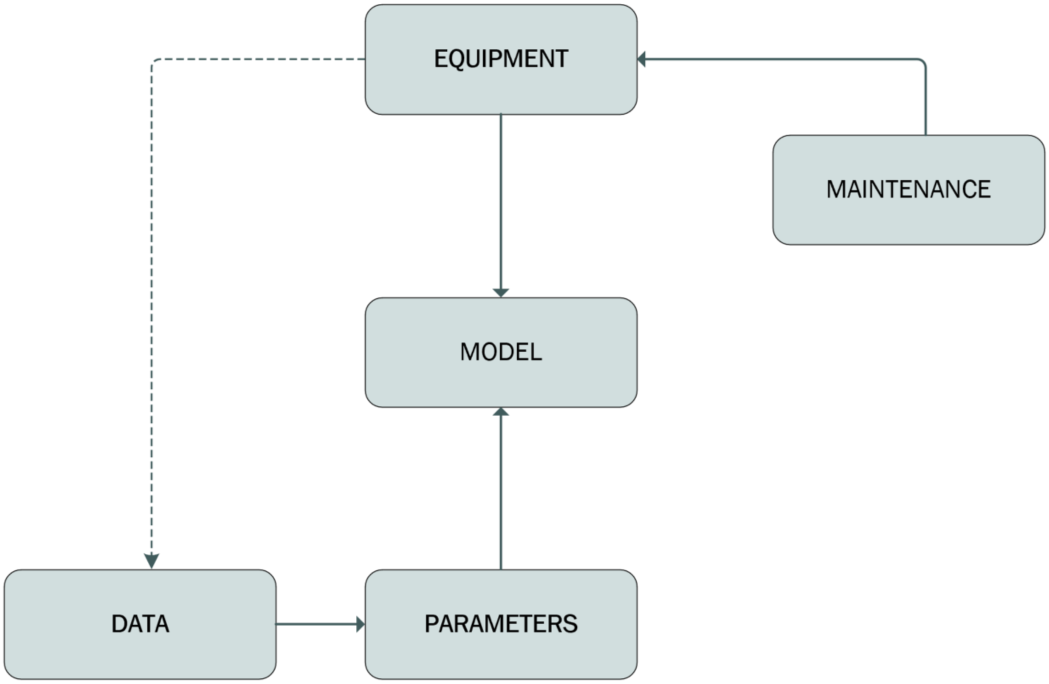


*Figure 6.2: Link between fundamental aspects of maintenance modelling and analysis*

### *6.4. Systems Framework for Study of Maintenance (Strategic Holistic Systems Approach)*

The study of maintenance in hydrosystems engineering requires a comprehensive framework that incorporates all the key elements. However, not all the elements would be relevant for a particular maintenance problem under consideration. The systems framework offers an effective means of solving maintenance problems while factoring in the impact from the natural system that the component under consideration is embedded in, organizational influences and other salient contributors to its performance. In this approach, the real world relevant to the problem is described through a characterization where one identifies the relevant variables and the interaction between the variables. This characterization can be done using language or a schematic network representation where the nodes represent the variables and the connected arcs denote the relationships. This is good for qualitative analysis. For quantitative analysis, one needs to build mathematical models to describe the relationships. Often this requires stochastic and dynamical formulations as system degradation and failures occur in an uncertain manner. In this section, we discuss the various key elements and some related issues.

Maintenance can be considered as a system with a set of processes and activities carried out in parallel with production or service systems. The primary outputs of the operation systems are services (power production, flood control), and the secondary output is degraded or failed equipment. This secondary output generates demand for maintenance. The maintenance system takes this as an input and adds to it know-how, manpower, and spares, and produces equipment/facilities in good operating condition, that provide capacity for production or service. The overall primary goal of hydrosystems is to provide flood control and maximize economic value.  Maintenance systems assist in achieving these goals, by increasing the operational availability of flow control systems and maximize profit from the available market opportunities. These are achieved by minimizing the plant downtime, improving the quality, increasing the productivity and by reliable timely intervention of disturbances in order to safeguard the safety of downstream population.

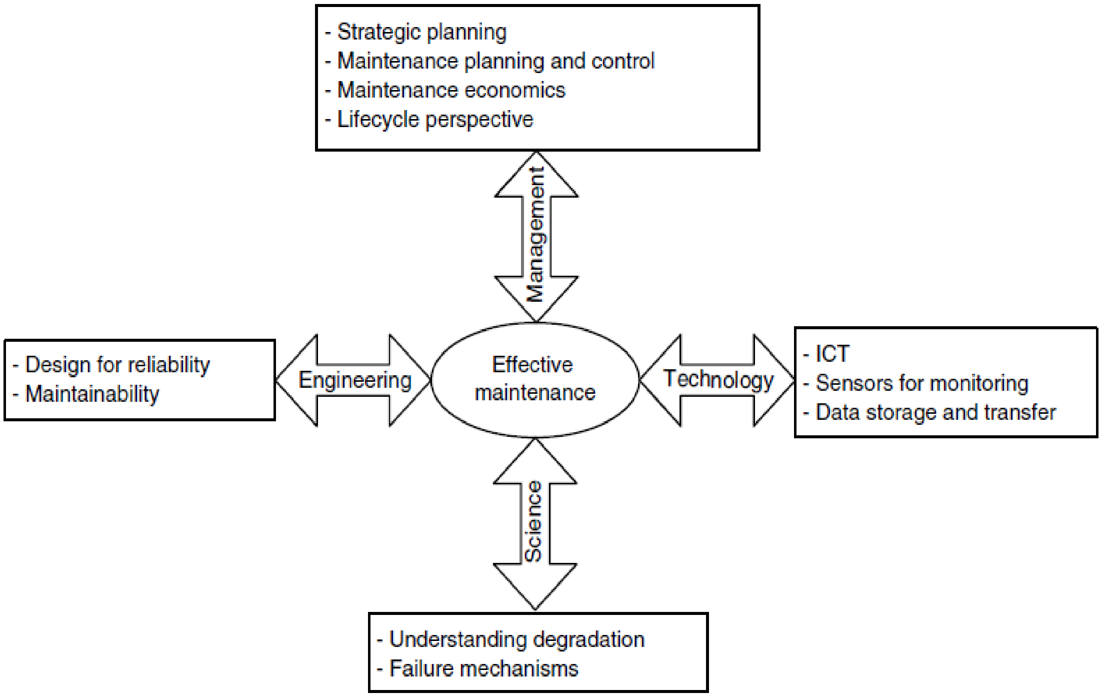


*Figure 6.3: Elements of Effective Maintenance. (Adapted from Ben Daya et. Al, 2016)*

A well-structured PM program is characterized by a sound methodology such as reliability centered maintenance (RCM) and based on a good understanding of the function and failure of the key subsystems of the engineered system. Such a program is usually a combination of various time-based, condition-based, and opportunistic maintenance policies (Ben-Daya et al., 2016).

Once the reliability models are estimated a discrete/continuous event simulation model reproducing the dynamic of the system as well as its stochastic behavior can be run in order to validate different maintenance policies and optimize their parameters. The idea is to evaluate the performances of the appropriate strategy before its implementation.

Once the reliability of the system is captured, an integrated systems framework will allow maintenance decision makers to design their production system, to model its functioning and to optimize the appropriate maintenance strategies. Thus the use of a systems approach to the study of dam systems allows us to consider all the technological, engineering and management aspects of maintenance capacity planning (Figure 6.3).

It should be noted that if we want to consider the wider scope of operational risks in dam systems, it is necessary to evaluate not only the interaction of the individual subsystems of the flow control components, but also its interaction with external systems, n\communication systems, etc. Thus, it becomes apparent that operational Risks in dam systems can be considered only with a systems approach. Moreover, regardless of the level at which one or the other system is considered, an acceptable solution can be found with the use of a systems approach.

### 6.4.1. Forecasting Maintenance Work

In this section, quantitative forecasting techniques for maintenance optimization aspects of preventive maintenance are presented. The models presented depend on the availability of the historical data and are usually based on life data of the components under consideration. These models either assume future values follow historical trends or that a predictor (independent) variable exists that can provide a model or a functional relationship that predicts the failure and repair characteristics of the components under study. For example, the age of the equipment can predict the number of maintenance hours required on the equipment.

Forecasting techniques can be classified into two approaches: qualitative and quantitative. Qualitative forecasting is based on the expert or engineering experience and judgment. Such techniques include historical analogy, surveys, and the Delphi method. Quantitative techniques are based on mathematical models that are derived from the historical data estimates for future trends. These models are either time series-based data such as moving averages and exponential smoothing or structural such as regression models (Johnson and Montgomery, 2009).

Maintenance systems have several characteristics that make capacity planning a rather complex problem. These characteristics are as follows:

- Maintenance as a function interacts with other technical and engineering functions in a complex fashion.
- The maintenance factors are highly dependent on each other.
- Maintenance as a function has many uncertain elements. These elements include demand for maintenance, time of arrival of job requests, content, time to complete a job, tools, equipment, and spare parts availability.

- The complexity of the maintenance capacity planning suggests that simulation is one of the most desirable approaches for modeling it (Duffuaa and Raouf, 2015). Stochastic simulation is the process of representing a system on the computer and then employing well-designed experiments (scenarios), to evaluate the system performance. Using this process, systems can be analyzed, planned, and designed.

#### *6.4.1.1 Stochastic Simulation*

Law and Kelton (2007) provide ten major steps for conducting a typical simulation study. In this section, these ten steps are summarized in eight steps and the relationships among them are outlined:

1. Purpose of simulation: The first step toward a successful simulation study is to state precisely the purpose of the study. Simulation has been used in maintenance systems for the following purposes: to determine the optimal crew size and staffing, to evaluate the effect of maintenance policies on production systems, to design and plan maintenance operations, and to determine the shutdown time periods.

2. Simulation models: The conceptual model used in building the computer simulation study will affect the simulation accuracy and efficiency. The simulation model should contain only the necessary information that captures the essence of the system under study.

3. Model assumptions: The assumptions of a simulation model will affect the realism of the simulation results. They also may affect the way results are interpreted. Therefore, each assumption should be reviewed carefully before putting it into effect. Availability of manpower, equipment, job standards, and spare parts are some of the assumptions used in maintenance systems.

4. Data Accuracy: Accurate data and their distributions are very essential for a reliable simulation model. To simulate a maintenance system, the distribution of equipment failures and repair times must be identified using sound statistical methodology.

5. Simulation languages and computers: One of the major jobs in building a simulation model is to convert the conceptual model into an actual computer simulation program.

6. Program verification and model validation: Verification is testing and checking the computer code to show that it performs as intended. Validation is to ensure that the model's assumptions are realistic and correct, and the simulation model fairly represents the behavior of the modeled system. Even though this step is fairly tedious and time-consuming, it is the most important step in simulation studies.

7. Output analysis: In any simulation study, it pays very well to spend time on output analysis. To check for the true estimate, test, validate, and decide on the output results from your simulation, statistical techniques that ensure reliable estimates for system performance must be used. These include deciding on the length of the simulation run, the number of runs, and confidence intervals for estimated measures of performance.

### *6.5. Key Issues and the Need for Multi-disciplinary Approach*

The key issues in the maintenance of an asset are shown in Figure 1.3. The asset acquisition is influenced by business considerations and its inherent reliability is determined by the decisions made during design. The field reliability and degradation is affected by operations (usage intensity, operating environment, operating\ load etc.). Through use of technologies, one can assess the state of the asset. The analysis of the data and models allow for optimizing the maintenance decisions (either for a given operating condition or jointly optimizing the maintenance and operations). Once the maintenance actions have been formulated it needs to be implemented.

## 6.6. *Modeling the impact of Maintenance Actions*

An operating system (machine) is observed to undergo failures. On failure, one of three actions was taken: failures were minimally repaired, given a minor repair or given a major repair. Furthermore, periodically the machine was stopped for either minor maintenance action or major maintenance action. In addition to the kind of maintenance action, the length of duration for each repair action is known. Either on failure or maintenance stoppage, both types of repairs are assumed to impact the intensity following a virtual age process of the general form proposed by Kijima. There are several possibilities for assumptions of the impact of repair: it can be assumed that a minor or major repair impact the virtual age of the item to an unknown fixed part. It is also possible to assume that the impact of repair depends on the repair time. The issue in this research is to identify not only the virtual aging process associated with repairs but also the form of the failure intensity associated with the system. A series of models appropriate for such an operating/maintenance environment are developed and estimated in order to identify the most appropriate statistical structure. Field data from an industrial setting are used to fit the models.

### 6.6.1. Generalized Renewal Process

According to Rigdon & Basu (2000), a system is called repairable if, when a failure occurs, it can be restored to an operating condition by some repair process other than replacement of the entire system. For situations where downtime associated with maintenance, repair or replacement actions is negligible, compared with the mean-time-between failures (MTBF), the point processes are used as probabilistic models of the failure processes

(Martorell et al., 2014). The commonly adopted point processes in PSA are as follows: (i) homogeneous Poisson process (HPP), (ii) ordinary renewal processes (ORP) and (iii) non-homogeneous Poisson process (NHPP). However, these approaches do not represent the real life-cycle of a repairable system (Modarres, 2006). Rather, they have some assumptions that conflict with reality. In HPP and ORP, the device, after a repair, returns to an as-good-as-new condition, and in a NHPP the device, after a repair, returns to an as-bad-as-old condition. Kijima & Sumita (1986) introduced the concept of generalized renewal process (GRP) to generalize the three point processes previously mentioned. With this approach, reliability is modeled considering the effect of a non-perfect maintenance process, which uses a better-than-old-but-worse-than-new repair assumption. Basically, GRP addresses the repair assumption by introducing the concept of virtual age, which defines a parameter q that represents the effectiveness of repair.

As mentioned, the probabilistic modeling to be considered in this work to approach repair action, especially imperfect repairs, is the generalized renewal process (GRP). Nevertheless, for a complete understanding about GRP, it is necessary to define the concept of virtual age (Vn). The Vn corresponds to the calculated age of particular equipment after the n-th repair action. Kijima & Sumita (1986) has proposed two ways to modeling this virtual age. The first one, commonly named type I, consists basically of the assumption that a repair action acts just in the step time just before. With this assumption, the virtual age of a component increases proportionally to the time between failures:

$$V_n = V_{n-1} + qV_n \tag{6.1}$$

whereas the assumption of q = 1 leads to an NHPP (as bad as old). The values of q that fall in the interval 0 < q < 1 represent the after repair state in which the condition of the system is ‘‘better than old but worse than new’’. On the basis of this proposition of virtual age, Kijima et al., (1988) has proposed the following approach to calculate the conditional probability of failure.

The type II model considers that the repair can restore the system considering the elapsed time since the beginning of its life. In this model, the virtual age increases proportionally to the total time.

$$V_n = q(Y_{n-1} + V_{n-1})$$

q can be defined as the repair effectiveness parameter (restoration factor) in both models.

1) q = 0 → “good-as-new”, i.e. ORP
2) q = 1 → “same-as-old”, i.e., NHPP
3) 0 < q < 1 → “better-than-old-but-worse-than-new”
4) q > 1 → “worse-than-old”  GRP

According to this modeling, the result of assuming a value of q = 0 leads to an RP (as good as new), whereas the assumption of q = 1 leads to an NHPP (as bad as old). The values of q that fall in the interval 0 < q < 1 represent the after repair state in which the condition of the system is ‘‘better than old but worse than new’’.

- **Perfect Repair (Ordinary Renewal Process: Good as new):** A repair completely resets the performance of the product so that upon restart the product operates as a new one. This type of repair is equivalent to a replacement of the faulty item by a new one, identical to the original.

- **Imperfect Repair (Better than Old but Worse than new):** A repair contributes to some noticeable improvement of the product. It effectively sets back the clock for the repaired item. After the repair the performance and expected lifetime of the item are as they were at an earlier age.

- **Minimal Repair (Non-Homogeneous Poisson Process: Same as Old):** A repair has no impact on the performance of the item. The repair brings the product from a 'down' to an 'up' state without affecting its performance.

- **Worse than Old Repair:** A repair contributes to some noticeable worsening of the product. It effectively sets forward the clock for the repaired item. After the repair the performance of the item is as it would have been at a later age.

### *6.7. Mathematical Models for Optimum Preventive Policies*

In this section, several maintenance policies for systems that are subject to stochastic failure are defined and mathematical models to determine the optimum level for each policy are formulated. Two basic preventive maintenance policies proposed by Barlow and Proschan (1996) are examined in the literature extensively. These are age-based and constant interval replacement polices known as type I and type II policies. The statements of the polices, their models, and generalizations are given in the next sections. In this part, the notations necessary for the formulation of the models are stated.

$C_p$ cost of preventive maintenance

$C_f$ cost of breakdown (failure) maintenance

$f(t)$ time to failure probability density function (p.d.f.)

$F(t)$ equipment or system failure distribution, and it is the integral of $f(t)$

$r(t)$ failure rate function

$N(t_p)$ number of failures in the interval (0, tp); N(tp) is a random variable

$H(t_p)$ expected number of failures in the interval (0, tp)

$R(t)$ reliability or survival function

M(tp) expected value of the truncated distribution with p.d.f. f(t) truncated at tp

$$M(t_p) = \int_{-\infty}^{\infty} \frac{tf(t)dt}{[1 - R(t_p)]}$$

$C(t_p)$ expected cost per cycle

$UC(t_p)$ expected cost per unit time

### 6.7.1. Optimal Age Preventive Replacement (Type I Policy)

Policy I (age preventive replacement) is defined as follows: perform preventive replacement after tp hours of continuing operation without failure; tp could be finite or infinite. In case of an infinite tp, no preventive maintenance (replacement) is scheduled. If the system fails prior to tp hours having elapsed, perform maintenance (replacement) at the time of failure and reschedule the preventive maintenance after tp operation hours. In this policy, it is assumed that the system is as good as new after any type of maintenance (replacement) is performed.

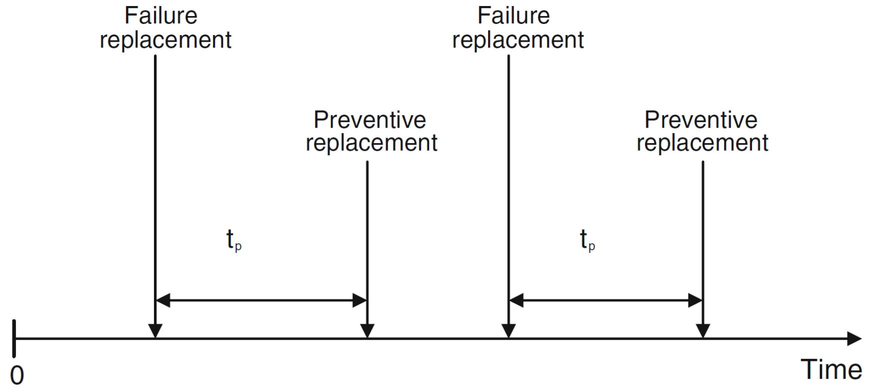


*Figure 6.4: Timeline of Preventive and Failure based Maintenance Policies*

This policy is suited for simple equipment or a single unit in which repair at the time of failure (or replacement) could nearly correspond to general overhaul. An example of such equipment is a vacuum tube. This policy is illustrated in Fig. 6.4. In this situation, as shown in Fig. 6.4, there are two operations cycles. In one cycle, the equipment operates till the time for preventive maintenance (replacement) tp, and in the second cycle, the equipment fails prior to the planned maintenance.

The main objective of maintenance policies is to optimize the maintenance actions according to certain criteria, such as risk, cost, reliability, and availability (Yan, 2014). The objective of the model in this section is to determine the optimal tp, meaning that the tp at which preventive replacement is performed after the equipment has operated continuously for tp hours without failure. The model determines the tp that minimizes the total expected cost of preventive and breakdown maintenance per unit time shown in Eq. 6.2.

$$UC(t_p) = \frac{Total\ expected\ cost\ per\ cycle}{Expected\ cycle\ length} \qquad (6.2)$$

The total expected cost per cycle consists of the cost of preventive maintenance in addition to the cost of breakdown (failure) maintenance, which is:

$$E(Cost) = \frac{E(cost\ per\ cycle)}{Cycle\ Length} \qquad (6.3)$$

The total expected cost per cycle consists of the cost of preventive maintenance in addition to the cost of breakdown (failure) maintenance, which is

$$C(t_p) = C_p \times R(t_p) + \ C_f[1 - R(t_p)] \qquad (6.4)$$

Where $R(t_p)$ is the probability the equipment survives till age tp, which is represented by the shaded area in Fig. 6.5.

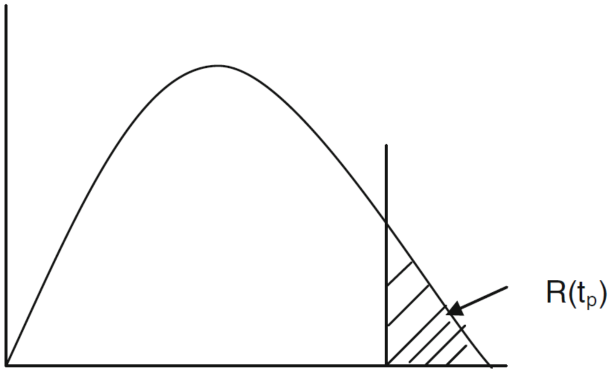


*Figure 6.5: Area under the probability distribution representing* $R(t_p)$

The expected cycle length consists of the expected length of preventive cycle plus the expected length of a failure cycle.

Expected Cycle length = $C(t_p) = t_pR(t_p) + M(t_p)\ \left(1 - R(t_p)\right)$ (6.5)

where

$$M(t_p) = \int_{-\infty}^{\infty} \frac{tf(t)dt}{[1 - R(t_p)]}$$

$$= \frac{cF(T_a) + p(1\ -\ F(T_a))}{\int_0^{T_a} t\,dF(t)\ +\ t_r\,F(T_a)\ +\ (T_a\ +\ t_m)(1\ -\ F(T_a))} \tag{6.6}$$

$M(t_p)$ is the mean of the truncated distribution at $t_p$(see Figure 6.4)

$$UC(t_p) = \frac{C_pR(t_p) + C_f[1 - R(t_p)]}{t_pR(t_p) + M(t_p)\ [1 - R(t_p)]} \tag{6.7}$$

### 6.7.2. AVAILABILITY MODEL

Availability is a measure of system readiness and it is one of the most important measures of effectiveness usually employed in mission-oriented situations especially in the dam safety environment. Operational availability, as defined earlier, is the probability that a system or equipment, when used under stated conditions in an actual operational environment, will operate satisfactorily when called upon. System availability is influenced both by the inherent failure proneness of the system and by the time and resources (support elements) it takes to restore a failed system to service. Times to failure or 'up times' and to restoration or 'down times' may vary considerably, and not necessarily independently, depending upon the mode of failure, the time required to diagnose the failure, availability of special tools, test equipment, and spare parts, and the proper documentation and the required personnel skills. The long-run availability or steady state is expressed as follows:

$$E(Availability) = \frac{E(Cycle\ UpTime)}{Cycle\ Length} \tag{6.8}$$

$$= \frac{\int_0^{T_a} t\, dF(t) + T_a(1 - F(T_a)))}{\int_0^{T_a} t\, dF(t) + t_r\, F(T_a) + (T_a + t_m)(1 - F(T_a))} \tag{6.9}$$

## CHAPTER 7: CASE STUDY 1- WOLF CREEK HYDROPOWER PROJECT

### *7.1. Background*

Wolf Creek Dam is a combination concrete gravity and earthfill structure located at mile 460.9 of the Cumberland River (fig 10.1) near Jamestown, Kentucky. The total length of the dam is 5,736 feet. The concrete section is 1,796 feet long, ties into the left abutment, and extends across the old river channel toward the right abutment. It has a maximum structural height of 258 feet (dam crest to base of concrete dam) and contains a gate control section, a powerhouse section, and non-overflow sections on both ends. US Highway 127 traverses the top of the dam. Normal storage in Lake Cumberland, created by the dam, is about four million acre-ft. Up to 6,089,000 acre-ft. can be impounded at a maximum pool elevation of 760. It is the largest reservoir east of the Mississippi River, and the ninth largest in the United States.

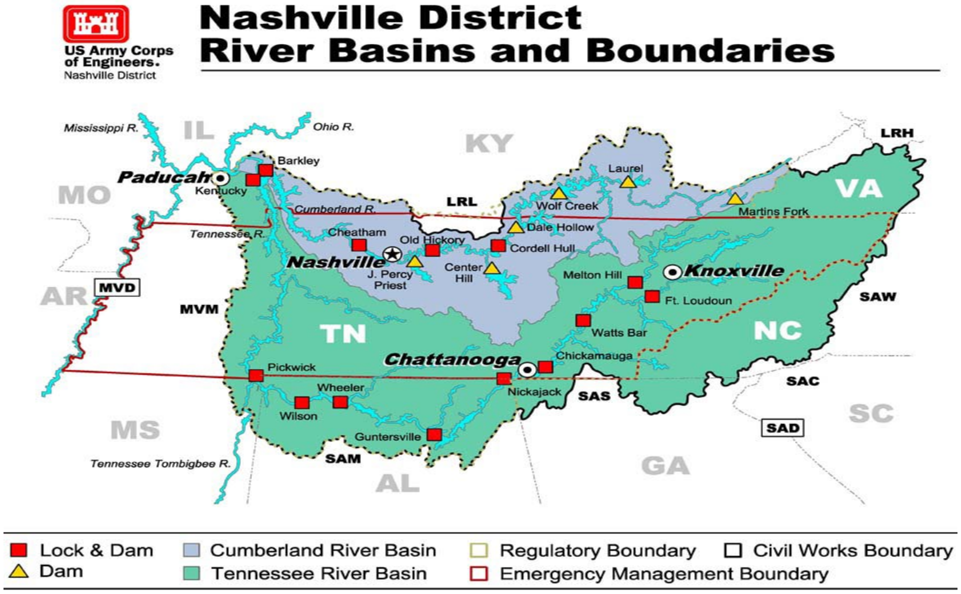


*Figure 7.1: Map of Nashville River Basins and Boundaries*

The control section within the concrete gravity section contains a spillway with ten, 50-feet wide, by 37-feet high tainter gates and six 4-feet by 6-feet low level sluices. The top of the dam is at elevation 773, the crest of the spillway is at elevation 723, and the top of the tainter gates is at elevation 760. The invert of the low-level sluices is at elevation 562.

Power can be generated when the pool elevation is at or above elevation 680. The powerhouse contains six turbines rated at 45,000 KW each (total 270 MW). The earth embankment section of the dam extends 3,940 feet from the end of Monolith 37 of the concrete section across the valley to the right abutment. The earth section is a non-zoned compacted clay embankment with a maximum structural height of 215 feet.

### 7.1.1. The Cumberland River Basin

The Upper Cumberland River Basin covers over 7,300 square miles, 5,180 in Kentucky and 2,130 in Tennessee. All or parts of 20 Kentucky counties lie in the basin. The basin contains nearly 15,100 miles of streams, 10,430 in Kentucky and 4,640 in Tennessee. From the headwaters of Looney Creek in Harlan County, 4,100 feet above sea level, and the Poor Fork in Letcher County, runoff flows down the Upper Cumberland River west to an elevation of 460 feet at the Kentucky-Tennessee line.

The Lake Cumberland reservoir is 101 miles long in length and has 1,255 miles of shoreline, providing a total storage capacity of 6,089,000 acre-feet (1 acre-foot = 1 acre, 1 foot deep or 325,850 gallons). The upper portion of the reservoir containing 2,094,000 acre-feet of area, is used to hold floodwaters which would otherwise cause flooding downstream. Such impounded water is utilized to the maximum extent possible for power production and the surplus water is released through the spillway gates after any flood danger had passed.

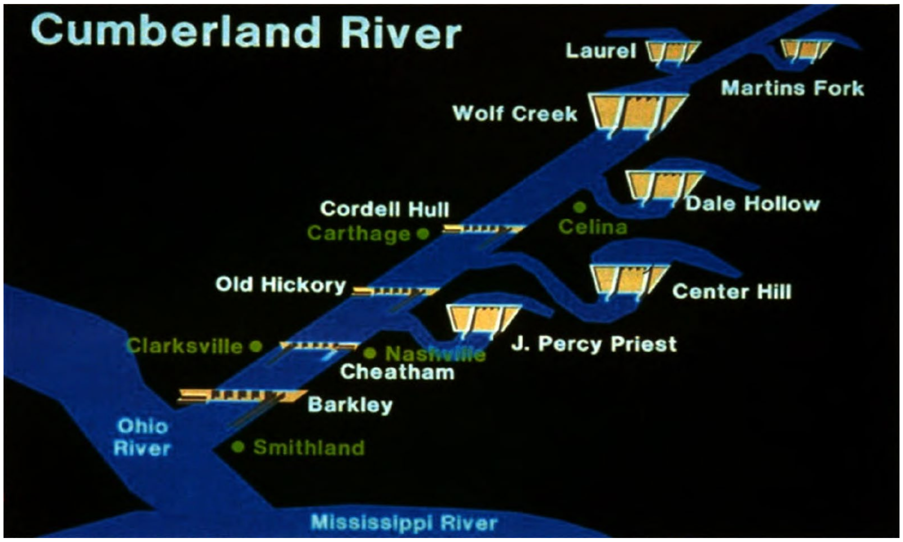


*Figure 7.2: Cumberland River System Schematic*

Of the remaining 3,995,000 acre-feet of reservoir capacity, 2,142,000 acre-feet, corresponding to a drawdown of 50 feet, is allocated specifically for power operation, leaving a minimum pool of at least 1,853,000 acre-feet available at all times for public use and conservation purposes. The electrical energy produced by the project is sufficient to supply the needs of an average city with a population of 375,000. Incidental to the production of power, the water released through the turbines provides a favorable streamflow below the dam. In supplementing low flows, this water improves domestic water supply, reduces stream pollution and provides aid to navigation. The reservoir normally fluctuates between 50,250 acres at the top of the power pool and a minimum surface area of 35,820 acres. During periods of high inflow, when it is necessary to utilize the flood storage, the surface area may reach 63,530 acres. However, such floods occur infrequently, and the levels resulting from minor floods and power operations do not seriously interfere with most recreational activities.

*Table 7.1. Wolf Creek Dam Statistical Information*

| | |
|---|---|
| **DAM** | |
| | |
| Type | Concrete-gravity and earth fill |
| Quantities: | |
| Concrete, cubic yards | 1,380,000 |
| Earth fill, cubic yards | 10,016,500 |
| Dimensions: | |
| Maximum height, feet | 258 |
| Length, feet (concrete, 1796; earth, 3940) | 5,736 |
| Elevations (above mean sea level): | |
| Top of dam | 773 |
| Top of gates | 760 |
| Spillway crest | 723 |
| Spillway crest gates: | |
| Number and type | 10, Radial |
| Size (width and height), feet | 50 X 37 |
| Discharge capacity, c.f.s. | 553,000 |
| Sluices | |
| Number of conduits | 6 |
| Size (width and height), feet | 4 X 6 |
| Total discharge capacity, c.f.s. | 9,800 |
| | |
| **HYDROPOWER** | |
| Installation | 270,000 kw in 6 units |
| Rating, each generator, kilowatts | 45,000 |
| Estimated energy output, average yearly, kilowatt-hours | 800,000,000 |

**Normal Dam Operation**: The hydropower pool for Wolf Creek Dam extends from the top of the conservation pool elevation of 673 ft. to 723 ft. The flood control pool extends from 723 ft. to 760 ft. A seasonal operating guide within the power pool is commonly referred to as the "SEPA power marketing zone" but is more accurately called the "Power Marketing Band" (PMB) in this document. SEPA is the acronym for the Southeastern Power Administration which is the Federal entity responsible for marketing the power generated by all USACE projects in the Nashville District. This operating zone was developed by SEPA, Tennessee Valley Authority (TVA) and the Corps. The power marketing band starts the year low in the power pool, fills through the spring reaching the top of the power pool by summer, and then gradually falls through the summer and fall, to an approximate elevation of 683 ft. in time for the flood season. This is a non-binding operating guide that maximizes hydropower benefits while also supporting flood control, water quality, navigation, and other downstream uses dependent on the release of stored water through the summer and fall. The normal operation at Wolf Creek is to favor the top of the PMB, targeting a June 1 elevation of 723 it.

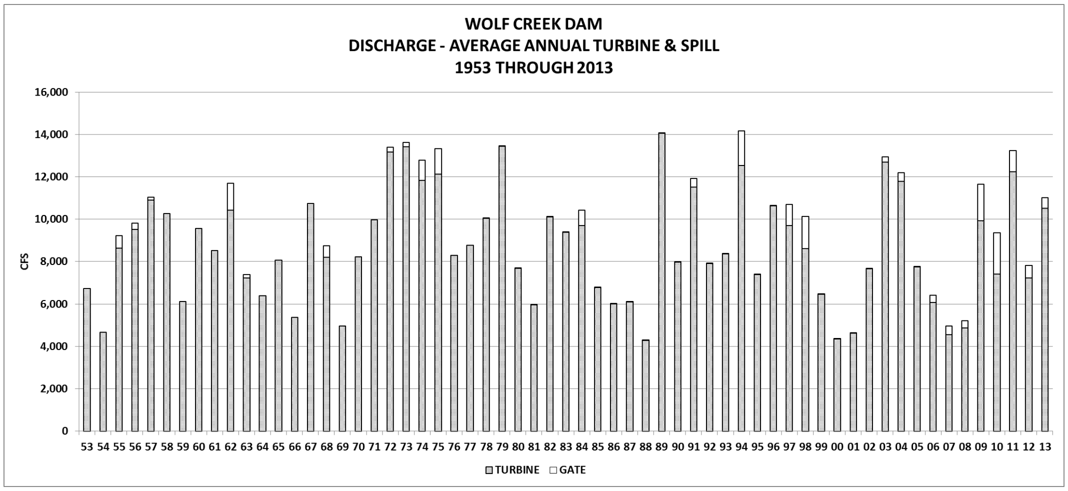


*Figure 7.3: Wolf Creek Average annual Outflows*

**Hydropower**: For the purposes of cumulative effects, the spatial boundary coincides with the SEPA power grid. Demands for this resource include peaking power at Wolf Creek Dam and its contribution to the power grid. Demands for the water used for hydropower include water for minimum flow, water quality, fish and wildlife management, and recreation. Under minimum flow releases, hydropower generation adds little oxygen to improve downstream water quality to support the cold water fishery. Instead, water for hydropower is diverted through a sluice gate to meet both minimum flow and water quality needs. Lowering the lake reduces the amount of water available for hydropower. When lake levels reach EL 676 it, no hydropower can be generated.

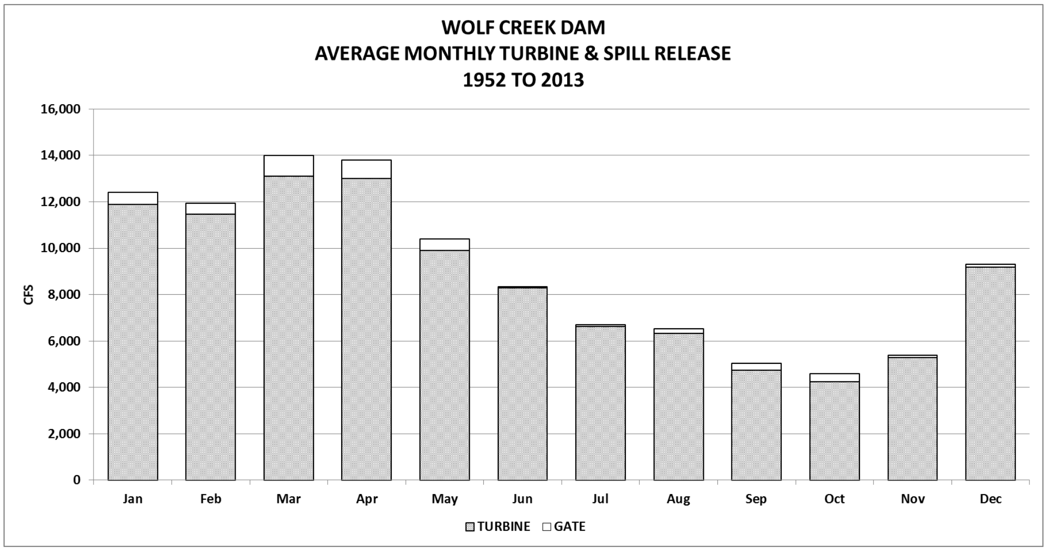


*Figure 7.4: average Monthly Outflows (Wolf Creek)*

### 7.2. <u>Wolf Creek Systems Model objectives and Framework</u>

The purpose of this project is to apply the systems reliability modeling approach to the Wolf Creek and John Day dams operated by the USACE. The project further promulgates the use of a systems modeling framework in the analysis of the performance of hydraulic flow control systems. One of the key objectives of the adopted modeling framework is to balance the main aspects of dam operation, performance and reliability into an integrated whole. That integrated whole is comprised of: (i) the natural siting of the dam with respect to its hydrology and geology, (ii) the physics behind water containment and the control of discharge, and (iii) the monitoring and control of operations.

The philosophy of systems engineering as a whole has two essential attributes:

- Structural performance and resilience; and
- Functional performance and resilience

Structural performance and resilience pertain to the ability of the dam to withstand the forces that are applied to it and to maintain the structural support and integrity required for the functions of the dam and reservoir. Functional performance and resilience pertain to processes, products and services that the dam is intended to provide. Specifically, the dam is intended to retain the stored volume and to pass all flows through and around the dam in a controlled manner.

The systems approach also gives consideration to the influence of disturbances to one or more functions for reasons that can be external or internal to the system. The possibility of one or more combinations of both external and internal disturbances, ranging from those that occur essentially simultaneously to those that occur at different times but in ways that the effects of the disturbances combine, are also considered.

One of the goals of this project is to understand how the interactions of systems components, control and combine to affect performance, and the potential for accidents and failures; thus, how simple but unforeseen chains of events might combine to affect the ability to control flows. Emphasis is placed on flow control components of the dam that will be modelled include the spillway gates, low level turbine intake sluices, lower level inlets for environmental flows, gate hoists, SCADA system reliability and human operator influences.

### 7.3. Hydrological Routing

Hydrologic routing is used to model the downstream conditions within the Wolf Creek River System in response to a given flow hydrograph at the upstream end of the reach. The modelling utilizes the continuity equation and analytic or empirical relationships between the channel storage and the discharge at the outlet. The continuity equation, as presented in chapter 4 for can be conceptualized as:

Continuous time

$$\frac{dS(t)}{dt} = I(t) - Q(t) \tag{8.1}$$

Discrete time

$$I - Q = \frac{\Delta S}{\Delta t} \tag{8.2}$$

Where for the discrete time formulation $I$ is the average inflow at the upstream end of the river reach during time interval $\Delta t$, $Q$ is the average discharge from the reach during time interval $\Delta t$ and $S$ is the reach storage. A 65-year history of streamflow data into the Cumberland river basin was used to generate stochastic Inflows through time series forecasting. A autoregressive-moving-average time series model was used to generate stochastic inflows.

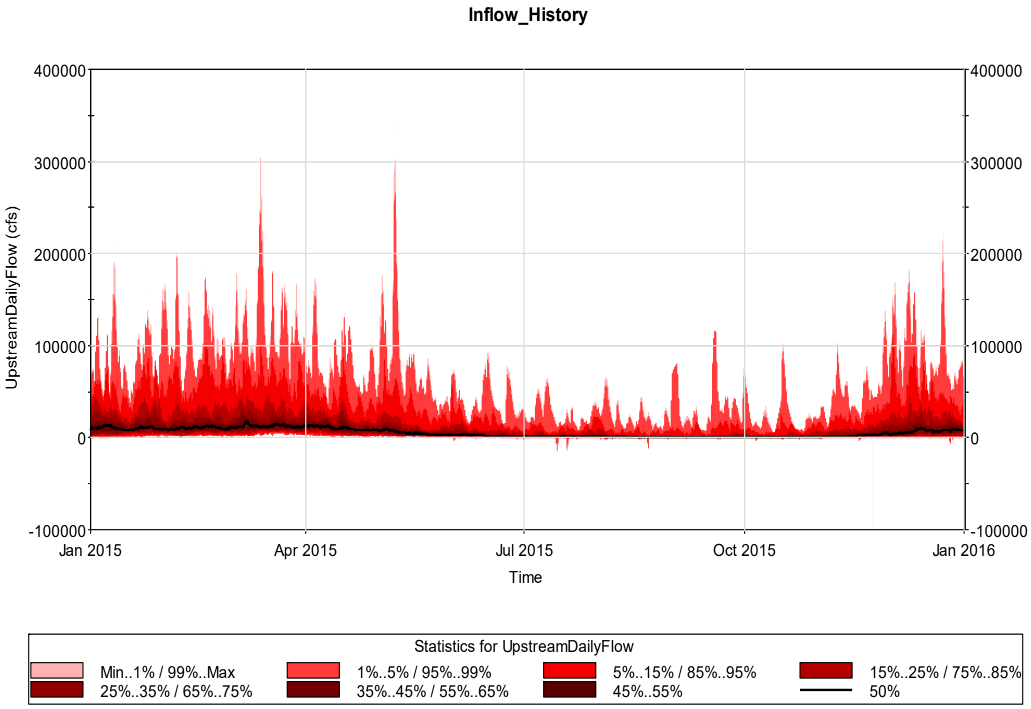


*Figure 7.5: 65-year Historical Upstream Inflow Series*

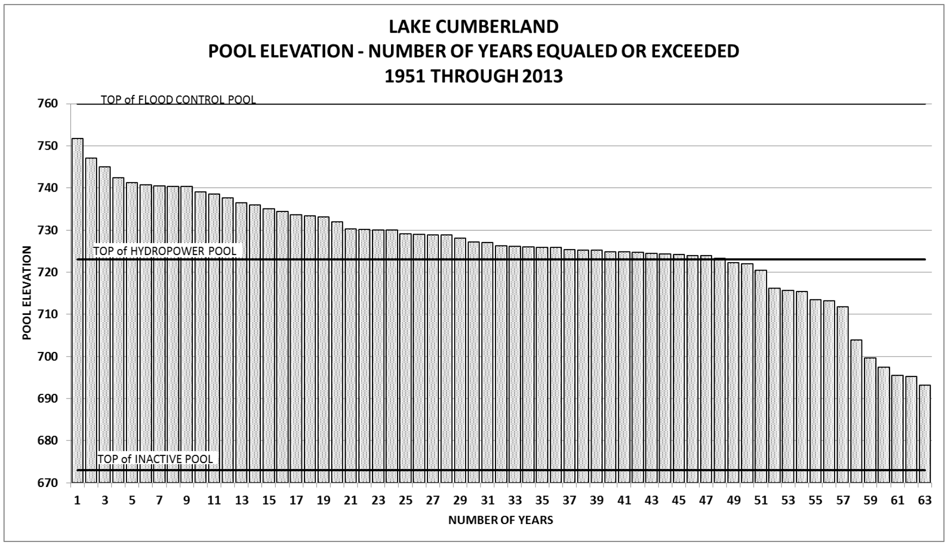


*Figure 7.6: Lake Cumberland Stage Exceedance History*

### 7.4. *Wolf Creek Hydraulic Modeling of Dam and Reservoir Components*

The Cumberland River watershed, which is the natural sitting of Wolf Creek dam is a complex system comprised of numerous inter-related, inter-dependent, and interactive components which can be influenced by random events. The operation of the system is mainly governed by the actual water levels in reservoirs, actual inflow and SEPA guide curves that is based on historic safe and optimal operation of the Wolf Creek dam and Powerhouse. However, the system can be greatly influenced by other random events such as failures of transmission system; failures of flow control equipment; and failures to shut down properly by operators; failure of structural components of the dam etc. Other operational challenges that further contribute to the complexity of the system and its operation include:

-Numerous contributing watersheds that are managed by other entities,

- Many facilities requiring sluiceway equipment to be manually operated on site,
- Fairly remote sites of these facilities,
- Limited resources available to manage all sites,
- Inaccuracy of the inflow flood forecast,
- Environmental and other stakeholder's requirements for water levels flow releases to maintain ecological and/or biological healthy system.

Simulation of such a complex system is not practical using analytical solutions. Therefore, a dynamic system simulation (a systems approach) is used to analyze and predict how all components comprising the System interact and behave as a whole. Dynamic system simulation is based on a mathematical representation that describes the physical system behavior and dynamics of the various system components. The mathematical representation of the system should ensure the following:

- Accurate representation of the system behavior under all conditions. Capability of handling the random characteristics of the system input variables.
- The variables may be continuous (such as inflows) or discrete (n out of N gates and/or turbines working etc.).
- Practical and manageable simplification of the real system.
- Ability to reasonably mimic the decision-making process in real time operation under various scenarios.

The GOLDSIM™ Platform was adopted to perform the dynamic system simulation. GOLDSIM™ is a Stock-and-Flow based simulation platform and has the benefits of hosting a range of water resources related features and statistical modeling and analytical tools including discrete events and Monte Carlo simulation. It is very flexible for visualizing and dynamically simulating physical, financial or organizational systems. Almost any system that can be quantitatively described using equations and/or rules can be simulated using GOLDSIM™.

### 7.4.1. Reservoir Modeling

*The main function of this component is that the model determines the release outflow based on the inflow at the time, the current water level, the expected water level of the time period (the rule curve), the turbine generation requirements, the gate position and the disturbance that may/may not occur at the time.*

*In functional terms, the purpose of the dam, reservoir and hydraulic structures together is to intercept upstream stream flows and transform them into controlled outflows. According to Afzali et al. (2008), the objective of reservoir outflow releasing philosophy is to minimize the sum of reservoir releases, while maximizing the sum of reservoir storages in each of the time periods. This is subject to a reliability constraint on the hydropower system's energy yield.*

The Goldsim™ platform is used to model the response of the reservoir component to hydraulic/hydrologic loads and disturbances. The reservoir element is programmed to iteratively compute the addition rate, withdrawal rate and other salient reservoir functions. For the Wolf Creek system, the addition rate is computed by defining it as a function of the upstream inflow rate while the withdrawal rate is defined as a function of both the Spill through the Spillway gates and the volume routed through the turbines.

Addition Rate=Upstream Daily flow (8.3)

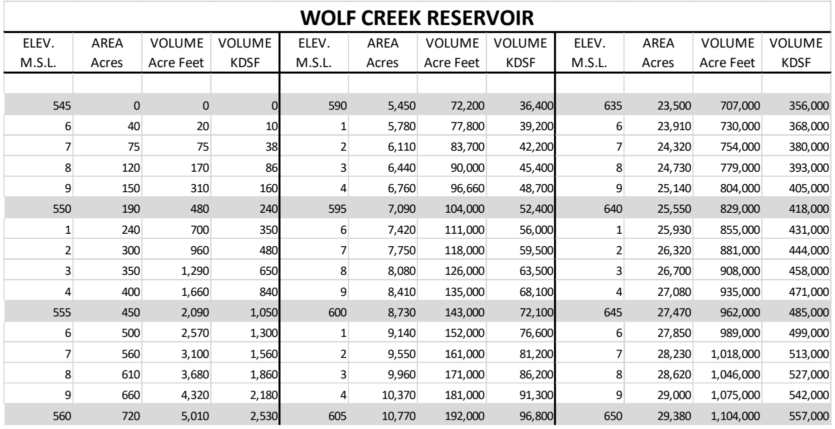
Withdrawal rate=Turbine Flow + Spillway Flow (8.4)

The balance of inflow, outflow and reservoir storage is at the heart of dynamic simulation. The water balance computations are done at each time step. Like an Integrator, a Reservoir requires an Initial Value and a rate of change. The rate of change, however, is specified in terms of two separate inputs, an Addition Rate and a Withdrawal Rate. The water balance equation is:

$$V\ (t) = \ Initial\ Value + \int \left(Rate\ of\ Addition\ -\ Rate\ of\ Withdrawal\right) dt \qquad (8.5)$$

The above equation states that the reservoir volume at the end of the time t (V(t)) is the result of the initial storage plus the inflow to the reservoir minus the outflow. There are two unknown variables in the water balance equation: the end reservoir storage and the reservoir outflow. The reservoir withdrawal (outflow) may consist of flow discharges of turbines, and/or gates/sluices, lower level outlets, and overtopping flow , discharge from navigation locks, (if water level exceeds the crest elevation of the dam).

The model computes the storage in the reservoir based on storage capacity tables (Figure 7.7) provided by the USACE for Wolf Creek Dam. Thus, the Model is programmed to interpolate from the storage capacity table to compute the volume increments and decrements and the elevation increments and decrements.



**WOLF CREEK RESERVOIR**

| ELEV. | AREA | VOLUME | VOLUME | ELEV. | AREA | VOLUME | VOLUME | ELEV. | AREA | VOLUME | VOLUME |
|---|---|---|---|---|---|---|---|---|---|---|---|
| M.S.L. | Acres | Acre Feet | KDSF | M.S.L. | Acres | Acre Feet | KDSF | M.S.L. | Acres | Acre Feet | KDSF |
| 545 | 0 | 0 | 0 | 590 | 5,450 | 72,200 | 36,400 | 635 | 23,500 | 707,000 | 356,000 |
| 6 | 40 | 20 | 10 | 1 | 5,780 | 77,800 | 39,200 | 6 | 23,910 | 730,000 | 368,000 |
| 7 | 75 | 75 | 38 | 2 | 6,110 | 83,700 | 42,200 | 7 | 24,320 | 754,000 | 380,000 |
| 8 | 120 | 170 | 86 | 3 | 6,440 | 90,000 | 45,400 | 8 | 24,730 | 779,000 | 393,000 |
| 9 | 150 | 310 | 160 | 4 | 6,760 | 96,660 | 48,700 | 9 | 25,140 | 804,000 | 405,000 |
| 550 | 190 | 480 | 240 | 595 | 7,090 | 104,000 | 52,400 | 640 | 25,550 | 829,000 | 418,000 |
| 1 | 240 | 700 | 350 | 6 | 7,420 | 111,000 | 56,000 | 1 | 25,930 | 855,000 | 431,000 |
| 2 | 300 | 960 | 480 | 7 | 7,750 | 118,000 | 59,500 | 2 | 26,320 | 881,000 | 444,000 |
| 3 | 350 | 1,290 | 650 | 8 | 8,080 | 126,000 | 63,500 | 3 | 26,700 | 908,000 | 458,000 |
| 4 | 400 | 1,660 | 840 | 9 | 8,410 | 135,000 | 68,100 | 4 | 27,080 | 935,000 | 471,000 |
| 555 | 450 | 2,090 | 1,050 | 600 | 8,730 | 143,000 | 72,100 | 645 | 27,470 | 962,000 | 485,000 |
| 6 | 500 | 2,570 | 1,300 | 1 | 9,140 | 152,000 | 76,600 | 6 | 27,850 | 989,000 | 499,000 |
| 7 | 560 | 3,100 | 1,560 | 2 | 9,550 | 161,000 | 81,200 | 7 | 28,230 | 1,018,000 | 513,000 |
| 8 | 610 | 3,680 | 1,860 | 3 | 9,960 | 171,000 | 86,200 | 8 | 28,620 | 1,046,000 | 527,000 |
| 9 | 660 | 4,320 | 2,180 | 4 | 10,370 | 181,000 | 91,300 | 9 | 29,000 | 1,075,000 | 542,000 |
| 560 | 720 | 5,010 | 2,530 | 605 | 10,770 | 192,000 | 96,800 | 650 | 29,380 | 1,104,000 | 557,000 |

*Figure 7.7: Wolf Creek Reservoir Storage Rating table*

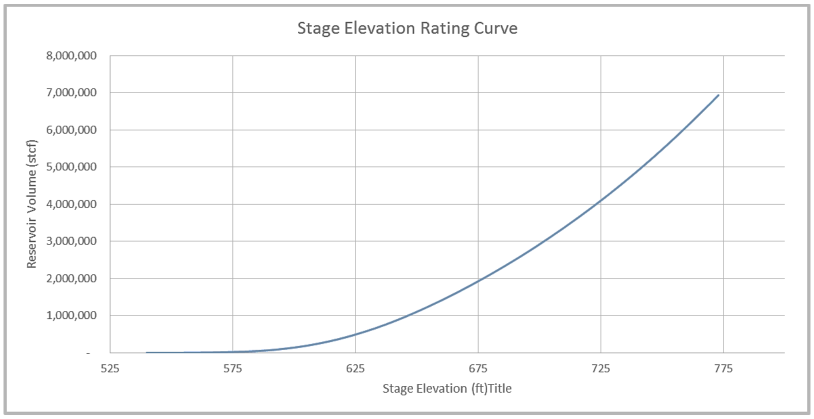


*Figure 7.8: Wolf Creek Stage Elevation Rating Curve*

If water level is denoted by $h_t$ then inflow within the interval [$t$, $t+1$) is not known at the time $t$ and it can be known only when it has been realized at the end of time interval and for that reason will be denoted by $q_{t+1}$. Storage has a unique property since its value $s_{t+1}$ at time $t+1$ can be calculated from its value $s_t$ at time t using the following formula:

$$s_{t+1} = s_t + q_{t+1} - d_{t+1} \qquad (8.5)$$

#### *7.4.1.1 Regulation Curve*

The regulation curve represents the primary guidance for operations at Wolf Creek Dam. It defines the operating limits of reservoir elevations as a function of time of year and is presented graphically in figure 8.10. The Wolf Creek guide curve consists of three "hard" lines and two "soft" lines. The hard lines are described as such because they form the congressionally authorized operating boundaries which horizontally divide the reservoir into three distinct "pools", as described below. The soft lines further subdivide the power pool and are discussed later in this chapter.

**Inactive Pool**: Inactive storage at Wolf Creek extends from the bottom of the reservoir up to elevation 673. Water is not released if it would bring the surface of the pool below the top of this zone. Inactive storage is provided primarily to offset lake sedimentation and provide head for hydropower. Other benefits of this permanent pool include depth for recreation, water intake installation, habitat for fish and other aquatic life, and insurance water for drought periods. 2.2.3.

**Power Pool:** The power pool extends from elevation 673 up to the second hard line at elevation 723. This 50 foot depth is the "normal" operating zone of the reservoir. This is the zone in which water is stored for the purpose of generating electricity. The power pool is usually permitted to fill during wet winter and spring months and remain near elevation 723 from mid-May through mid-June. During the summer and fall seasons, hydropower releases result in a steady drawdown of the reservoir. The power pool is further subdivided by two curves which define a continually varying zone within the power pool. This is called the "SEPA power marketing zone" or the "SEPA band". SEPA is the acronym for the Southeastern Power Administration which is the Federal entity responsible for marketing the power generated at all USACE projects in the Nashville District. The SEPA band ranges in depth from 4.8 to 18 feet, but for most of the year it about 11 feet in depth. The location of the band within the full power pool varies. Its low point throughout December is at elevation 682, nine feet above the bottom of the power pool. Its high point is from May 15th until June 15th when its top is at elevation 723, which corresponds to the top of the power pool. The lines which bound this zone are sometimes referred to as "soft lines" because there is not a specific requirement to keep the pool within this zone.

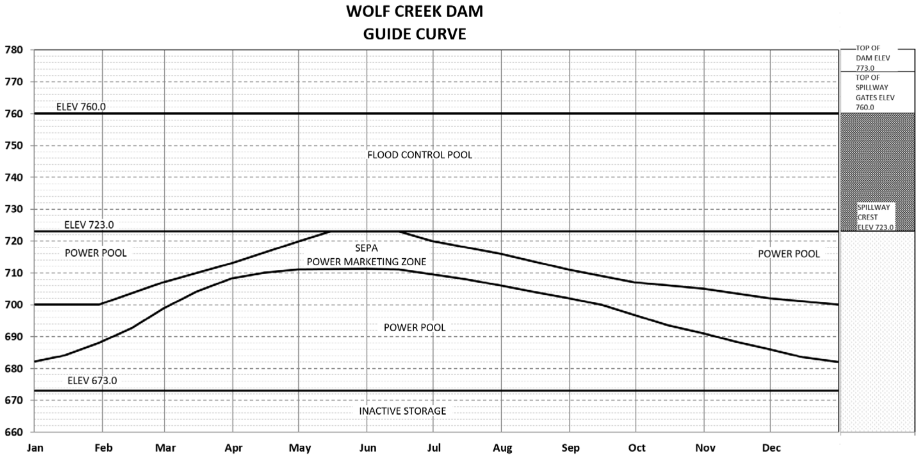


*Figure 7.9: Wolf Creek Dam Guide Curve*

**Flood Control Pool**: The flood control pool extends from elevation 723 up to the top most hard line at elevation 760. The normal condition is for this pool to remain empty so that the space is available to store water during flood events and thus reduce the downstream damages due to flooding. Following a flood event water is released from this pool as quickly as possible based on downstream conditions in order to restore the capability to provide protection from future flood events.

**Goldsim™ Model Representation**: The Goldsim™ model of the reservoir incorporates the stage elevation rating curves shown in Figure 7.8 to simulate the reservoir elevations at every point in time within the simulation. The limits of the reservoir pool elevation follow the operating rule requirements. During periods of normal regulation, the water surface elevation behind the dam is maintained within the hydropower pool limits (see Figure 7.11) and all releases are made through the turbines as governed by the demand for power. There is a large amount of flexibility in operating the Wolf Creek project within the bounds of the power pool, which is 50 feet deep. As further guidance, the SEPA band is used to locate a more specific desirable location for the water surface, but there is still a fair amount of flexibility within the band, and there is no absolute requirement for the pool to remain within the band. The reservoir system is modeled to follow the SEPA top curve but is also constrained by the upstream daily flows. The water level $h_{t+1}$ at time $t+1$ can be determined from the storage $s_{t+1}$ using the stage-storage relationship from the stage rating curves.

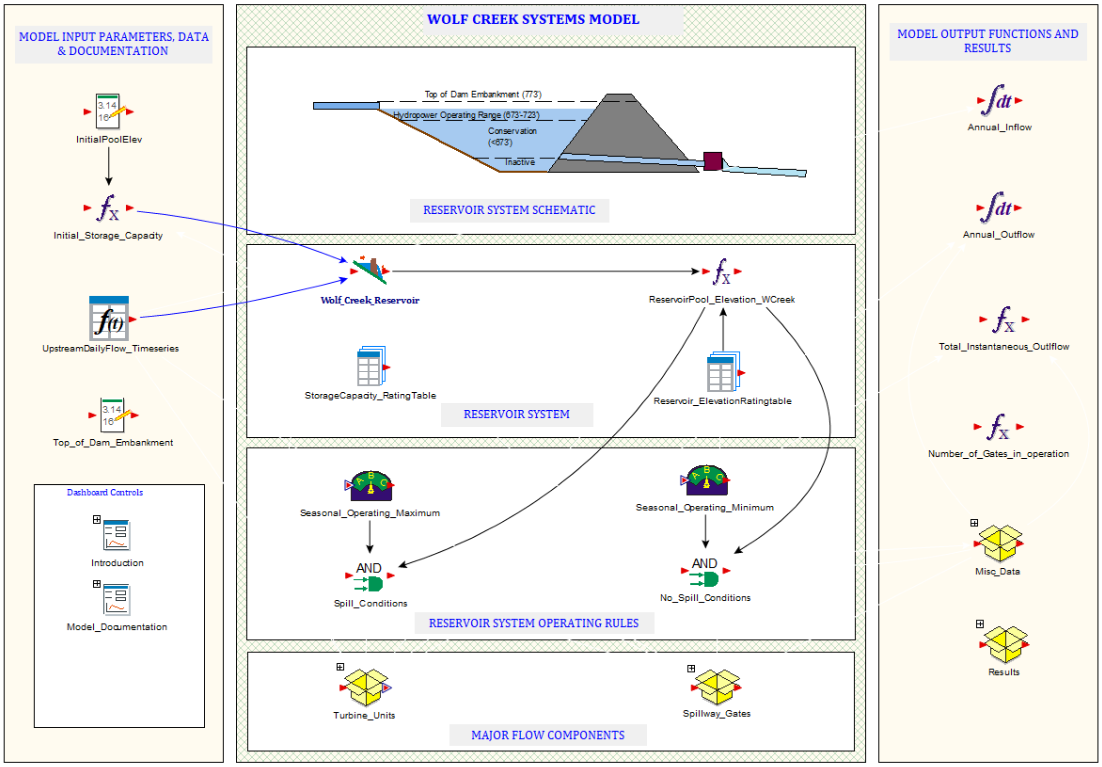

MODEL INPUT PARAMETERS, DATA & DOCUMENTATION
InitialPoolElev
Initial_Storage_Capacity
UpstreamDailyFlow_Timeseries
Top_of_Dam_Embankment
Dashboard Controls
Introduction
Model_Documentation
WOLF CREEK SYSTEMS MODEL
Top of Dam Embankment (773')
Hydropower Operating Range (673'-723')
Conservation (<673')
Inactive
RESERVOIR SYSTEM SCHEMATIC
Wolf Creek Reservoir
ReservoirPool_Elevation_WCreek
StorageCapacity_RatingTable
Reservoir_ElevationRatingtable
RESERVOIR SYSTEM
Seasonal_Operating_Maximum
Seasonal_Operating_Minimum
AND
Spill_Conditions
AND
No_Spill_Conditions
RESERVOIR SYSTEM OPERATING RULES
Turbine_Units
Spillway_Gates
MAJOR FLOW COMPONENTS
MODEL OUTPUT FUNCTIONS AND RESULTS
Annual_Inflow
Annual_Outflow
Total_Instantaneous_Outlflow
Number_of_Gates_in_operation
Misc_Data
Results

*Figure 7.10: GoldSim Model Interface*

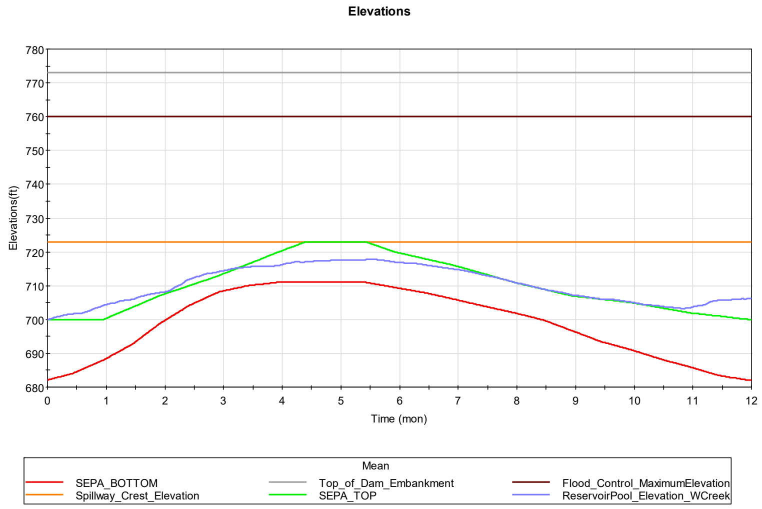


*Figure 7.11: Simulated Mean elevations and SEPA stage prescriptions*

## 7.5. *Wolf Creek Operating Rules and Power Generation*

The following descripts the critical aspects of operating the hydropower plant together with the salient aspects of the Spillway gate and Turbine systems.

### Critical Operating Elevations

- Powerhouse is evacuated and bulkheads are installed at tailwater of 605 ft.
- Powerhouse floods due to tailwater overtopping bulkhead at 610 ft. corresponding with a release of about 235,000 cfs
- If the gates are not fully lifted before the headwater reaches about 757.8 ft. then more efficient spillway weir flow cannot be established and releases will continue to be in pressure orifice flow
- If the gates are fully opened and the headwater is rising the spillway nappe will impinge on the bottom lip of the open spillway gates impeding free weir flow for headwaters above ~768 ft.
- When the headwater exceeds elevation 768.21 ft. then water can flow over the top of the fully opened gates

### Spillway Gates

- 10 Spillway Gates – 50-ft. x 37-ft. (W x H)
- Ogee spillway crest elevation - 723.0 ft.
- Top of Gates in Closed Position - 760 ft.

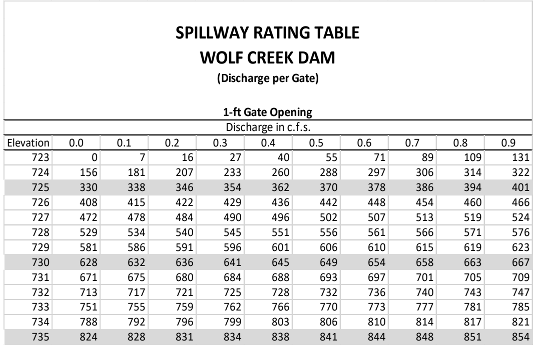
- Bottom of Gates in Maximum Open Position - 754.7 ft. (31.7 ft. Opening)
- Maximum Headwater at which Gates must be Fully Opened in order to Transition from Pressure Orifice to Free Weir Flow - 757.8 ft.
- Top of Gates in Maximum Open Position - 768.21 ft.
- Low Chord of Bridge over Spillway - 765.8 ft.
- Centerline of Spillway Gate Trunnion - 735.75 ft.

**Turbines**

- 6 Francis Hydropower Turbines
- Penstock Diameter - 20 ft.
- Centerline of Penstock on Upstream Side - 621.9 ft.
- Top Elevation at 633.5 ft. and Bottom Elevation at 610.0 ft.
- Bottom of Power Pool (Lowest Headwater for Power Generation) - 673 ft.
- Nameplate 45 Megawatts per Unit Rating

### 7.5.1. Spillway Gate Flow Modeling

There 10 ogee style Radial (gates) Spillways. The top of the dam roadway embankment is 773 ft. The discharge through the spillway gates at each simulated time step is calculated from the spillway rating tables (Figure 8.11). The maximum Wolf Creek PMF headwater elevation was 769.3 ft. which is 3.7 ft. below the top of the dam. During the peak storm events, in addition to the turbines being operated at their capacities, there may be a need to open the Spillway gates to route out excess flows. Within the model, the pool elevation is controlled with a built-in logic to operate the turbines to actively follow the prescribed SEPA Top curve. However, should the pool elevation rise above the spillway gate crest elevation of 723m, the spillway gates are opened to route out the excess flows and return the pool elevation to within the SEPA prescribed levels. Figure 10.15 shows the model flow statistics from wolf creek dam showing similar parameters as the model outputs.

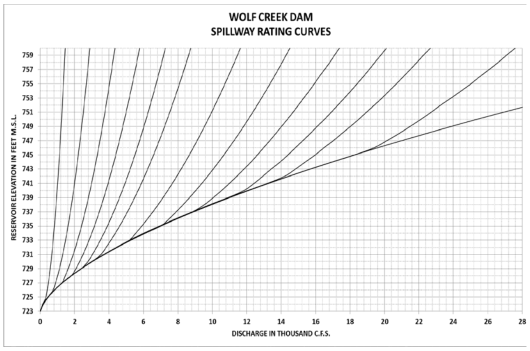


SPILLWAY RATING TABLE
WOLF CREEK DAM
(Discharge per Gate)

1-ft Gate Opening

|  | Discharge in c.f.s. |  |  |  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|---|---|---|---|
| Elevation | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| 723 | 0 | 7 | 16 | 27 | 40 | 55 | 71 | 89 | 109 | 131 |
| 724 | 156 | 181 | 207 | 233 | 260 | 288 | 297 | 306 | 314 | 322 |
| 725 | 330 | 338 | 346 | 354 | 362 | 370 | 378 | 386 | 394 | 401 |
| 726 | 408 | 415 | 422 | 429 | 436 | 442 | 448 | 454 | 460 | 466 |
| 727 | 472 | 478 | 484 | 490 | 496 | 502 | 507 | 513 | 519 | 524 |
| 728 | 529 | 534 | 540 | 545 | 551 | 556 | 561 | 566 | 571 | 576 |
| 729 | 581 | 586 | 591 | 596 | 601 | 606 | 610 | 615 | 619 | 623 |
| 730 | 628 | 632 | 636 | 641 | 645 | 649 | 654 | 658 | 663 | 667 |
| 731 | 671 | 675 | 680 | 684 | 688 | 693 | 697 | 701 | 705 | 709 |
| 732 | 713 | 717 | 721 | 725 | 728 | 732 | 736 | 740 | 743 | 747 |
| 733 | 751 | 755 | 759 | 762 | 766 | 770 | 773 | 777 | 781 | 785 |
| 734 | 788 | 792 | 796 | 799 | 803 | 806 | 810 | 814 | 817 | 821 |
| 735 | 824 | 828 | 831 | 834 | 838 | 841 | 844 | 848 | 851 | 854 |

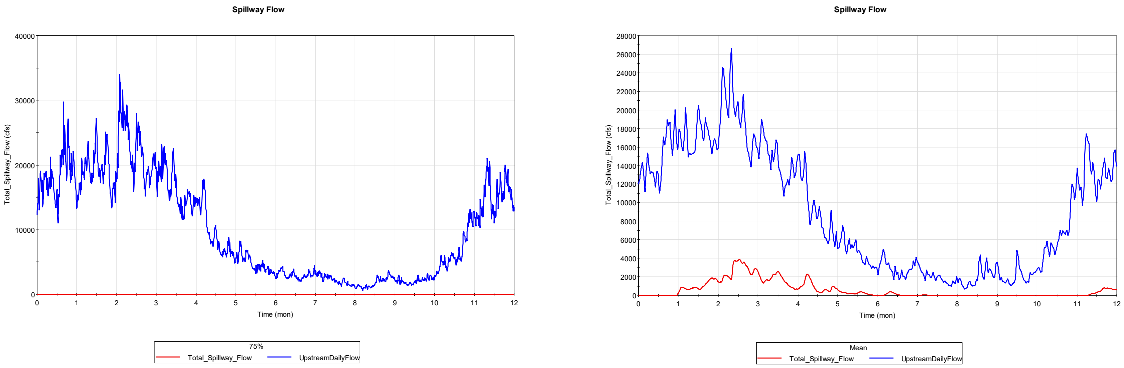
*Spillway Gate Rating Table*



*Sluice Rating table*

*Figure 7.12: Spillway Gate Rating Table and Curve*

*The Spillway discharges are a function of the reservoir pool elevation and the height of Gate opening and are interpolated from the Sluiceway rating tables provided by the dam Operator.*



75th Percentile

Mean of 100 realizations

*Figure 7.13: Spillway flow and reservoir inflow statistics*

Figure 7.13 shows the mean and 75th percentile functions of the Spillway and reservoir inflows. At the 75th percentile, there are no inflows when the simulation is run for a 12-month period over 100-year historical realizations. This shows that historically, at least in 75% of the years since wolf creek began operation, there has been no need to use the spillway gates for releases. Also shown in Figure 7.13 is the mean inflow over the 100-

year historical realizations. This points to the months between November and July as the periods that have a high likelihood of needing the Spillway gates for flood control. This is critical information for maintenance and other operational purposes.

### *7.6. Model Results: Operating patterns and flow Routing*

The modelling framework conceives of the flow-control system as a number of components. The outputs of each component generally form the input to the next component in the system logic. The system is however usually not linear, but contains feedback loops and interdependencies.

The reservoir inflows from upstream drainage basins are routed through the reservoir to create a demand function on the spillway outflow structure. Both the routed flow and the control system outputs are used to simulate the flow control system functioning. All possible means of passing the flow through the dam (spillways with gates and/or stop logs, emergency and overflow spillways, valves and turbines of the generating equipment) may be included in the flow control system. The reservoir component contains many computations that has been described in detail in the prior section.

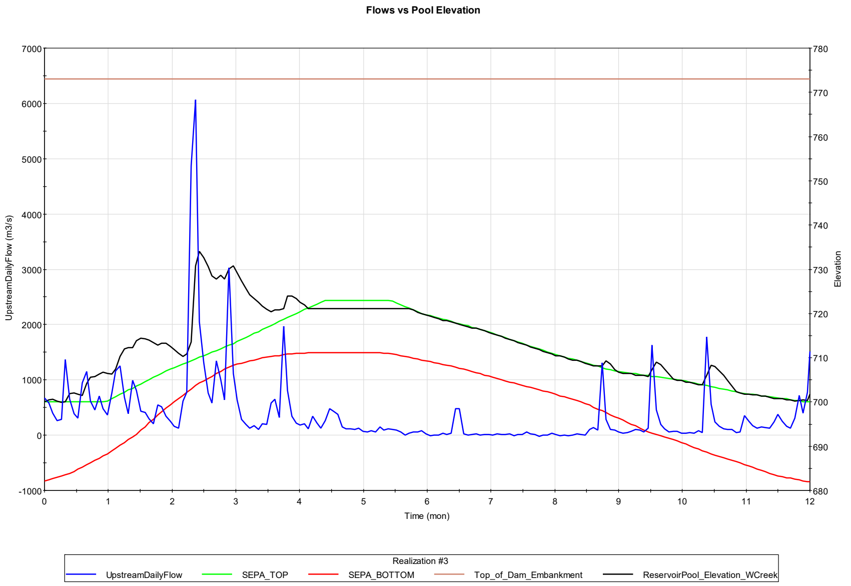


*Figure 7.14: Simulated Reservoir Response*

Imminent Dam Failure during reservoir inflow floods (Overtopping Failure) occurs when water reaches a stage specified in the operating documents as imminent dam failure elevation; thus when the elevation exceeds the imminent dam failure elevation, the dam is overtopped. A simulation for a year from start of a calendar year to end of calendar year was run with a 1000 realizations. Figure 7.14 shows a snapshot of the pool elevation and upstream flow as a function of time for an elapsed time of 1 year; the imminent dam failure elevation is marked to show the buffer between the operating elevations and the failure elevation (top core of dam). This plot shows the response of our reservoir and gate operations to variations in daily inflows.

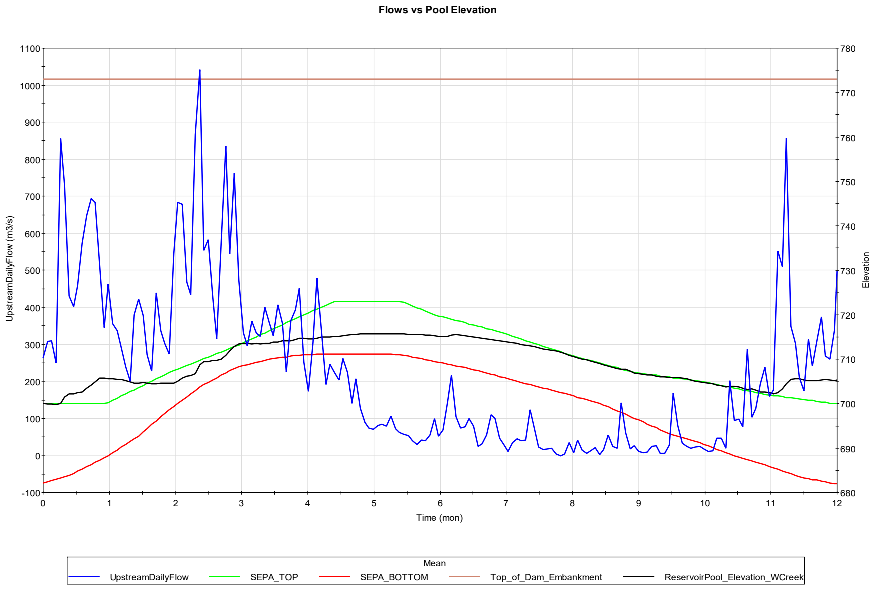


*Figure 7.15: Simulated Reservoir Response (Mean)*

Within the model, the spillway gates are operated with a built-in logic (Operating Rule) to maintain the reservoir elevation along the prescribed SEPA Top curve (Figure 7.14) However, should the pool elevation rise above the spillway gate crest elevation of 723m, the spillway gates are opened to route out the excess flows and return the pool elevation to within the SEPA prescribed levels. . Also shown is the mean of a 1 year 100 realization simulation run. The mean plot shows the seasonality of the inflows and highlights periods of high inflows where there likelihood of the spillway gates being required to route out excess flows is high. This as creates a demand on downstream functions and reliability of flow control components.

### 7.6.1. Operation for Power Generation and Turbine Flows

During periods of normal regulation, the water surface elevation behind the dam is maintained within the hydropower pool limits and all releases will be made through the turbines as governed by the demand for power. There is a large amount of flexibility in operating the Wolf Creek project within the bounds of the power pool, which is 50 feet deep. As further guidance, the SEPA band is used to locate a more specific desirable location for the water surface. Maintain headwater elevation within the limits of the hydropower pool and release all water through the turbines as governed by hydropower generation schedules. In general, hydropower releases are scheduled to meet peak energy demands. The generation units consist of 6 Francis hydropower turbines, each with a maximum generation capacity of 45 MW.

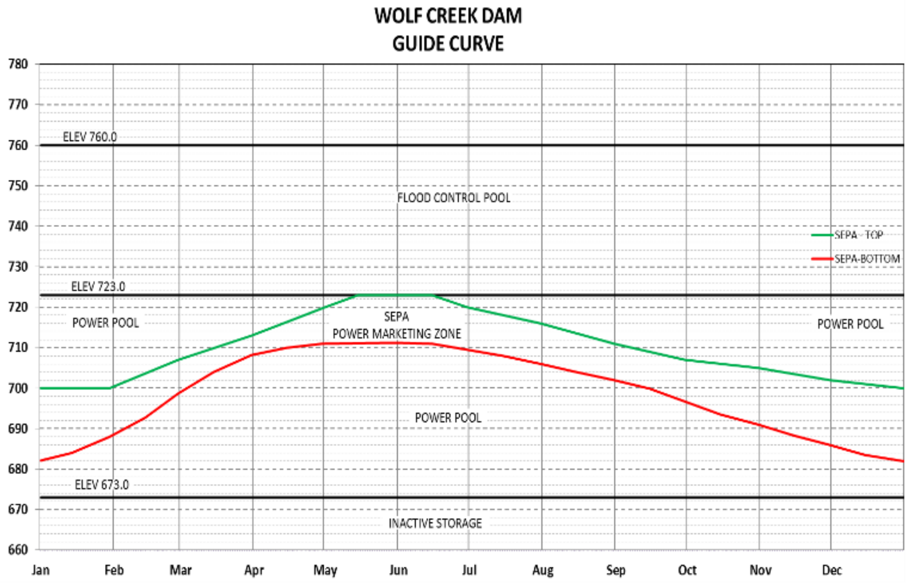
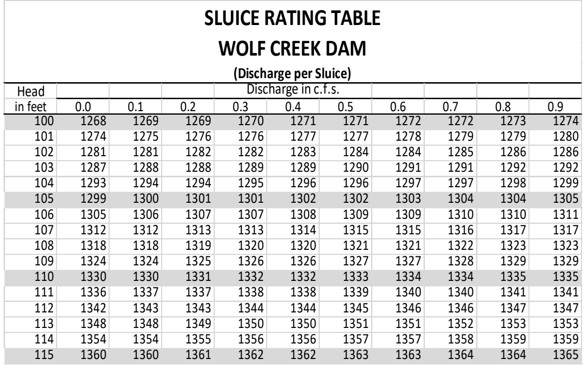


*Figure 7.16: Turbine SEPA guide Curve*

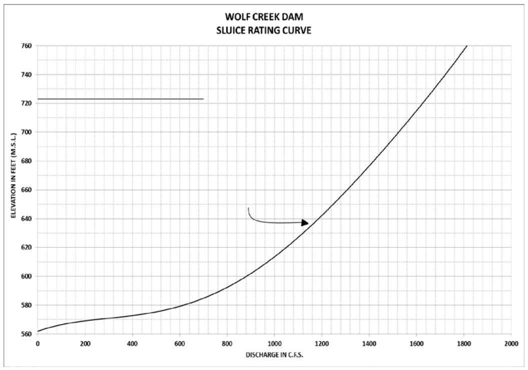
The power pool at Wolf Creek extends between elevations 673.0 and 723.0 (See Figure 7.16). Except during flood control operations, when the reservoir level is within the power pool all releases are made through the turbines as governed by hydropower generation schedules. If the headwater level approaches the lower limit of the power pool, elevation 673.0, reduce or curtail hydropower discharges as necessary to prevent the headwater from falling below elevation 673.0.



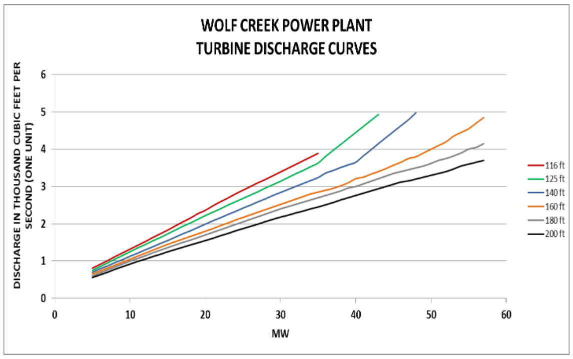
SLUICE RATING TABLE
WOLF CREEK DAM
(Discharge per Sluice)

| Head | Discharge in c.f.s. | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| in feet | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| 100 | 1268 | 1269 | 1269 | 1270 | 1271 | 1271 | 1272 | 1272 | 1273 | 1274 |
| 101 | 1274 | 1275 | 1276 | 1276 | 1277 | 1277 | 1278 | 1279 | 1279 | 1280 |
| 102 | 1281 | 1281 | 1282 | 1282 | 1283 | 1284 | 1284 | 1285 | 1286 | 1286 |
| 103 | 1287 | 1288 | 1288 | 1289 | 1289 | 1290 | 1291 | 1291 | 1292 | 1292 |
| 104 | 1293 | 1294 | 1294 | 1295 | 1296 | 1296 | 1297 | 1297 | 1298 | 1299 |
| 105 | 1299 | 1300 | 1301 | 1301 | 1302 | 1302 | 1303 | 1304 | 1304 | 1305 |
| 106 | 1305 | 1306 | 1307 | 1307 | 1308 | 1309 | 1309 | 1310 | 1310 | 1311 |
| 107 | 1312 | 1312 | 1313 | 1313 | 1314 | 1315 | 1315 | 1316 | 1317 | 1317 |
| 108 | 1318 | 1318 | 1319 | 1320 | 1320 | 1321 | 1321 | 1322 | 1323 | 1323 |
| 109 | 1324 | 1324 | 1325 | 1326 | 1326 | 1327 | 1327 | 1328 | 1329 | 1329 |
| 110 | 1330 | 1330 | 1331 | 1332 | 1332 | 1333 | 1334 | 1334 | 1335 | 1335 |
| 111 | 1336 | 1337 | 1337 | 1338 | 1338 | 1339 | 1340 | 1340 | 1341 | 1341 |
| 112 | 1342 | 1343 | 1343 | 1344 | 1344 | 1345 | 1346 | 1346 | 1347 | 1347 |
| 113 | 1348 | 1348 | 1349 | 1350 | 1350 | 1351 | 1351 | 1352 | 1353 | 1353 |
| 114 | 1354 | 1354 | 1355 | 1356 | 1356 | 1357 | 1357 | 1358 | 1359 | 1359 |
| 115 | 1360 | 1360 | 1361 | 1362 | 1362 | 1363 | 1363 | 1364 | 1364 | 1365 |

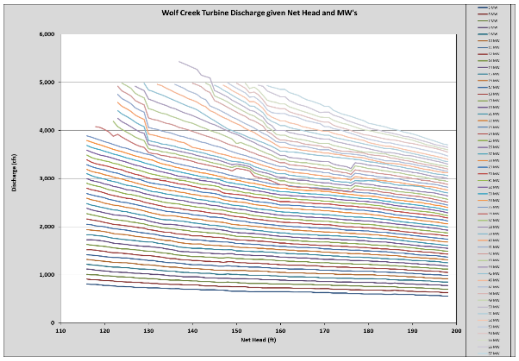
*Sluice Rating Table*



*Sluice Rating table*



*Turbine Discharge Curves*

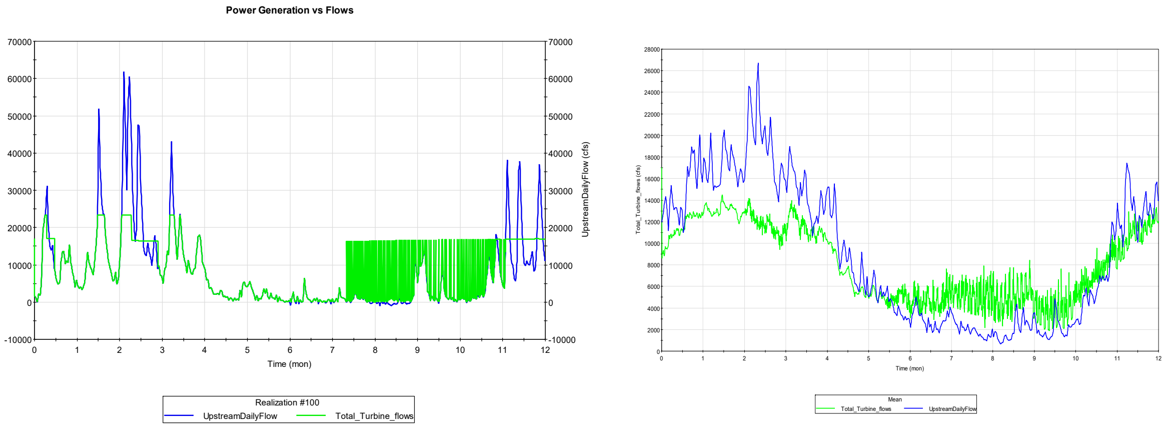


*Turbine Discharge Curves*

*Figure 7.17: Wolf Creek Discharge Curves*

The Hydropower plant at Wolf Creek is operated by following the best efficiency power generation for a given head while attempting to keep the pool elevation at the SEPA top prescribed elevation. values provided in the unit rating table when upstream flow is equal to or more than the specified discharges for best efficiency power generation. Figure 7.18

shows an annual plot of the Turbine flows for one realization. Also shown in Figure 7.18 is the mean flow statistics for pool elevation and power production respectively, as a function of time. The mean is averaged over the entirety of the simulation forecasts.



*1 Realization*

*Mean*

*Figure 7.18: Turbine Flows vs Reservoir Inflow*

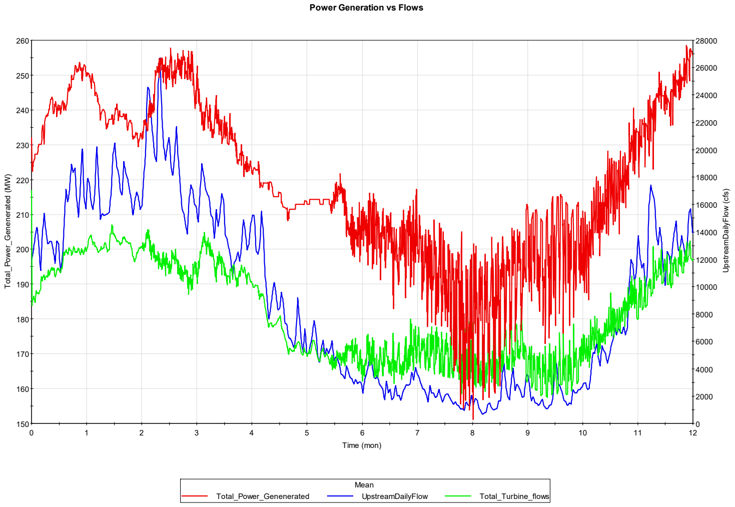


*Figure 7.19: Wolf Creek Power Plant Turbine Discharge Curves*

The plot also shows the direct correlation between the reservoir inflows and the power generated. Finally, Figure 7.19 shows the expected correlation between the upstream flows, turbine flows and the power generation. The freshet (high inflow) period is consistent with increase in reservoir storage prescribed by SEPA while the low inflow period is consistent with the gradual drawdown of the to prepare for the following seasons high inflows.

### *7.7. Systems Reliability of Flow Control Components*

Goldsim™'s reliability module leverages the power Dynamic fault tree analysis via Monte-Carlo framework. The dynamic fault tree Dynamic simulation then allows the analyst to develop a representation of the system whose reliability is to be determined, and then observe that system's performance over a specified period. It also provides the ability to model the interdependencies of components, as well as the capability to define multiple independent failure modes for each component.

The Dynamic fault trees also enable the use of real-world systems reliability metrics such as availability and Reliability. Availability is more commonly used to represent a maintainable system which is a function of reliability and maintainability. The nature of the Monte Carlo framework makes it possible to compute the average unavailability/availability of components of interest based on failure rates, repair rates and demand failure probabilities (stand by failure rate) time to failure and time to repair over a period. Additionally, the system can evolve into any feasible state and its properties can change suddenly or gradually as the simulation progresses. The system can also be affected by random processes, within the system itself (internal failure) or from external an external event that may influence the system (external failure). The modeling framework affords us the ability to track all the unique System and subcomponent states during the simulation (i.e., whether the component is operating, if a particular failure mode has occurred, if it is undergoing maintenance, is turned off, or its requirements- or fault tree shows the component cannot operate). These unique states also record the states of any reliability elements referenced as part fault-tree.

*Table 7.2: System state variable tables*

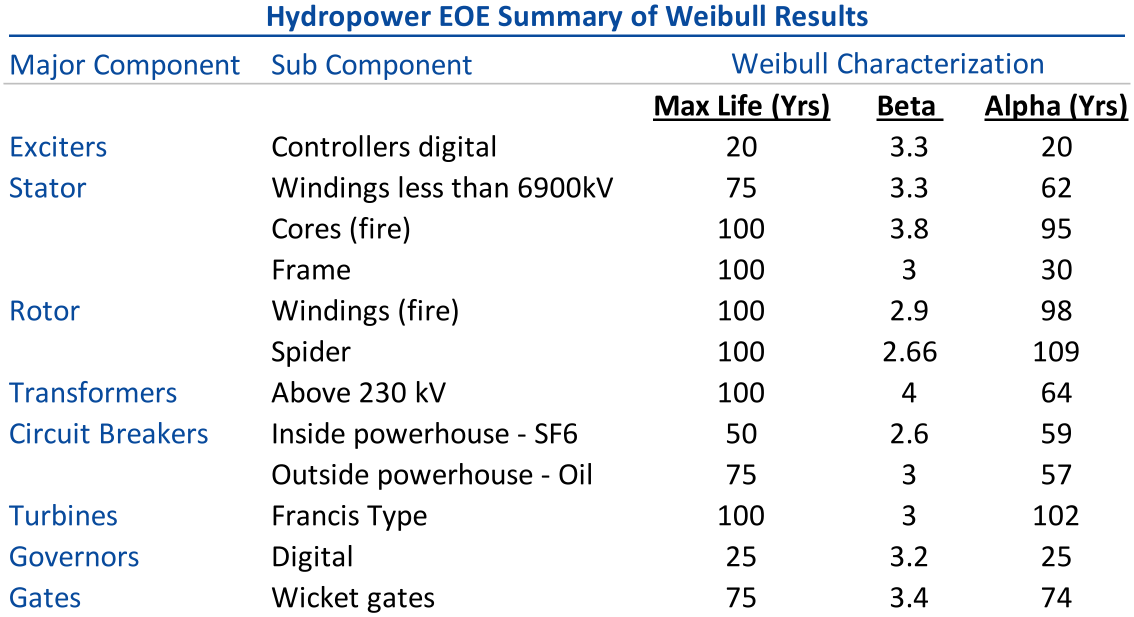
System State Variables

| 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 not met. |
| 3 | External requirements not met. |
| 4 | Element is not turned on. |
| 5 | Parent element not operating. |
| 6 | An operating resource equirement is not med. |

### 7.7.1. Turbine Reliability Modeling

Passing the flow through the turbines of a hydroelectric generating station requires that the generating equipment is available and that the generated power can be accepted by the grid. Modeling of the availability of turbines to pass the flow requires the parametric characterization of life data of the salient components and sub-components of the turbine units. Extensive failure data was available for the generating units in the Wolf Creek Dam System. The parametric characterization of the degradation/failure time data was used to produce the Weibull characterizations shown in figure 7.20. Wolf Creek GS has six generating units with the following characteristics.

*Table 7.3: Weibull Characterization of hydropower components*



Hydropower EOE Summary of Weibull Results

| Major Component | Sub Component | Weibull Characterization | | |
|---|---|---|---|---|
| | | Max Life (Yrs) | Beta | Alpha (Yrs) |
| Exciters | Controllers digital | 20 | 3.3 | 20 |
| Stator | Windings less than 6900kV | 75 | 3.3 | 62 |
| | Cores (fire) | 100 | 3.8 | 95 |
| | Frame | 100 | 3 | 30 |
| Rotor | Windings (fire) | 100 | 2.9 | 98 |
| | Spider | 100 | 2.66 | 109 |
| Transformers | Above 230 kV | 100 | 4 | 64 |
| Circuit Breakers | Inside powerhouse - SF6 | 50 | 2.6 | 59 |
| | Outside powerhouse - Oil | 75 | 3 | 57 |
| Turbines | Francis Type | 100 | 3 | 102 |
| Governors | Digital | 25 | 3.2 | 25 |
| Gates | Wicket gates | 75 | 3.4 | 74 |

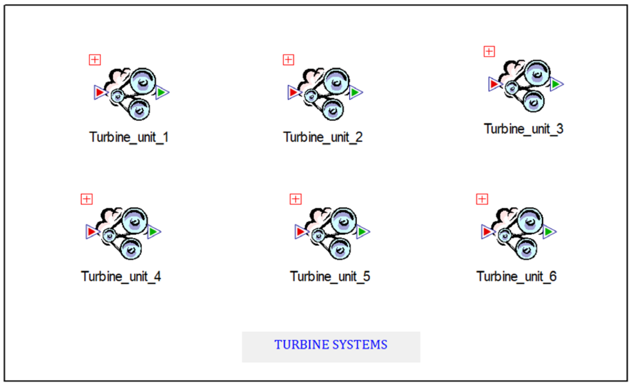
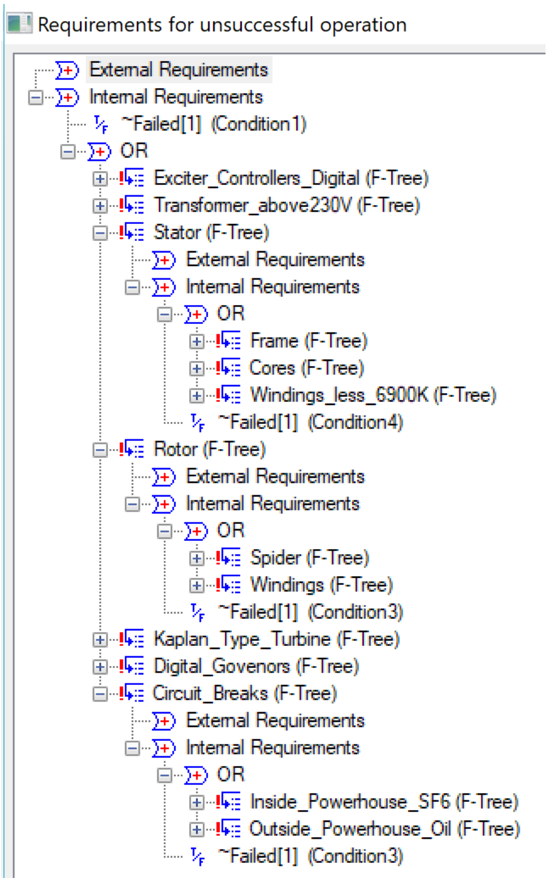


*Figure 7.21: Goldsim™ Turbine Unit Reliability Modeling Interface*

Figure 7.22 shows the fault tree diagram of the hydropower unit incorporated into the systems reliability model. The duration of failures is characterized by the exponential distribution with a mean delay time until repaired specified for each subcomponent.



Requirements for unsuccessful operation

- External Requirements
- Internal Requirements
  - ~Failed[1] (Condition1)
  - OR
    - Exciter_Controllers_Digital (F-Tree)
    - Transformer_above230V (F-Tree)
    - Stator (F-Tree)
      - External Requirements
      - Internal Requirements
        - OR
          - Frame (F-Tree)
          - Cores (F-Tree)
          - Windings_less_6900K (F-Tree)
        - ~Failed[1] (Condition4)
    - Rotor (F-Tree)
      - External Requirements
      - Internal Requirements
        - OR
          - Spider (F-Tree)
          - Windings (F-Tree)
        - ~Failed[1] (Condition3)
    - Kaplan_Type_Turbine (F-Tree)
    - Digital_Govenors (F-Tree)
    - Circuit_Breaks (F-Tree)
      - External Requirements
      - Internal Requirements
        - OR
          - Inside_Powerhouse_SF6 (F-Tree)
          - Outside_Powerhouse_Oil (F-Tree)
        - ~Failed[1] (Condition3)

*Figure 7.22: Goldsim™ dynamic Fault tree representation of Turbine Unit*

*Figure 7.23 shows the failure of one of the major Turbine unit components for one annual realization. This shows that the component only failed once during the 100-year simulation run but was unavailable due to other external failures which rendered the entire turbine unit inoperable.*

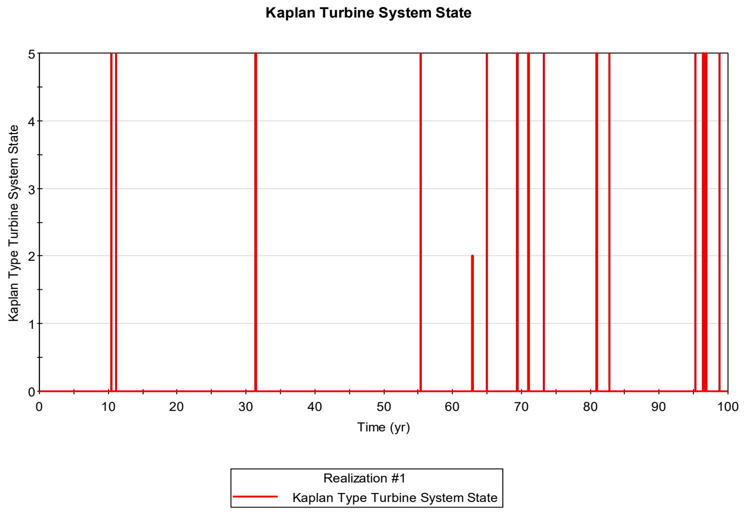
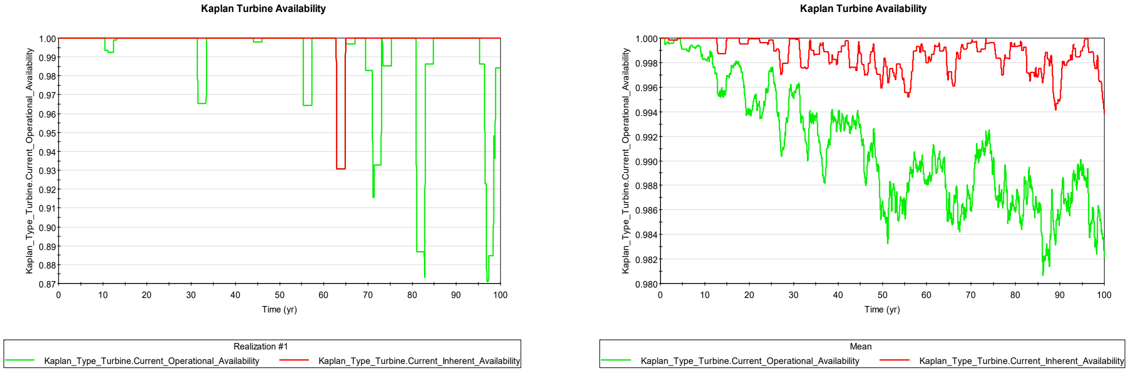


*Figure 7.23: Plot of Turbine System State as a function of time*

***Kaplan type turbine Operational Availability:*** *This is the fraction of time the element was operating over a specified time period immediately previous to the current time. Although the component had only inherently failed once, it was operationally unavailable due to other component failures external to the Kaplan type turbine. Kaplan type turbine Inherent Availability: This is the fraction of time the element was inherently operable over a specified time period immediately previous to the current time. This does not include all other instances of unavailability due to other component failures external to the Kaplan type turbine. An example is the entire Turbine unit being unavailable due to failure of the stator but the Kaplan type turbine although not failed, is unavailable because the entire unit is shut down for repairs due to the series arrangement of all the major components that need to function for the unit to be operable. Hence, the Inherent Availability is always greater than or equal to the Operational Availability. See Figure 7.24 for the mean Operational and inherent availabilities over 100 year and 100 realizations simulation run.*



*1 Realization*

*Mean*

*Figure 7.24: Kaplan Turbine Operational and Inherent Availability*

When a unit is unavailable, the total discharge capacity through that turbine is only 0 m$^3$/s. At full capacity, the discharge capacity through turbines equals 45 m$^3$/s each. Occurrence of failures is characterized by Weibull distributions with a specified Mean time between failure characterized by exponential or lognormal distributions depending on the component/subcomponent. These parameters were determined by fitting parametric distributions to the failure data with the best performing (fitting) distribution chosen to characterize the failure of the turbine units. The duration of the failures; which is a sum of the time to repair and the actual repair duration, is characterized by an exponential distribution for each of the turbine unit subcomponents.

When a Turbine is available, the amount of discharge through the turbine is dictated by the SEPA curve in combination with the upstream daily flow. If Head elevation exceeds the SEPA prescribed maximum, then the turbines will be operated at capacity. On the other hand if the Head water elevation is below the prescribed Minimum SEPA level, then the turbines will be shut to conserve head.

### 7.7.2. Spillway Gate Reliability Modeling

Gated Spillway systems are generally designed to set of defined engineering standards, however with the effects of aging, exposure, preventative maintenance, and lack of frequent operations in combination with human error seem to make these systems more vulnerable than one would think.  The on-demand failures of gated Spillways are complex and may be caused by a gate component that can be repaired in minutes to hours or a component that may cause complete failure of the gate system and unexpected release of the reservoir containment.

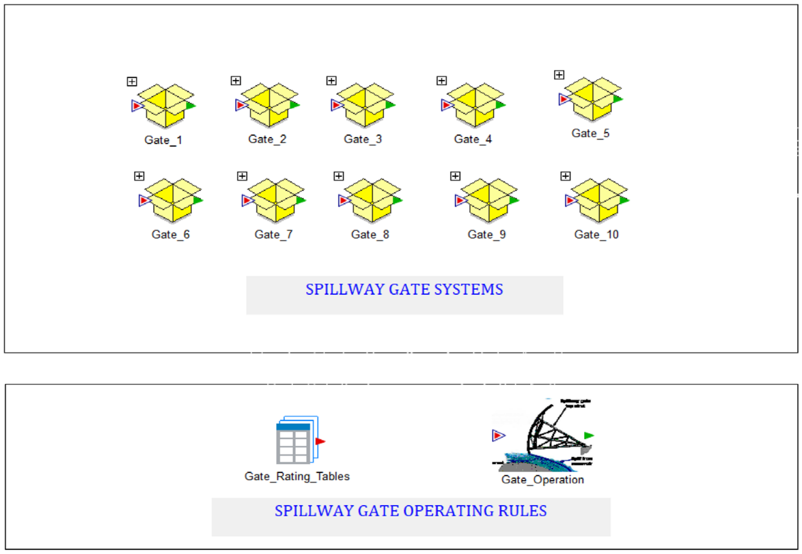


*Figure 7.25: Spillway Gate Systems Goldsim™ Model Interface*

#### *7.7.2.1 Failure Time Characterization in Goldsim™*

Goldsim™ supports two forms of the Weibull failure distribution. The characteristic life and slope factor or the mean life and slope factor can be specified. The PDF of the Weibull distribution has the following shape:

$$f(x) = \left(\frac{\alpha}{\beta}\right)\left(\frac{x}{\beta}\right)^{(\alpha-1)} e^{-\left(\frac{x}{\beta}\right)^{\alpha}}$$

where α is the shape parameter and β is the characteristic life. Both parameters can be dynamic, but the value of the control variable at failure is only recalculated when the component is placed in service, replaced, or the failure mode repaired.

Goldsim™'s reliability module leverages the power Dynamic fault tree analysis monte-carlo framework. The dynamic fault tree Dynamic simulation then allows the analyst to develop a representation of the system whose reliability is to be determined, and then observe that system's performance over a specified period of time. It also provides the ability to model the interdependencies of components, as well as the capability to define multiple independent failure modes for each component. Figure 7.22 shows the major components of the spillway gates incorporated into the systems reliability model.

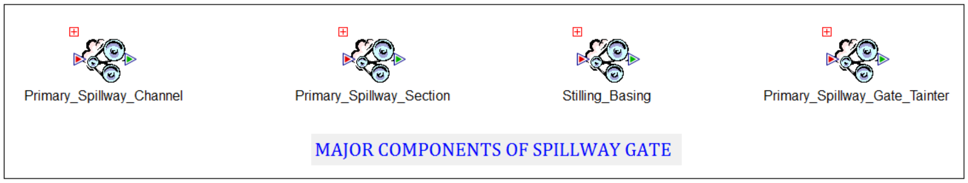


*Figure 7.26: Spillway gate subcomponent interface*

### *7.7.2.2 Modeling Repair Times in Goldsim™*

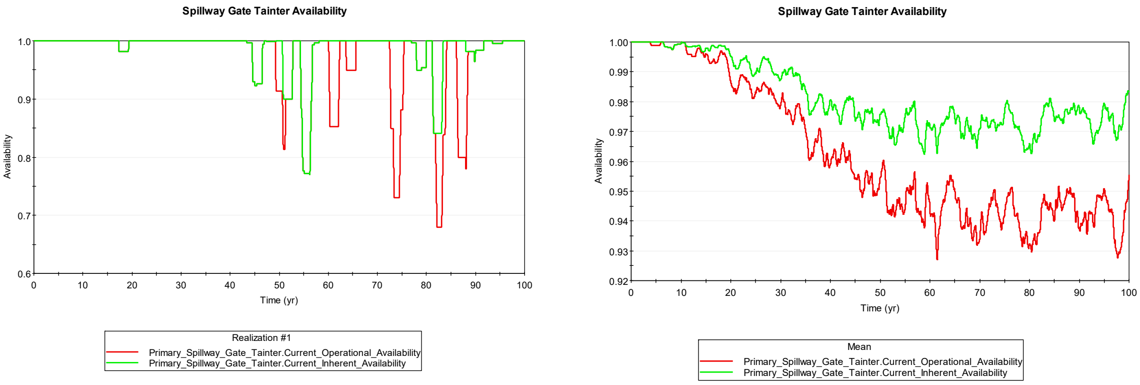
The simple failure rate is the default failure mode for both the Function and the Action element. It is equivalent to the Exponential/Poisson failure mode, and uses Total time as its control variable. This mode cannot be repaired automatically; it can only be repaired using the Replace trigger. The probability distribution function of the underlying Exponential/Poisson distribution has the following shape and equation:

$$f(x) = \frac{1}{\mu} e^{\frac{-x}{\mu}}$$

*Equation 1: Failure Rate for Exponential/Poisson distribution*

When a unit is unavailable, the total discharge capacity through that spillway is 0 m$^3$/s. At full capacity, the discharge capacity through turbines equals 40,000 cfs each. The mean time between failures (MTBF) for each sub component is characterized by an exponential distribution with the parameter $\lambda\,(days)$ being the output of the life data analysis on component repairs. Hence, the duration of the failures; which is a sum of the time to repair and the actual repair duration, is characterized by an exponential distribution for each of the spillway unit subcomponents.

### *7.7.2.3 Reliability Outputs*

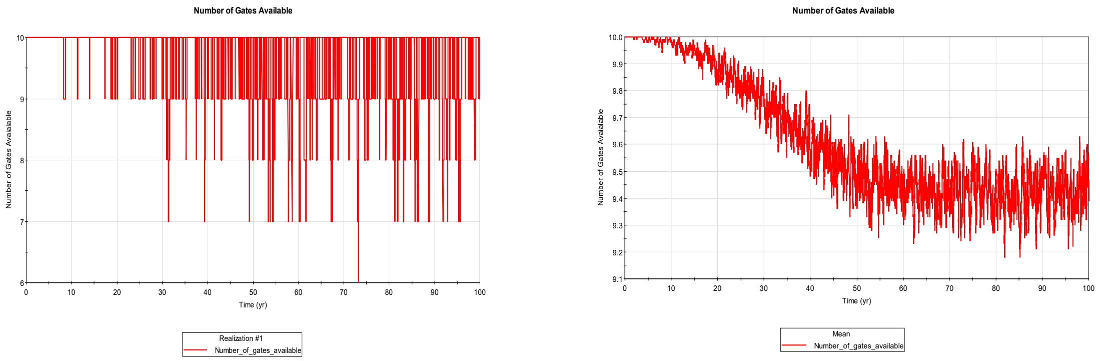


*1 Realization*

*Mean*

*Figure 7.27: Spillway Gate Tainter Operational and Inherent Availability*

Figure 8.27 shows a plot of one of the Major components of the spillway gate—the spillway gate tainter—over a 100-year, 100 realization simulation run. The operational availability of the tainter gate is the availability of the entire spillway gate system itself where's the inherent availability of the tainter gate represents the availability of the Spillway gate tainter component.



1 Realization

Mean

Figure 7.28: Number of Spillway Gates Available

The number of spillway gates available is a function of failure. This enables us to observe the availability on demand of the spillway gates as degradation sets in over time. The systems reliability model for wolf creek affords us the ability to track all the unique System and subcomponent states during the simulation (i.e., whether the component is operating, if a particular failure mode has occurred, if it is undergoing maintenance, is turned off, or its requirements- or fault tree shows the component cannot operate).

# CHAPTER 8: CASE STUDY 2 - MATTAGAMI RIVER HYDROPOWER PROJECT

Systems simulation is being applied to an Ontario Power Generation (OPG) project in northeast Ontario. The project is a cascade of four power stations on the Lower Mattagami River. The number of riparian's in the river flood plain is few and there is no commercial riverine navigation, so potential loss of life is negligible and operational safety dominates the engineering considerations. The problem facing the engineering analysis was to conceptualize a systems engineering model for the operation of the dams, generating stations, spillways, and other components; then to employ the model through stochastic simulation to investigate protocols for the safe operation of the project.

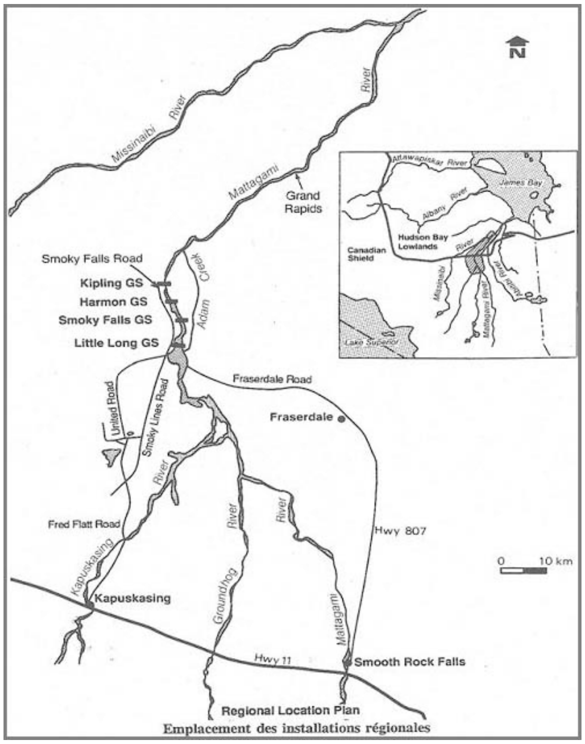


*Figure 8.1. Map of the LMR Complex generating stations (Courtesy, OPG).*

The system borders two physiographic regions: the Canadian Shield extending from the south and, to the north, the Hudson Bay Lowlands. Several hydroelectric generating stations (GS) were built in the basin during the early twentieth century (Figure 8.1). In late 1989, Ontario Hydro purchased the plants and through its successor organizations has operated the facilities since.

## *8.1. Lower Mattagami River Hydroelectric (LMR) Complex*

The Lower Mattagami River Hydroelectric (LMR) Complex consists of four hydroelectric generating stations (GS) (Figure 8.3). These are located on the Mattagami River, which joins with the Missinaibi Rivers downstream of the project to form the Moose River, which ultimately flows into James Bay 90 km north of the Town of Kapuskasing.

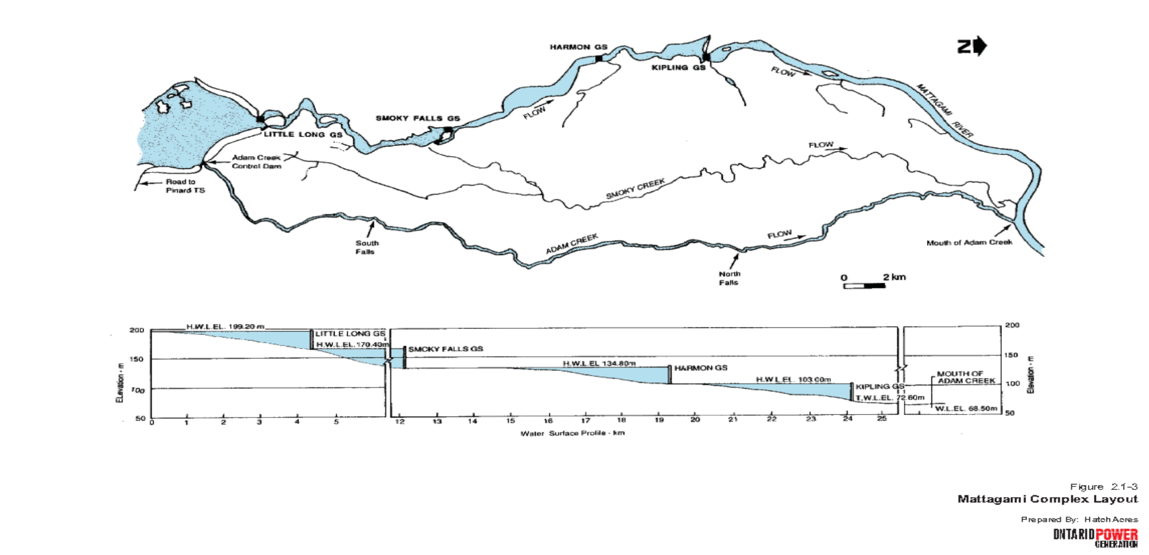
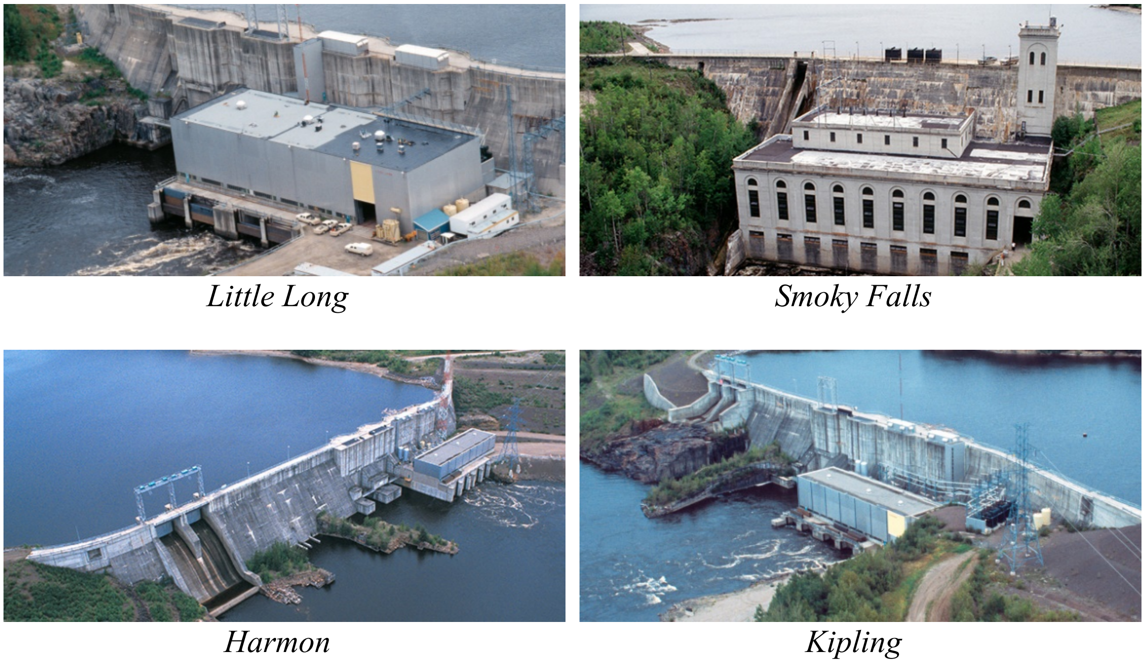


*Figure 8.2. Layout of the LMR Complex generating stations (Courtesy, OPG).*



*Little Long*

*Smoky Falls*

*Harmon*

*Kipling*

*Figure 8.3: The four dams and generating stations of the Lower Mattagami Project of Ontario Power Generation.*

**Little Long GS** at the top of the cascade is a base load station with four vertical Francis type units and a capacity of 52 MW. Smoky Falls GS, Harmon GS, and Kipling GS each have two fixed-blade propeller type units and operate as peaking stations with station capacities of 136 MW, 140 MW and 156 MW respectively. Smoky Falls GS was the first GS to come in service in 1931 while Little Long GS, Harmon GS, and Kipling GS came into service between 1963 and 1966.

When river flows exceed the maximum power flow of Little Long Dam, a bypass spillway, located 2.5 km east of the station, is used to pass excess water into the Adam Creek channel. The bypass spillway has eight sluices with a total capacity of 4870 cms. The bypassed waters flow north and re-enter the river about 17km downstream of Kipling GS. A secondary spillway structure constructed at the dam and releasing into the main Mattagami River channel has a capacity of 1217 cms, and provides flow to the downstream stations.

**Smoky Falls GS** has a concrete, which incorporates intakes for a powerhouse, a spillway structure to bypass flows in the event of a sudden unit outage, and an earth-fill retaining structure located near the spillway. The head pond extends upstream 7 km, has a surface area of 5.3 km$^2$, and a live storage of 106 mcm. The existing spillway structure consists of ten gated sluices, each 8.4m wide by 9.2m high, plus a 230m long overflow crest. The spillway structure was originally designed (prior to the construction of the bypass) to convey what was then the full design flood flow on the river.

**Harmon GS** has a single concrete dam that incorporates the intakes for the power station and a spillway to bypass flows in the event of a plant outage. The head pond extends 4 km upstream. Its surface area is approximately 3 km$^2$ and live storage is about 6.9mcm. The operating head is 31m and the rated flow is 525cms.

**Kipling GS** has a single concrete dam incorporating an intake structure and spillway. The head pond is 5.6 km. It has a surface area of 1.2 km$^2$, with live storage of 3.2mcm. The power plant is similar to those upstream but operates at 0.5m lower generating head.

The Moose River Basin encompasses a drainage area of 109,000 km2. The Mattagami River flows in a northerly direction from its headwaters at Mesomikenda. Lake and is approximately 418 km long, covering a drainage basin area of 35,612 km2. It is generally a shallow and slow-flowing river with a seasonal flow regime. The long-term average river flow for the Little Long GS as recorded by OPG is approximately 412 cms, based on a period of record from 1926 to 2005. Since OPG's hydroelectric stations along the LMR are in close succession, intermediate drainage areas are small and the contribution from inflows between the stations is unimportant for planning purposes.

Highway communication for the project is provided by Fred Flatt Road, the Smoky Line Road, and the Smoky Falls Road. The Fred Flatt Road is a 51 km long, two-lane gravel road leased by Tembec Inc. The road is open to the public and OPG currently contributes financially to its maintenance. The Smoky Line Road is a 42 km long, single-lane gravel road owned by OPG. The Smoky Falls Road is an 18 km long, two-lane gravel road, also owned by OPG. Highway 643 (formerly Highway 807) links Smooth Rock Falls to Fraserdale via a 73 km long two-lane paved road.

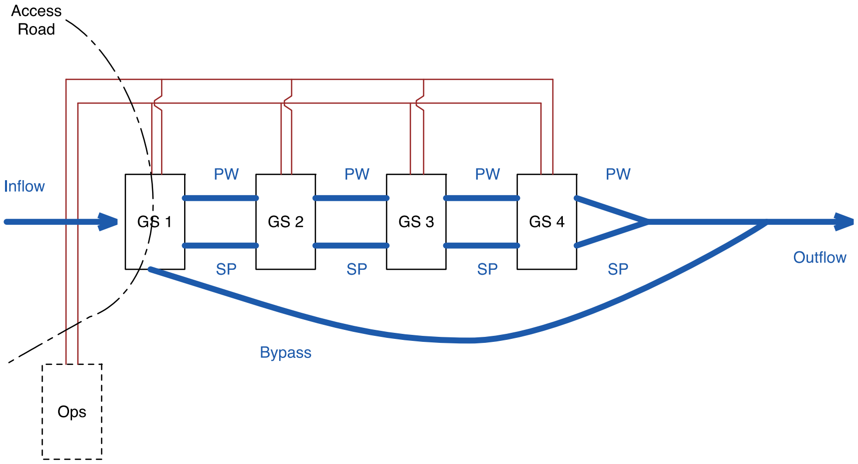
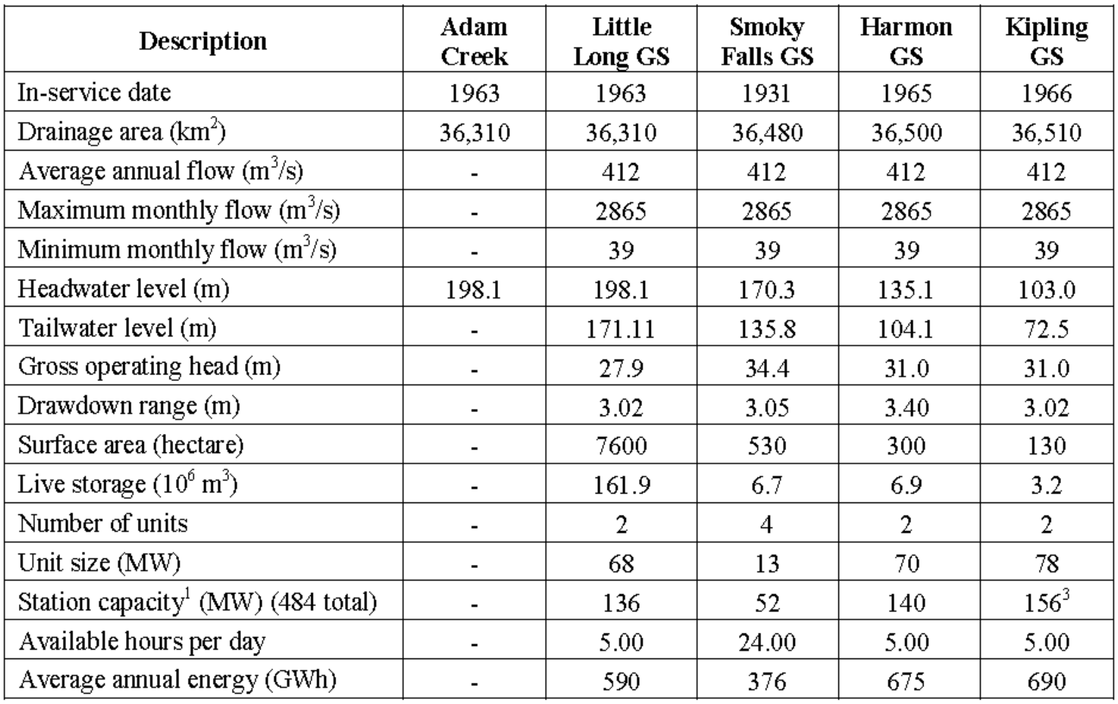


*Figure 8.4: Project layout. Water flows are shown in blue. Electrical lines are shown in red. North is to the right*

*Table 8.1. Characteristics of LMR Complex Stations*

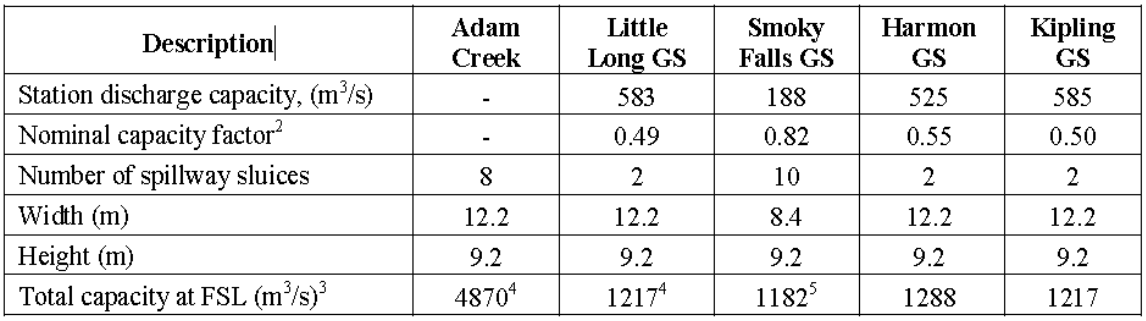


| Description | Adam Creek | Little Long GS | Smoky Falls GS | Harmon GS | Kipling GS |
|---|---|---|---|---|---|
| In-service date | 1963 | 1963 | 1931 | 1965 | 1966 |
| Drainage area (km$^2$) | 36,310 | 36,310 | 36,480 | 36,500 | 36,510 |
| Average annual flow (m$^3$/s) | - | 412 | 412 | 412 | 412 |
| Maximum monthly flow (m$^3$/s) | - | 2865 | 2865 | 2865 | 2865 |
| Minimum monthly flow (m$^3$/s) | - | 39 | 39 | 39 | 39 |
| Headwater level (m) | 198.1 | 198.1 | 170.3 | 135.1 | 103.0 |
| Tailwater level (m) | - | 171.11 | 135.8 | 104.1 | 72.5 |
| Gross operating head (m) | - | 27.9 | 34.4 | 31.0 | 31.0 |
| Drawdown range (m) | - | 3.02 | 3.05 | 3.40 | 3.02 |
| Surface area (hectare) | - | 7600 | 530 | 300 | 130 |
| Live storage (10$^6$ m$^3$) | - | 161.9 | 6.7 | 6.9 | 3.2 |
| Number of units | - | 2 | 4 | 2 | 2 |
| Unit size (MW) | - | 68 | 13 | 70 | 78 |
| Station capacity[1] (MW) (484 total) | - | 136 | 52 | 140 | 156[3] |
| Available hours per day | - | 5.00 | 24.00 | 5.00 | 5.00 |
| Average annual energy (GWh) | - | 590 | 376 | 675 | 690 |

Transmission of electrical energy from the four stations is provided by a 230 kV transmission line from Kipling GS via Harmon GS to Little Long GS substation and from there to the Pinard transformer station near Fraserdale (

Figure 8.4). Generation from the existing Smoky Falls GS is fed into a 115 kV transmission line that runs directly to the Tembec paper mill in Kapuskasing. Relevant characteristics for each GS as well as the nearby Adam Creek watershed are listed in Table 8.2.

*Table 8.2: Characteristics of LMR Complex Stations*



| Description | Adam Creek | Little Long GS | Smoky Falls GS | Harmon GS | Kipling GS |
|---|---|---|---|---|---|
| Station discharge capacity, ($m^3/s$) | - | 583 | 188 | 525 | 585 |
| Nominal capacity factor[2] | - | 0.49 | 0.82 | 0.55 | 0.50 |
| Number of spillway sluices | 8 | 2 | 10 | 2 | 2 |
| Width (m) | 12.2 | 12.2 | 8.4 | 12.2 | 12.2 |
| Height (m) | 9.2 | 9.2 | 9.2 | 9.2 | 9.2 |
| Total capacity at FSL ($m^3/s$)[3] | 4870[4] | 1217[4] | 1182[5] | 1288 | 1217 |

## 8.2. *Objectives of the study and modelling framework*

The objective of the simulation was to understand systems interactions in the cascade, and the potential for accidents or failures caused by the interactions. The approach was the following:

1) Formulate and construct a model to characterize the hydrodynamics of the cascade including the dynamics of transport, storage, and power generation.

2) Apply the systems modelling framework to understand the systems interactions in the cascade of four dams.

3) Holistically integrate river basin hydrology, routing of inflows through the reservoir system, operating rules and human factors of operating the spillway, and the dam component fragilities (structural, mechanical and electrical).

4) Investigate unforeseen chain of events that could lead to accidents and failures by forecasting inflows for several thousand years and multiple realizations.

5) Model the inherent disturbances (lightening, seismic, floating ice, grid disturbances and debris) via a probabilistic framework.

6) Review the current operating rules to determine whether further optimization techniques can be adopted to improve the power generation capabilities of the system.

The general model interface with the salient aspects of the physical system being modelled is developed and presented herein.

## *8.3.* *Hydrologic modelling and flow routing*

The 50-year historical data on reservoir inflows from the lower Mattagami basin into Little Long Reservoir was used to generate stochastic Inflows through time series forecasting. A autoregressive-moving-average time series model was used to generate stochastic inflows. A random starting point was chosen from the historic series to incorporate uncertainty in forwarding the historic series. This randomly sampled a starting point in the data set for each realization.

### 8.3.1. Normal operation and power generation

Under normal operations, water flows for the GSs are provided from the uppermost reservoir. The water level is normally within the operating headwater level range. The limit of the headwater level is the "absolute maximum operating level." The difference between the absolute maximum and maximum operating levels is the flood allowance, which is used to hold water in extreme conditions to reduce downstream flooding. The storage between the absolute minimum and minimum operating levels is used if a system energy emergency occurs. Under normal operating conditions with equivalent discharges at each station, the full operating range would rarely be utilized.

Under normal operating conditions, the outflow from the uppermost reservoir passes through all the GSs. During any outage of a GS, the spillway at the station experiencing the outage will be operated to pass the flow to the other GSs. During high river flow conditions (e.g., spring runoff) when the uppermost reservoir is near its maximum limit, the spillway into the diversion is operated in conjunction with GS to pass the full river flow.

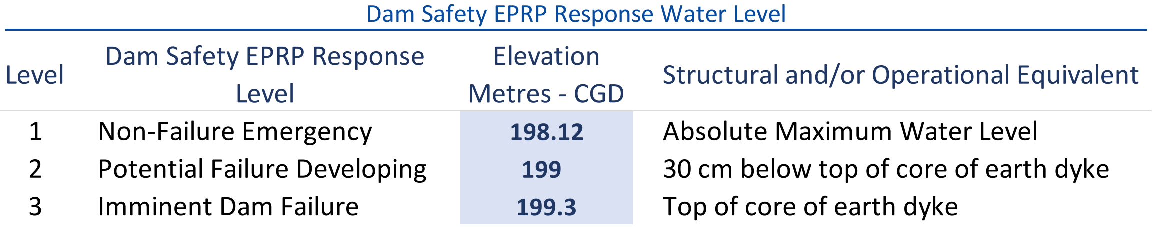
### 8.3.2. Flow Routing at Little Long

Current applications require Little Long to generate electricity at full capacity within its operating range. This means the turbines will be operated at maximum best efficiency flow until the lower operating limit at of the Little Long Reservoir is reached; at which point the turbine flow becomes equal to the inflow into the reservoir if inflows fall below the flow required for best efficiency flow. On the other hand, if inflows are greater than the requirements for best efficiency flow, the excess is used to fill up the Reservoir until its peak operating limit. In this case the excess Inflow is spilled through the Adam creek bypass. There are 8 gates that open into the Adam creek and two that open into the Mattagami River. The two that open into the Mattagami River are only to be used in case the 8 gates at Adam creek are insufficient. Below is a summary of the operating notes from OPG for Little Long.

### 8.3.3. Operation (Little Long)

The Adam Creek Diversion bypasses the Mattagami River plants from above Little Long GS to below Kipling GS and is the primary floodwater route. Dam Safety Response Water Levels have been established in accordance with the requirements of Dam Safety Emergency Preparedness and Response Plan (EPRP) standards to guide operators in case of hydraulic emergency (See Table 5).   At the start of freshet, the Little Long forebay should be filled to an elevation not exceeding 198.00 meters. After achieving that elevation, any inflow greater than the amount of water required for two-unit operation (583 m3/s) should be spilled down Adams Creek.

*Table 8.3. Dam Safety Water Response Levels*



Dam Safety EPRP Response Water Level

| Level | Dam Safety EPRP Response Level | Elevation Metres - CGD | Structural and/or Operational Equivalent |
|---|---|---|---|
| 1 | Non-Failure Emergency | **198.12** | Absolute Maximum Water Level |
| 2 | Potential Failure Developing | **199** | 30 cm below top of core of earth dyke |
| 3 | Imminent Dam Failure | **199.3** | Top of core of earth dyke |

The reason for this maximum level of 198.00 meters is to allow for safe operation of the station in the event of a contingency that results in the loss of units and operating control (e.g. a lightning strike). Such a contingency would make it impossible to remotely control sluice gate operation of Adams Creek. This 12-centimeter of storage will allow for the four-hour time lag required to dispatch operator agents to the station to deal with the contingency. The maximum forebay level of 198.00 meters is during the freshet period only. There is no requirement to spill through the main dam. This practice should be avoided to improve operating efficiency at Smoky Falls during freshet. Another reason for avoiding this practice is to eliminate the stranding of sturgeon in the spillway pools and the subsequent rescue operation. The forebay should be filled gradually to 198.12 meters in the last seven days of freshet.

Sluicegates 5, 6, 9, and 10 are controlled locally by the operator agents at the gates. Two to four hours may be required to reach the site. There is a concern of further undermining of the sluiceway apron at Adams Creek sluicegates 8 and 9. An engineering assessment, which included a diving inspection, carried out in September 1996 confirmed that no restrictions are required on sluicegates 3 to 10 at this time. The area is to be re-inspected subsequent to each major spill in which sluicegates 8 and 9 are utilized. As a minimum, the area of the sluiceway apron is to be inspected every three years. The last inspection in July 2001 reported no further erosion of the bedrock below the sluice apron since 1996.

As the differences in water levels across the trash racks of Little Long G.S. have frequently been found to be excessive, these differences must be measured frequently and kept in moderation by clamming. In addition to the dangers of potentially drawing air into the penstocks, the head losses associated with large trash rack differentials can be quite costly.

### 8.4. Mattagami Basin Systems Reliability Model

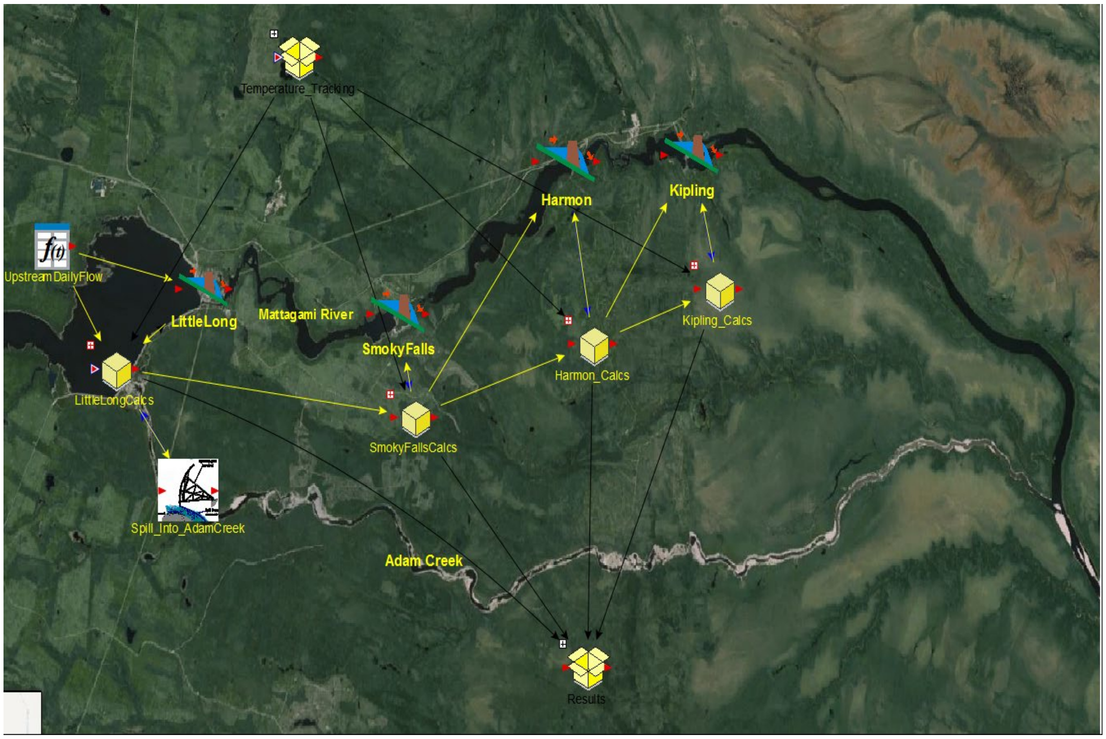


*Figure 8.5: Goldsim™ Model Interface*

### 8.4.1. Gate operations and gate fragility

At each component, the upstream demand function is applied to the operation of the component. Engineering reliability models are used to evaluate the performance of that component in relation to the demand function as later shown in this chapter. For example, the performance of the component can be described by a relationship between the demand placed on the component and the probability of its failure.

These loads/demand functions are related to gate availability through fragility curve relations. A fragility curve represents the probability of adverse performance or failure as a function of the load on the structure. The inputs to the gate operations simulation at any time step are the respective states of the input and disturbance variables. The outputs are the gate availabilities (probability of use on demand).

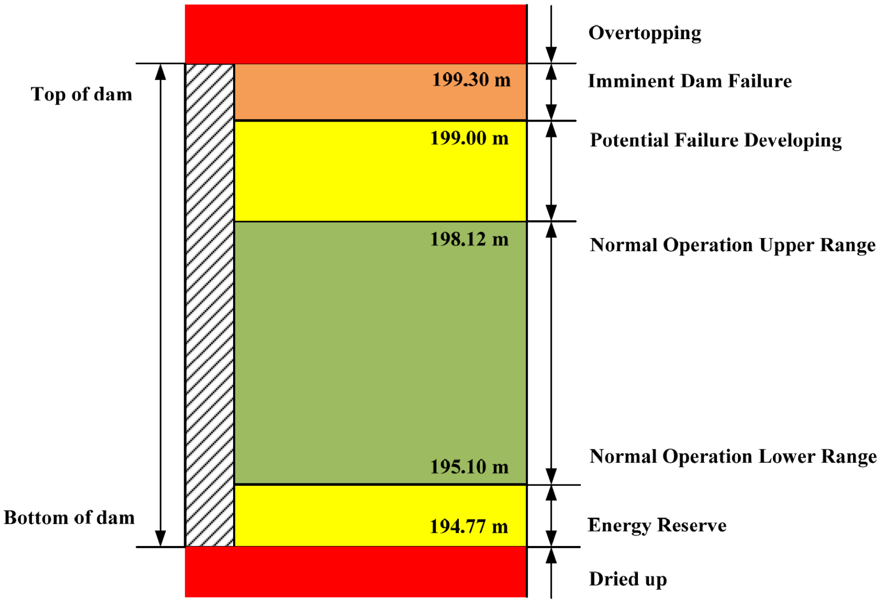


Figure 8.6*: Little Long Dam Operating Elevations*

Gated spillways are designed to engineering standards, however with aging, exposure, preventative maintenance, and lack of frequent operations they become vulnerable to non-availability. On-demand failures of gated spillways may be caused by a gate component that can be repaired in minutes to hours or a component that may cause complete failure of the gate system and unexpected release of the reservoir containment.

Gated spillways are a complex integration of structural, mechanical, and electrical (SME) components that must operate on demand. For Little Long reservoir, there are a total of 10 sluices with gates. Two of the 10 sluices (Nos. 1 and 2) are alongside the generating station and open into the river, while eight are 3.2 km upstream and open into the bypass. Sluices 1, 2, 3, 4, 7 and 8 are remotely controlled. Sluices 5, 6, 9 and 10 are locally controlled by agents at the gate. The sluices are numbered from left to right looking downstream.

Gate operations are also affected by instrumentation, supervisory control and data acquisition (SCADA) systems and controls. The simulation approach is well suited to uncovering the implications of component performance assumptions on overall systems operations.

Figure 8.7 shows a simulated result over a 12-month period of gate operation including SCADA performance and gate binding. The red curve shows reservoir inflow in cubic meters over time. The inflow rises during the spring freshet in May and June based on the stochastic time series of inflow data. As the pool level rises, these SCADA systems generates control instructions to the gates. At two points in late June early July, for whatever reason in the simulation, instances of gate binding occur. These are shown by the green spikes. Depending on other factors in the simulation, these two instances of the gate binding may or may not lead to adverse systems behavior.

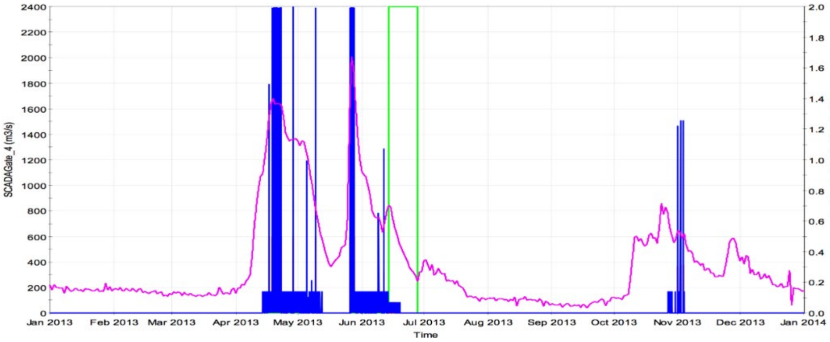


*Figure 8.7. Simulated effect of disturbances: red is reservoir inflow, blue is SCADA controlled spill, and green is structural binding of gate.*

### 8.4.2. Mechanical fragility

In risk assessment, limit states or probability of failure serve as yardsticks of system performance. The *fragility curve* is used to predict the probably of dam failure, given an hydraulic load (Chase, Sr, 2012). A fragility curve is defined by the cumulative distribution function (CDF) of the system response curve to a load. A typical fragility curve for probability of mechanical gate failure as a function of gate opening under full pool is shown in Figure 8.8. The fragility curve is the standard way in which structural and geotechnical reliability functions are captured. Fragility curves are pre-calculated, usually using an event tree or a fault tree representation.

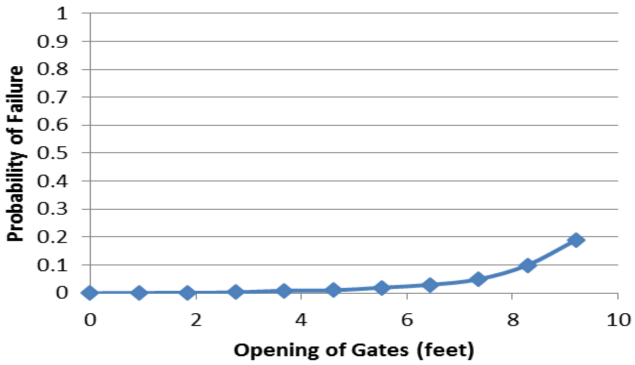


*Figure 8.8. Fragility Curve for Mechanical Gate Failure*

Structural and mechanical reliabilities of spillway gates are dependent on the level of water on the gates, while the electrical reliabilities are randomly distributed in time with a fixed occurrence rate (here, 0.017 failures per day). In the present model, unavailability due to electrical gate failures are far more common than mechanical failures, and occur a number of times per year. Structural failures are even less probable in the current model.

Figure 8.9 shows gate failures for one annual realization of Spillway Gate 4. This was a peculiar year. There were several electrical failures and one structural failure. The structural failure was modelled as a gamma distribution with mean delay time until repaired of six months and a standard deviation two months. The effect of this random repair time delay was that the structural failures took a long time to repair whereas electrical gate unavailability were usual repaired within the same day.

The effect of failure on the performance of the entire system can be observed from Figure 8.10. Spillway Gate 4 was inoperable due to its failed state under structural failure and was down for repair sometime before the peak flow for the year (April). Between April ending and mid-October, Spillway Gate 4 was down for repair. During this time the SCADA controlled gates were required to route excess inflows out of the reservoir. Bearing in mind that each gate has a capacity of 608 cms, it can be observed in Figure 8.10 that with Spillway Gate 4's failure, the SCADA gate system was routing about 1800 cubic meters of water out of the reservoir instead of the total capacity of about 2400 cubic meters during peak flows.

### 8.4.3. Electrical Failure

The Failure Rate (also known as the hazard rate) represents the mean failure rate and has dimensions of inverse time. Failure is assumed to be a Poisson process (which implies that if the rate is constant, the time between events is exponentially distributed). Failures modeled in this way are computed with respect to the time since the simulation started an hence the time is the failure mode control valuable.

Electrical Reliability, specified as the electrical availability On Demand of the System (including operator push button error and external and internal power failures) is estimated at 0.017 failures per day.

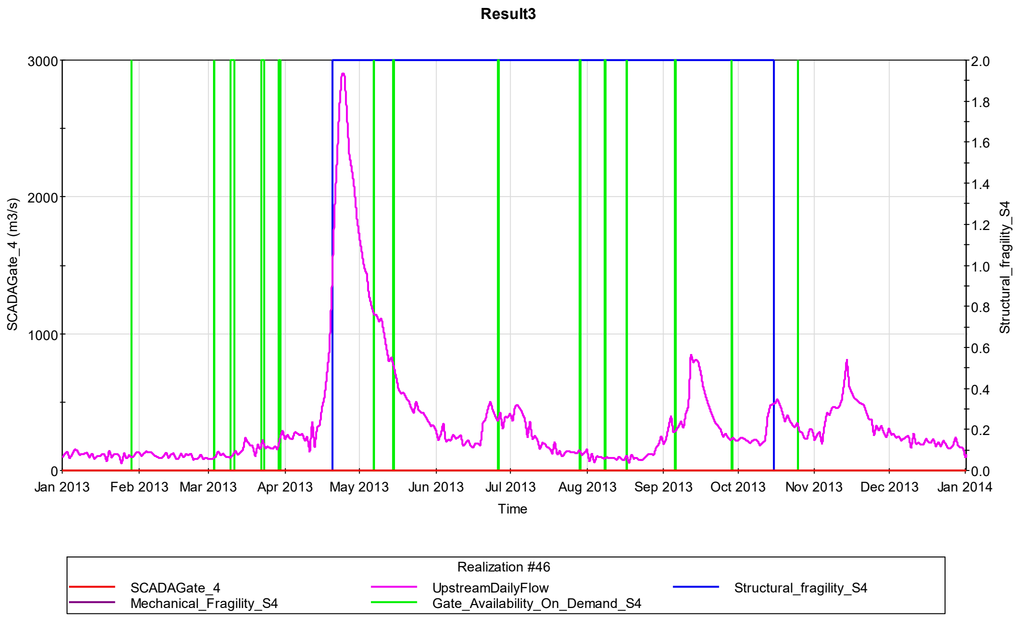


*Figure 8.9: Plot of component Reliabilities vs upstream daily flow vs time*

Figure 8.9 and Figure 8.10 also shows another comparison of mechanical failure coinciding with the demand for spillway flow. From the plots, it can be observed that around the start of freshet, there was a mechanical failure at Gate 4. This failure lasted for about seven days in the month of May. It coincided with the start of freshet, meaning the spillway gates were unavailable on demand. The effect of this mechanical failure was the loss of capacity of the SCADA controlled Spillway system. As can be observed, the rest of the spillway gates started operating just as the freshet started to peak with a combined discharge of about 1800 cubic meters instead of the total capacity of about 2400 cubic meters. This occurs until Gate 4 is fixed and adds an additional 600 cubic meter capacity to the SCADA controlled gate system.

Figure 8.10 also shows the probabilities of mechanical failure as a function of time for 1 realization for Spillway gate 1. The probability of mechanical failure is usually higher around the peak of freshet when the elevation of water on the gates are the highest. Figure 8.11 shows the mean of mechanical failure, Spillway Discharge and upstream flow over many realizations. There is a strong correlation between all three parameters.

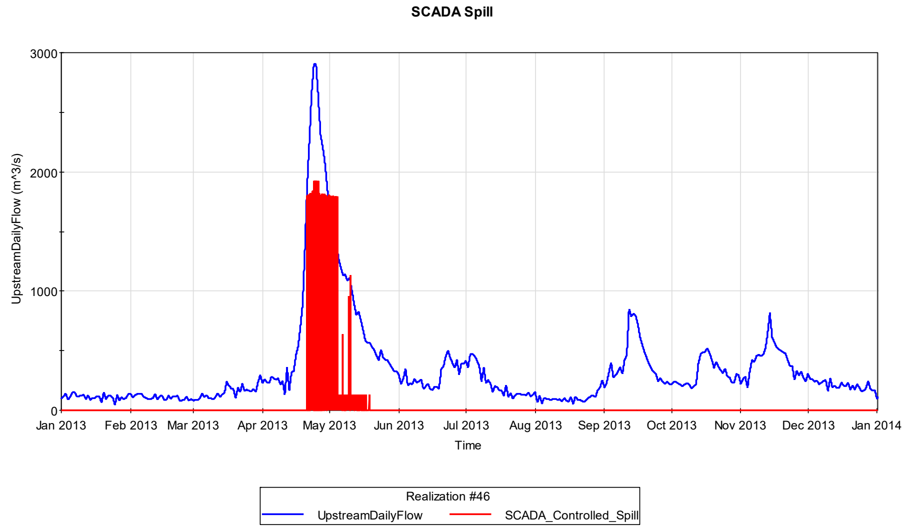


*Figure 8.10: Plot of SCADA Controlled spill* vs. *upstream daily flow.*

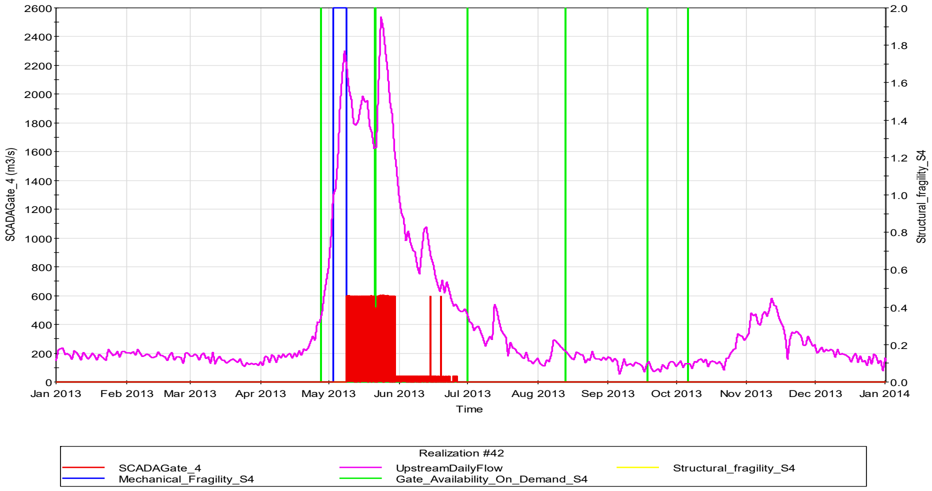


*Figure 8.11: Plot of SCADA (gate 4) Controlled spill vs upstream daily flow vs time*

### 8.4.4. Disturbances

Sometimes in the course of the operation of a dam system an extraordinary event occurs, such as an earthquake, an earth or rock slide into the reservoir or conveyance works, a major fire in the drainage area, or the like, at a time which cannot be anticipated, but that may affect dam operations or even dam safety. Within the simulation, such events, and their more modest siblings, are treated as exogenous disturbances. *Disturbances*, can in principle include a broad variety of phenomena, both of natural origin such as lightning strikes affecting power supplies or instrumentation, or of anthropogenic origin such as the grid being unable to accept power and thus the powerhouse waterway having diminished discharge capacity, or operational incidents or accidents such as powerhouse fires. The exact definition is a matter of modelling convenience; severe floods or droughts may for instance be considered as disturbances or alternatively just as aspects of the stochastically modelled catchment hydrology.

A disturbance of major concern in the project is ice buildup. The stochastic input for this simulation is the variability in daily temperature generated from a statistical time series identified to temperature data over the past century. Daily temperatures are simulated, and Stefan's Equation (USACE 2002) is used to calculate ice thickness on the reservoir. Stefan's equation uses anticipatory degree-days below freezing with an empirical constant to forecast ice development.

### 8.4.5. Modeling Ice Storms Disturbance

Ice storms can damage structures because of the weight of accumulated ice. Ice storms are known to occur in Eastern Ontario and Quebec. On average, Ottawa and Montreal receive freezing precipitation 12 to 17 days a year. However, this type of precipitation generally lasts only a few hours. Though it did not occur near the LMR Complex, in January 1998, a severe ice storm occurred in Eastern Ontario and Quebec; over 90 millimeters of freezing drizzle fell during the 5-day storm. This magnitude has an annual probability of occurrence of about 1 in 100 (Ontario Power Generation Inc., 2009).

The occurrence of Ice storms that affect Spillway gate occurrence is modelled as a discrete process since the only information we have on Ice storm occurrence is that of a severe Ice storm of 90mm thickness which has a probability of 1 in a hundred years of occurring. The time of initiation of the event is simulated as a Poisson process, *such that the expected* number of occurrences over some time period T is equal to the product of the Rate (.01/year) and time T. The duration is modelled as a gamma distribution for structural member failure and an exponential distribution for structural binding failure (Table 9.4).

*Table 8.4: Down times and repair times of component failures*

| Ice Storm Failure Type | Repair Duration Type | Mean Down Time | Standard Deviation |
|---|---|---|---|
| Structural Member Failure | Gamma Distribution | 6 months | 2 months |
| Structural binding failure | Exponential Distribution | 1 day | - |

Figure 15 shows the fragility curves for both Structural member failure and Structural binding failure. The fragility curve shows intensity on the x-axis and probability of failure on the y-axis. As discussed earlier, the intensity is not incorporated I the model is a discrete variable. That is either 0 or 90mm of ice on the gates. Since the data for the amount of ice accumulation at each of the sites is unavailable, modeling the intensity of Ice storms as a continuous variable is outside the scope of this thesis.

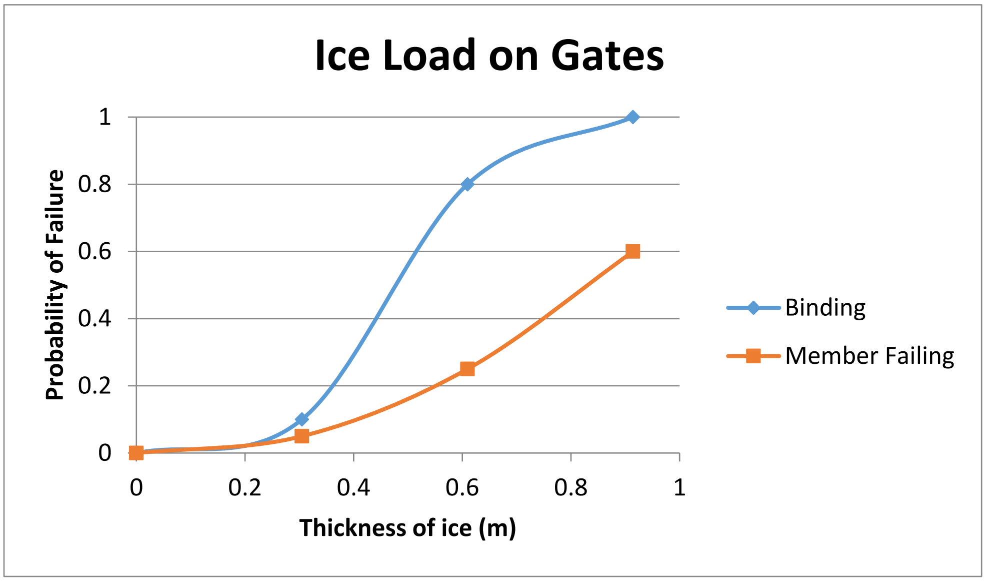


*Figure 8.12: Fragility curves for Ice Loads on Spillway gate*

Figure 96 also shows how the Ice Storm Failure mode is incorporated into the event tree analysis for one of the Spillway gates.

### 8.4.6. Modeling floating Ice

The ice thickness is a fundamental parameter for practically all ice problems. At the simplest level, one can use empirical analyses based on the Freezing Degree Days (FDDS). This can be refined in various ways, especially if ice thickness data are available for calibration. The ice thickness is a fundamental parameter for practically all ice problems. Usually, the engineer is confronted with the problem of predicting the ice thickness, and often its return period as well, with little information. The LMR complex case study also has the same caveat with no historic data on floating ice available. However by tracking the Freezing degree days, Steffan came up with a formula for calculating the height of accumulated ice. The historic temperature data in Figure 8.13  was used to calculate the height of accumulated ice at any given point in time.

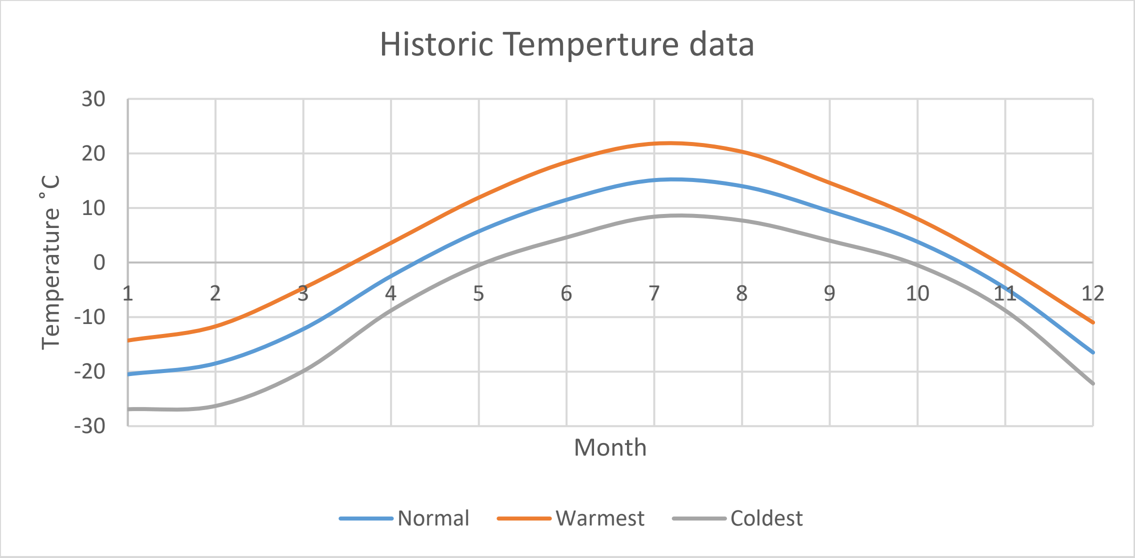


*Figure 8.13: Historic temperature data LMR complex*

8.4.7. <u>Simplified Thermal Analyses</u>

The ice thickness is a fundamental parameter for practically all ice problems. At the simplest level, one can use empirical analyses based on the Freezing Degree Days (FDDS). This can be refined in various ways, especially if ice thickness data are available for calibration. The ice thickness, h, produced by static ice formation is most commonly predicted based on the accumulated Freezing Degree Days (FDDs), as given in Table 10.6. This Stefan equation, $h = \alpha\sqrt{FDD}$, is derived by solving the differential equation for the thermal growth rate, and by making various simplifying assumptions (USACE 2002). Where $\alpha$ is an empirical coefficient that varies from site to site depending on local conditions such as the snow cover, winds, and solar radiation.

*Table 8.5: Stefan equation values for α.*

| Typical values of α (degrees-C) | |
|---|---|
| Ice Cover Condition | α |
| Windy Lake w/no snow | 2.7 |
| Average Lake with Snow | 1.7-2.4 |
| Average river with snow | 1.4-1.7 |
| Sheltered small river | 0.7-1.4 |

*Table 8.6. Potential external disturbances at the LMR complex*

| Condition | Principal Affected Component(s) of the Project |
|---|---|
| Flooding | Integrity and function of external structures and systems.<br>Integrity and function of dams. |
| Ice | Integrity and function of dams and water intake systems. |
| Forest Fire | Integrity and function of GS and associated facilities. |
| Severe Weather | Integrity and function of external structures and systems. |
| Seismic Events | Integrity and function of dams, spillways and powerhouses. |
| Climate Change | Integrity and function of external structures and systems.<br>Integrity and function of operating regime. |

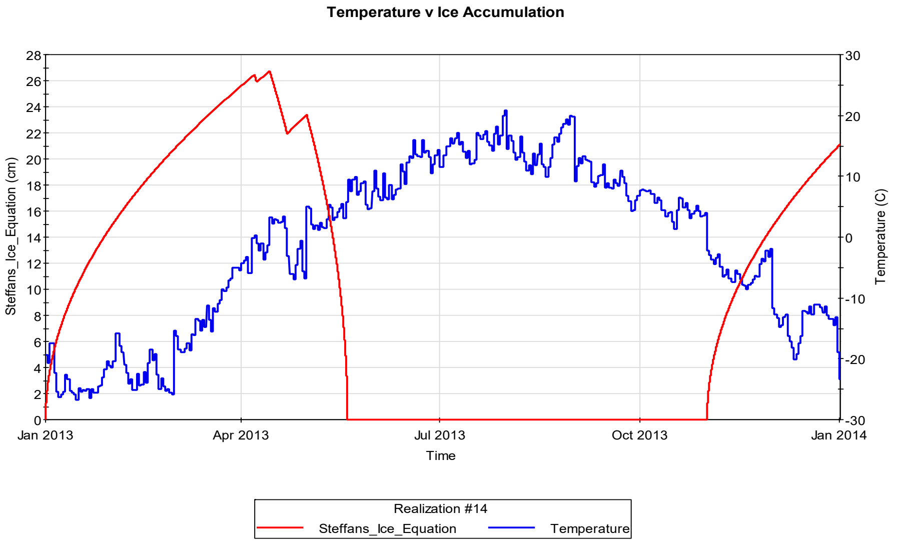


*Figure 8.14: Simulation Results showing seasonal variation in temperature (°C) and Ice build-up in cm*

The disturbances included in the present model are limited to external loss of grid availability, lightening (affecting grid availability), floating ice, icing on structures, instrument or SCADA mis-operation, and human error. Each is treated as a Poisson process in time, possibly with a corresponding probability distribution of magnitude.

Ice storms can damage structures because of the weight of accumulated ice. Ice storms are known to occur in Eastern Ontario and Quebec. On average, Ottawa and Montreal receive freezing precipitation 12 to 17 days a year. Nevertheless, this type of precipitation generally lasts only a few hours. Though it did not occur near the LMR Complex, in January 1998, a severe ice storm occurred in Eastern Ontario and Quebec; over 90 mm of freezing drizzle fell during a 5-day storm. This magnitude has an annual probability of occurrence of about 1 in 100 (OPG 2009).

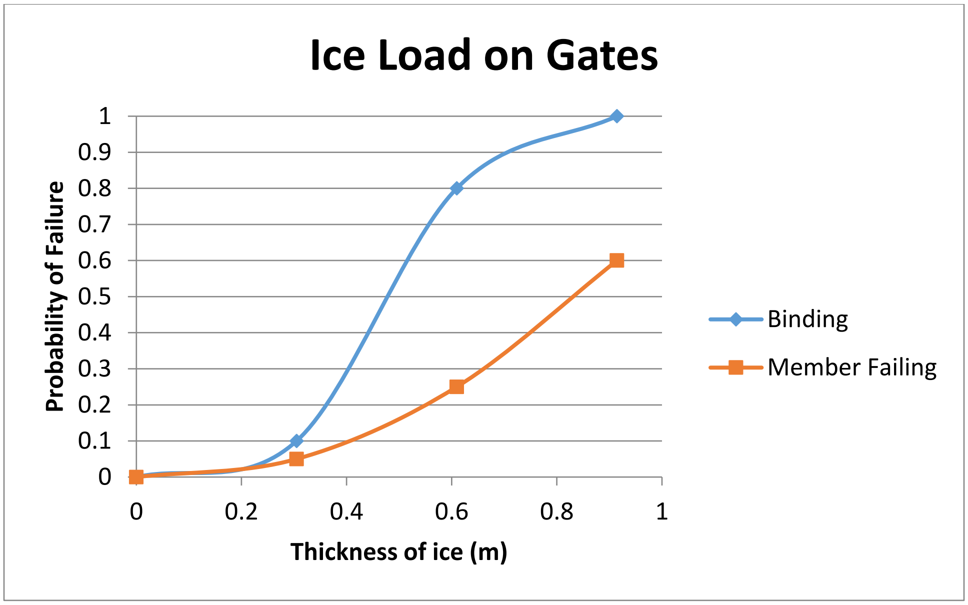


*Figure 8.15: Fragility curves for Ice Loads on Spillway gate. Structural failure in red; binding in blue.*

The occurrence of ice storms that affect spillway gate operation was modelled as a discrete process since the only information then available on ice storm occurrence is that of a severe ice storm of 1988. Figure 8.15 shows fragility curves for structural member failure and structural binding failure of a gate. The time of initiation of the event is simulated as a Poisson process, such that the *expected* number of occurrences over some time period T is equal to the product of the rate (0.01/year) and time. The duration is modelled as a gamma distribution for structural member failure and an exponential distribution for structural binding failure. For this section, human operators as pertaining to the LMR complex will be treated as "humans in the loop" as if they are any other sub-component of the complex technological systems. This simplistic assumption allows us to model human operator delays as on a probabilistic distribution.

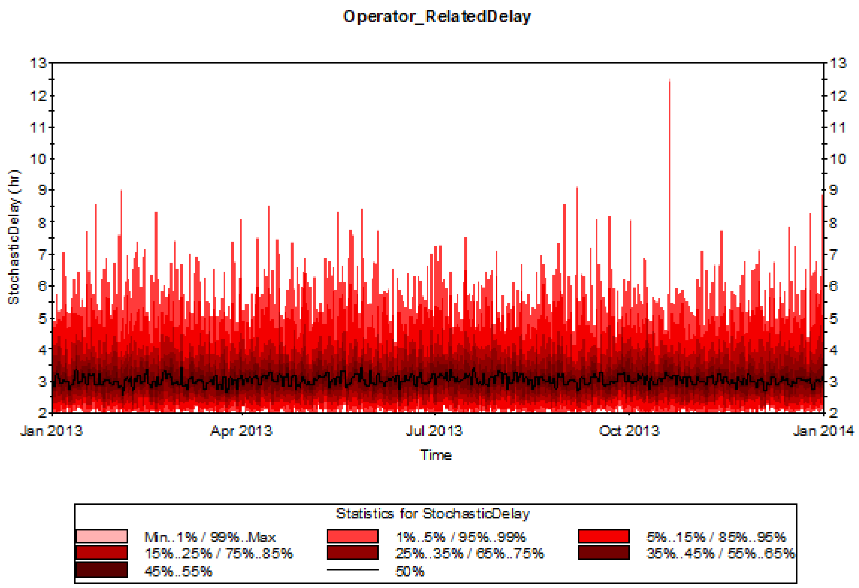


*Figure 8.16: Modeling Operator Related Delay*

According to the operating rules for Little Long GS, operators are to be dispatched to Little Long GS when the 4 Spillway gates that open into the Mattagami River are insufficient in routing peak flows out of the dam to keep the reservoir below its operating range maximum. It generally takes operators 2 to 4 hours to get to the site after they're dispatched but it may take longer due to inclement weather scenarios in which case it might take much longer to gain access to the control station of the dam as roads might blocked etc. To capture these rare but possible scenarios outside the usual 2-4 hour time required to get operators on site, a truncated lognormal distribution with an upper limit of 24 hrs and a minimum limit of 2 hrs with a true mean of 3 hrs. as can be seen in figure 56. Figure 8.16 shows a plot of the operator related delay modelled over a year from January-December for the 51 year historical data.

## *8.5. Model results: Operating patterns and flow routing*

Flows in the Mattagami River are highly regulated by the presence of hydropower generating facilities and water control structures that provide electricity generation and flood mitigation.

During the spring freshet, flows in the Mattagami River typically exceed the flow capacities of the GSs and therefore must be diverted through the Adam Creek Diversion. Adam Creek then discharges this overflow into the Mattagami River downstream of the Kipling GS. Figure 8.17 shows historic daily inflows into Little Long reservoir. When flows exceed 583 cms, excess water that cannot be used by the Mattagami River GSs is diverted to Adam Creek. The average peak flows during the spring freshet are above 1,500 cms and can be variable.

### 8.5.1. Little Long Flow Routing

As discussed earlier in the hydraulic modeling chapter, Little Long GS is operated within an operating range of 195.10 m-198.12 m with the main aim of the operating rules being to optimize power generation and route flow safely downstream.

Each of the gates were modeled independently as they each have independent reliability components at both the component and subcomponent level.

As discussed in the chapter 4, Little Long forebay is filled to an elevation not exceeding 198.00 meters. After achieving that elevation, any inflow greater than the amount of water required for two-unit operation (583 m3/s) is spilled down Adams Creek. The difference of 12-centimeter of storage will allow for the four hour time lag required to dispatch operator agents to the station to deal with the contingency. The maximum forebay level of 198.00 meters is during the freshet period only. There is no requirement to spill through the main dam.  This practice should be avoided to improve operating efficiency at Smoky Falls during freshet. Sluice-gates 5, 6, 9, and 10 are controlled locally by the operator agents at the gates.  Two to four hours may be required to reach the site.

### 8.5.2. Reservoir Operations Summary

The water flows for the four GSs are provided from the Little Long GS reservoir. The water level is normally within the operating headwater level range. The extreme limit of the headwater level is the "absolute maximum operating level". The difference between the absolute maximum and maximum operating levels is referred to as the "flood allowance", which is only used to hold water in extreme conditions to reduce downstream flooding. The storage between the absolute minimum and minimum operating levels is only used if a system energy emergency occurs. Under normal operating conditions with equivalent discharges at each station, the full operating range in the Smoky Falls GS, Harmon GS and Kipling GS head ponds would rarely be utilized and head pond levels will be significantly more stable during operation.

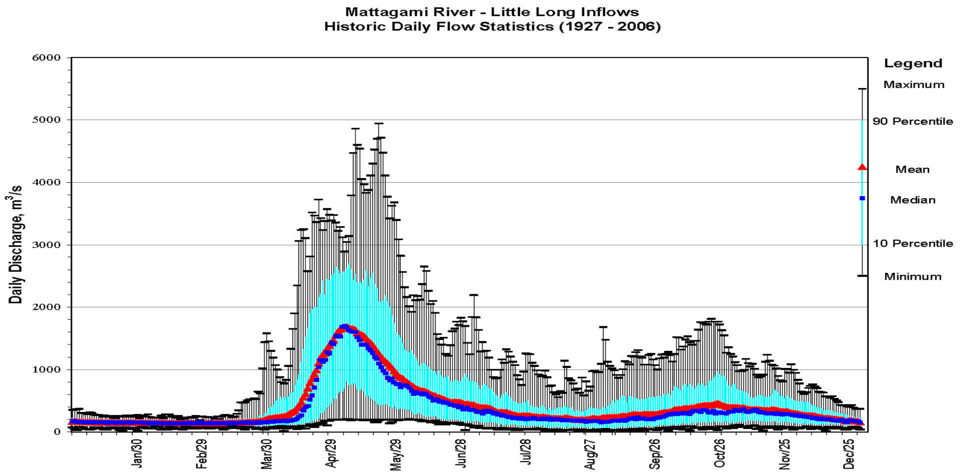


*Figure 8.17: Historic Daily Inflow Statistics, Little Long GS*

Under normal operating conditions, the outflow from the Little Long GS reservoir will pass through all the GSs. During any outage of a GS, the spillway at the station experiencing the outage will be operated to pass the desired flow to the other GSs. During high river flow conditions (e.g., spring) when the Little Long GS reservoir is near its maximum limit, the spillway at Adam Creek is operated in conjunction with Little Long GS to pass the full Mattagami River flow.

Imminent Dam Failure during reservoir inflow floods (Overtopping Failure) is assumed to occur when water reaches a stage specified the operating documents as imminent dam failure elevation; thus when the elevation exceeds the imminent dam failure elevation. A simulation for a year from start of a calendar year to end of calendar year was run by sampling a calendar years' worth of inflow data from the historic time series and routing it through the system. Figure 8.18 shows a snapshot of the pool elevation and upstream flow as a function of time for an elapsed time of 1 year; the imminent dam failure elevation is marked to show the buffer between the operating elevations and the failure elevation (top core of dam). This plot shows the response of our reservoir and gate operations to variations in daily inflows.

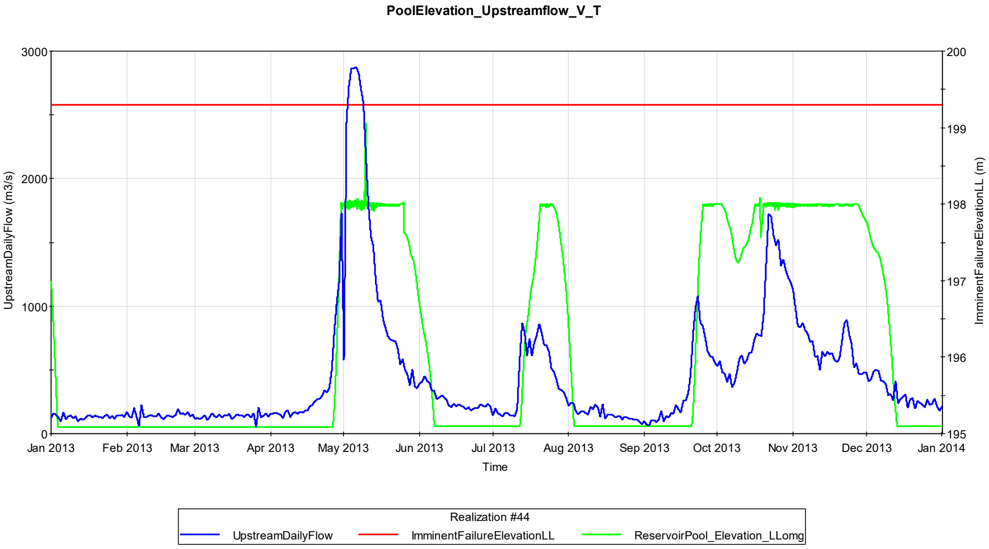


Figure 8.18: *Simulated effect of Inflows on pool elevation*

### 8.5.3. Power Generation

The Little Long GS provides a maximum power flow of 583 cms at a head of 28 m. The estimated turbine and generator characteristics for each station are shown in Table 8.7. With the salient aspects of the model formulated and constructed, the next step is to generate results and analyze whether it accurately replicates the real system. This is part of the model validation process and hence outputs from the model were compared to data from the LMR complex.

*Table 8.7. Turbine and Generator Characteristics*

| Parameter | Little Long GS | Smoky Falls GS | Harmon GS | Kipling GS |
|---|---|---|---|---|
| No. of units | 2 | 4 | 2 | 2 |
| Gross head (m) | 27.9 | 34.4 | 31 | 31 |
| Station discharge capacity (cms) | 583 | 188 | 525 | 585 |
| Station turbine capacity (MW) | 136 | 52 | 140 | 156 |
| Unit capacity (MVA)/ Turbine | 68 | 13 | 70 | 78 |
| Best Efficiency Rate kW/(cms) | 235.7 | 288.9 | 272.3 | 272.7 |

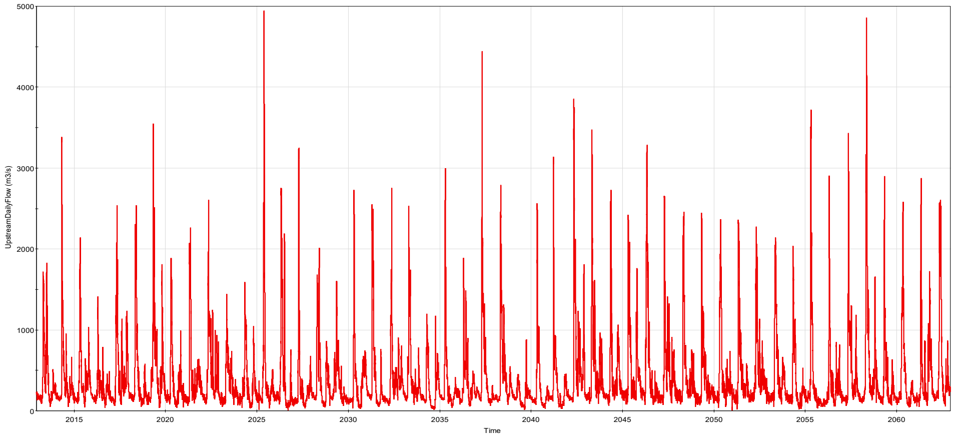


*Figure 8.19: Upstream daily flow Simulation Results over 51-year period*

The practice of Spilling into the main river is generally discouraged and the two Spillway gates at Little Long only come into use as a contingency when the eight spillway gates that open into Adam creek are insufficient in routing peak flows to keep the reservoir pool elevation within the operating range.

### 8.5.4. Pool and Volume Capacities

For the 51-year run, it's important to analyze how the flow routing procedures ensure that reservoirs are mostly operating within the operating range. The operating range for Little Long reservoir is 195.10m – 198.12m. As can be observed in figure 44, the performance of the flow routing techniques generally keeps the elevation in the dam below the imminent dam failure elevation but occasionally exceeds the maximum operating elevation about once every 2 years by just skimming at the plot of course this does not affect dam operations with regards to power performance or safety as it's still a full meter below the imminent failure elevation.

Figure 8.19 shows upstream daily flow from the Mattagami River into Little Long Reservoir over 50 years. The peaks are the freshet flows each year. The maximum inflow over this 50-year simulation was 4942 cubic meters which is consistent with the maximum inflow from the data set. Figure 8.20 shows the spill into Adam Creek which follows a similar profile as that of the upstream daily flows.

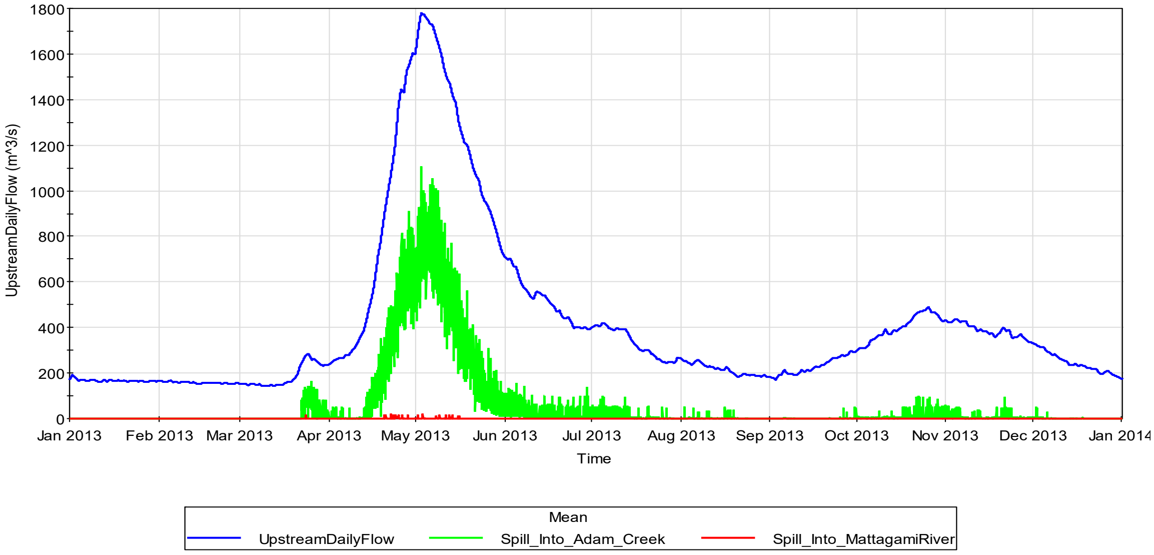


*Figure 8.20: 50-year simulation Run of Spill into Mattagami River and Adam Creek Bypass*

### 8.5.5. Power Production

As dictated by the operating rule, the dam is filled to an elevation of 198 m and the calculated head over the turbine intake is 27.28 m. At maximum reservoir operating capacity of 198.12 m, maximum head over the turbines is 27.9 m. The difference-as noted-is to allow for the four-hour time lag required to dispatch operator agents to the station to deal with the contingency. Hence the model is programmed such that Little Long Reservoir fills to 198 m. If the inflow into the reservoir exceeds what is required for best efficiency power generation as provided in the unit-rating table, the excess inflow is routed out of the reservoir through the spillway gates.

Consequently, if the inflow into the reservoir is below that required for best-efficiency flow, and the reservoir elevation is at the minimum operating elevation, then same head is maintained while inflow water is routed through turbine intake sluices. On the other hand if the inflow into the reservoir is less than the minimum for best-efficiency flow but the reservoir elevation is above the minimum operating elevation, then the reservoir elevation is gradually lowered while generating the minimum best efficiency power until the minimum operating threshold is crossed.

In the simulation, the Little Long GS is operated for best-efficiency power generation, provided in the unit rating table when upstream flow is equal to or more than the specified discharges for best-efficiency power generation. Where the inflow is more than the best efficiency discharges, the excess inflow is routed through the spillways automatically controlled through the SCADA system into Adam Creek.

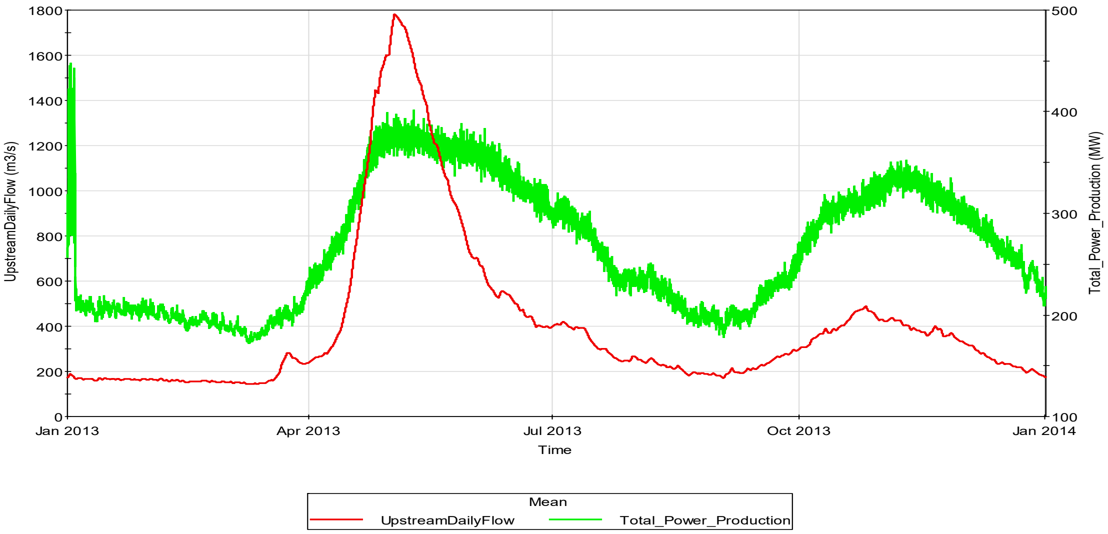


*Figure 8.21: Plot of Mean Total Power upstream daily flow for a year run and 50 realizations.*

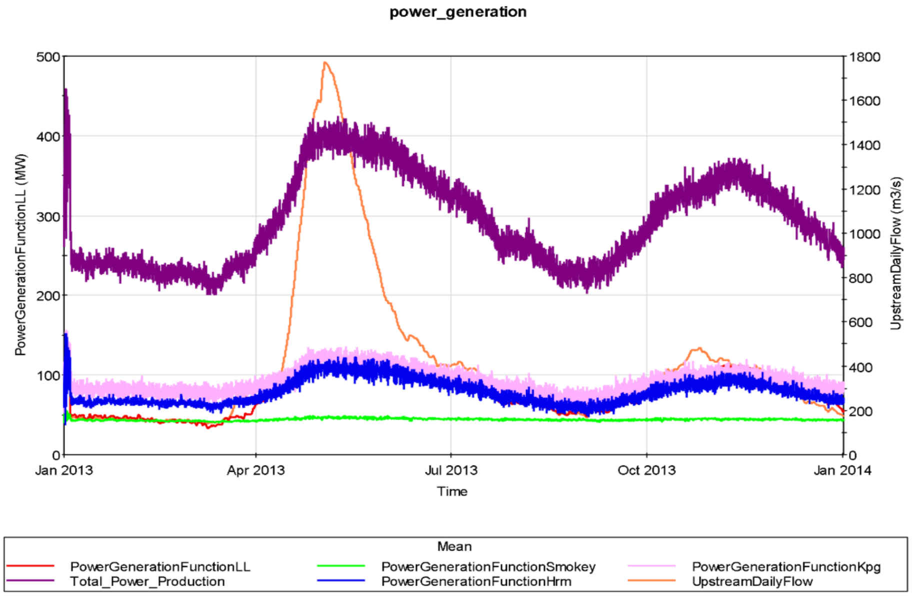


*Figure 8.22: Plot Showing Seasonal Variation for total power production at all 4GS*

If the four SCADA controlled gates that open into the bypass are insufficient (*i.e.,* when reservoir elevation is greater than 198 m and upstream flow exceeds the total of turbine flow and spilled flow), human operators are dispatched to the site to operate the additional gates that open into the bypass with a mean lag time of four hours. If all the gates opening into Adam Creek bypass are still insufficient, the additional two gates that open into the Mattagami River are used to supplement spilled flow and keep the dam from overtopping.

Figure 8.21 shows a plot of daily power production as a function of time from start of January to end of December for many replications. As can be expected, the profile of power generation is correlated with that of upstream daily flow. Figure 8.22 shows the seasonal variation in Power Generation across all four stations.

### 8.5.6. Model results: Reliability and dam safety analysis

The main function of Spilway gates is to safely pass water from one point to another; usually from a reservoir, through a dam to a downstream river or reservoir  This is achieved by keeping the main components, namely: the rate of flow, the physical conveyance of flow and the kinetic and potential energy of the flow under control.

The components of water conduits are all natural or manmade structures with civil, mechanical, and electrical functions, and with certain capabilities to resist the dynamic and static loads imposed on them. For a spillway to perform its task safely, flow must be kept to within a range that does not exceed the design capacities of it's subcomponents (electrical, structual, mechanical, *etc*.). Thus, the reliable peformance of a spillway system is both a function of time and the loads placed upon upon it.  As discussed earlier, the structural and mechanical reliabilities of the Spillway gates are dependent on the opening of the spillway gates while the electrical gate failures are exponentially distributed in time with an occurrence rate of 0.01 failures per day.

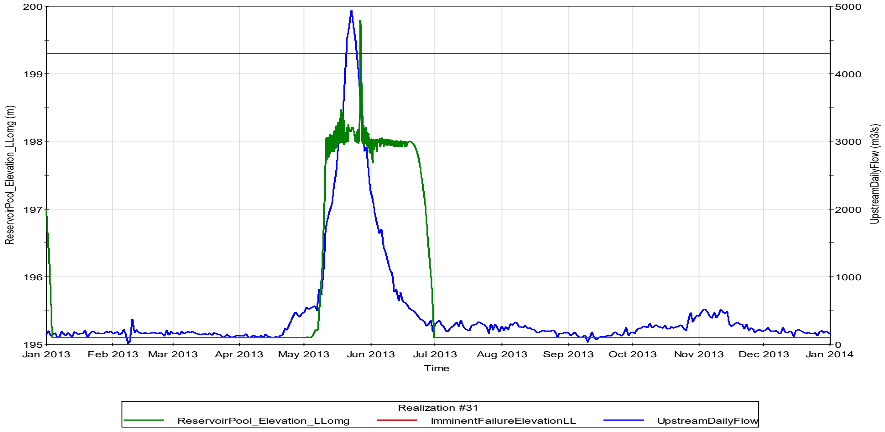
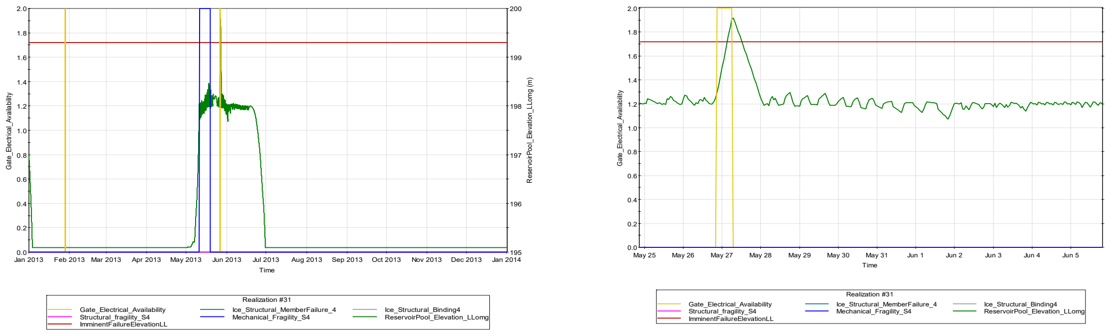


*Figure 8.23: Plot of component Reliabilities vs upstream daily flow vs time*

The result of this is that unavailability due to electrical gate failures are far more common and occur a number of times per year with structural failures being the rarest. Figure 8.23 shows the gate failures for realization 31 (Spillway gate 4) of the simulation run. The mechanical failure discussed earlier has a gamma distributed delay time until repair (MTTR) with a mean of 1 week and a standard deviation of 1 week. The effect of this is that mechanical failures take much longer to repair while electrical gate unavailability- with a gamma distribution (mean=10hrs, Standard deviation=8hrs) are usual repaired within the same day. The right side of the y-axis is the survival mode and the value of 2 represents failure due to the fact that internal requirements are not met. From Figure 8.23 it can be observed that the electrical failure followed right after a mechanical failure on SCADA gate 4. The electrical supply is from one source (no back-up, total correlation) hence electrical failure causes the loss of capacity of all 10 spillway gates. This event happening concurrently with a 50-year storm peak caused the imminent dam failure elevation to be exceeded and hence failure of the entire dam system.



*1 Realization*

*Zoomed Plot*

*Figure 8.24: Plot of component Reliabilities vs Reservoir Elevation*

By delving deeper into the model to investigate what exactly caused the minimum dam failure elevation to be exceeded, it can be observed from Figure 8.24 that there were 2 electrical failures and a mechanical failure throughout the year.

### 8.5.7. Gate Operations and Results Analysis

Imminent Dam Failure during reservoir inflow floods (Overtopping Failure) is assumed to occur when water reaches a stage specified the operating documents as imminent dam failure elevation; thus when the elevation exceeds the imminent dam failure elevation.

A high-level model is useful in understanding some of the behavior patterns responsible for the unavailability of a spill way gate on demand; which induces a high risk of system failure. A simulation for a year from the start of a calendar year to end of calendar year was run by sampling a calendar years' worth of inflow data from the historic time series and routing it through the system. Figure 8.25 shows a plot of SCADA controlled Spills within a single calendar year as a function of time. A graph of the upstream daily flow is also superimposed on the plot to enable viewing the correlation between the upstream daily flow and the SCADA controlled Spillway discharges (withdrawals). As expected, the two are heavily correlated with the peak flows coinciding with the peak Spillway discharges by the SCADA controlled gates. Each Spillway gate has a maximum capacity of 608.8 cubic meters; meaning the combined capacity of the four spillway gates is about 2400 cubic meters. During peak inflows we can see that the combined effect of the four gates is around this capacity.

Where the combined effect of the four SCADA controlled Spillway gates are rendered insufficient due to high inflows, operators are dispatched to the site to operate the additional four manually operated gates to add additional spill capacity to the gates and prevent the dam from being overtopped. Figure 72 shows a plot of the operator controlled Spill as a function of time with a graph of the upstream daily flows superimposed on the plot. These gates double the Spill capacity of the Little Long GS.

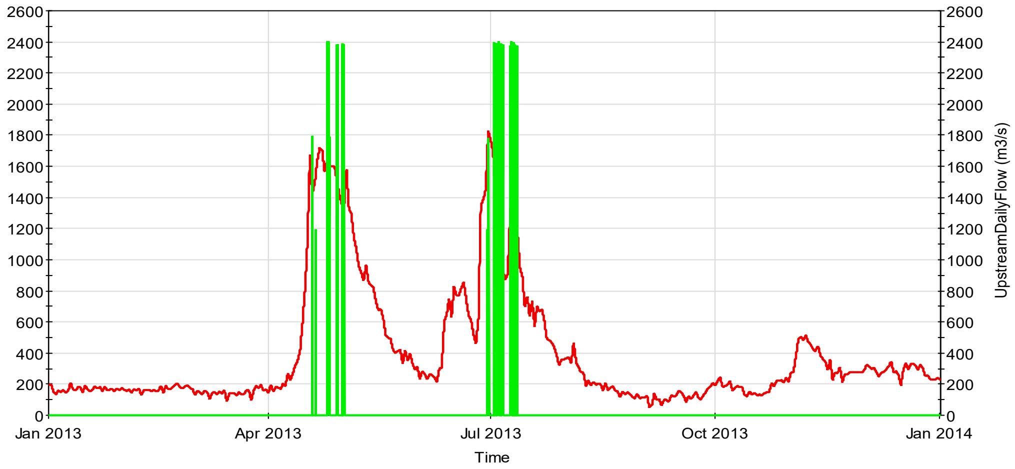


*Figure 8.25: Plot of Upstream Daily flow vs Operator Controlled Spill Vs Time*

When the four Human Operated gates are also rendered insufficient in routing the excess inflows, there are two additional SCADA controlled gates that open into the Mattagami River that are instructed to be used in these rare scenarios where the 8 that open into the creek are insufficient.

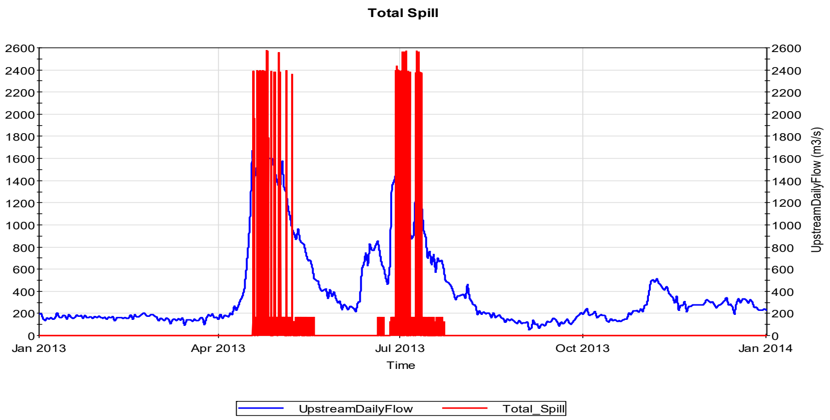


*Figure 8.26: Plot of Upstream Daily Flow Vs Total Spillway flow*

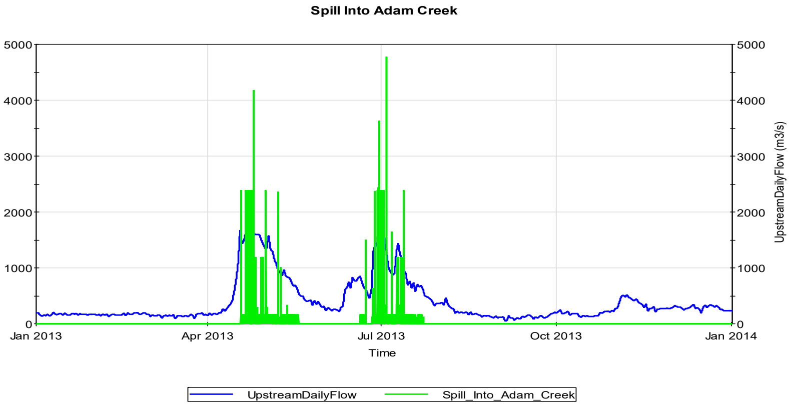


*Figure 8.27: Plot of Upstream Daily Flow Vs Spill Into Adam Creek*

Figure 8.27 shows a plot of the total spill into Adam Creek bypass as a function of time. As can be observed from the plot, there was no need to spill through the Mattagami River since the Spillway gates that open into the bypass where sufficient in routing out the peaking flows. Figure 8.27 shows a plot of the total spill into Adam creek bypass as a function of time.

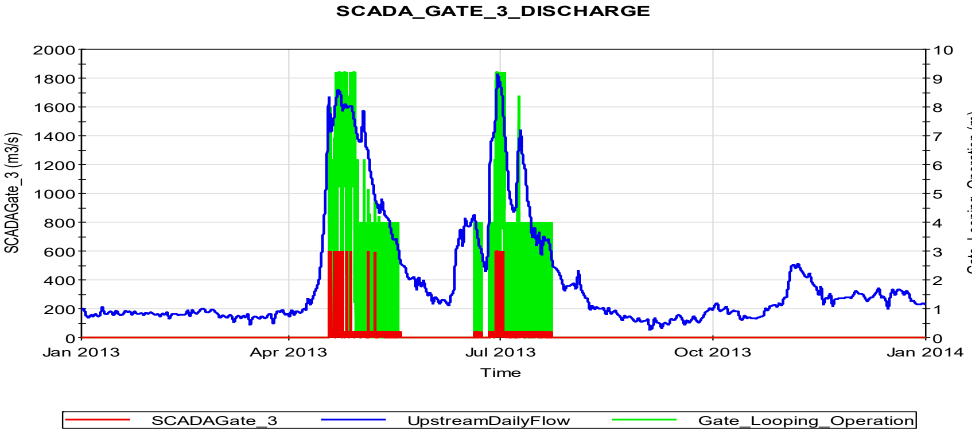


*Figure 8.28: Plot of SCADA Gate 3 Discharge Vs Gate Opening Vs Upstream flow*

To demonstrate the effect of the gate opening and closing on discharge, a plot of the spillway discharge rate (in red) and the gate opening height (green) was plotted; see Figure 8.28. The height of the gate opening is generally at a maximum of 9.2m during the peak flow periods to enable maximum routing water from the reservoir. The gate opens at an average of 0.68m/min and closes at the same rate. Its opening is triggered by the operating rule requirements which enables the SCADA systems to open the gate when these requirements are met and vice versa.

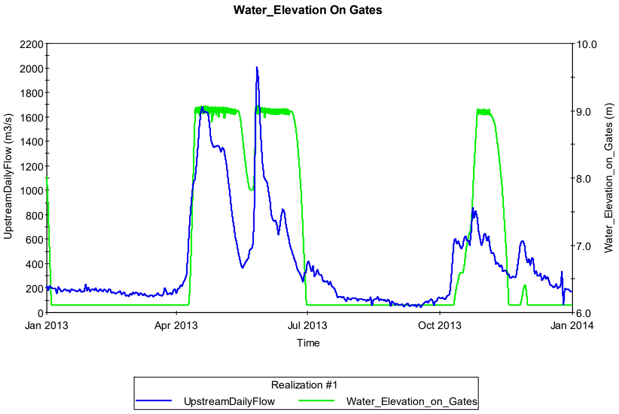


*Figure 8.29: Plot of Water Elevation on Spillway Gates vs Upstream Daily flow Vs Time*

Figure 8.29 shows the correlation between high inflows and the upstream daily flow. The sill of each Spillway gate is at elevation 188.98m which means that within the operating range, there is always some level of water on the gates. This affects the reliability of the gates since the water on the gates induces both hydrostatic and hydrodynamic forces on the gates. Level of water on the gates are the failure mode control variable for both the Mechanical and structural failures; meaning the higher the water elevation on the gates, the higher the effect of the aforementioned forces and consequently the higher the probability of failure.

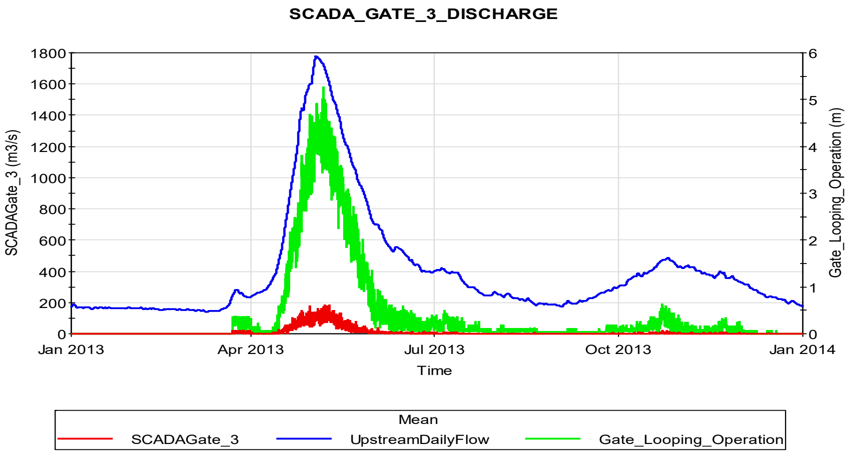


*Figure 8.30: Mean Statistics for Upstream flow vs Gate Opening vs Discharge*

Figure 9.30 shows a plot of the mean upstream daily flows, gate opening range and discharge form Spillway gate 3 (Adam creek) for the 51 years of historic data. This shows the correlation between the peak inflows and the maximum gate opening ranges and also with the highest routing capacities.

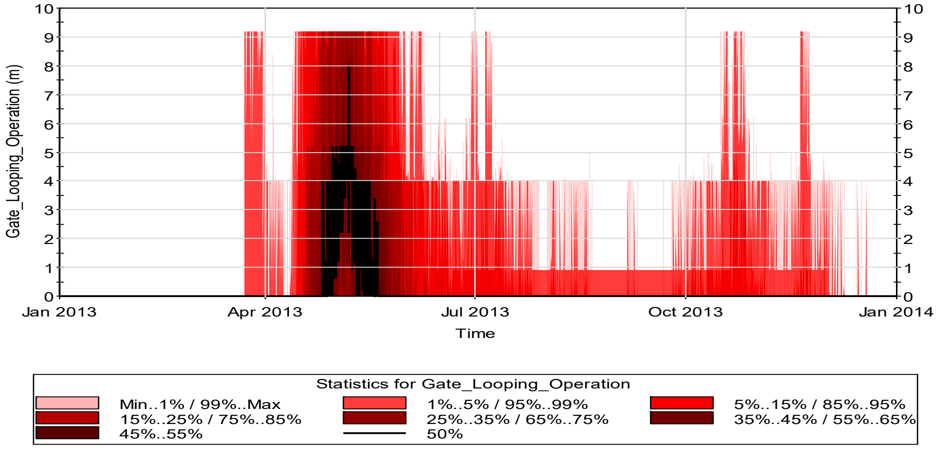


*Figure 8.31: Probabilities for Gate opening as a function of time.*

Figure 8.31 also demonstrates the annual probabilities of gate opening operations. This is important because should a number of gates fail during the period of April to July and are not able to get fixed quickly, the likelihood of the dam being overtopped is much higher than for the rest of the year. It is imperative that during this period when the requirements on the gates are high, contingencies are put in place to backup any gate failures.

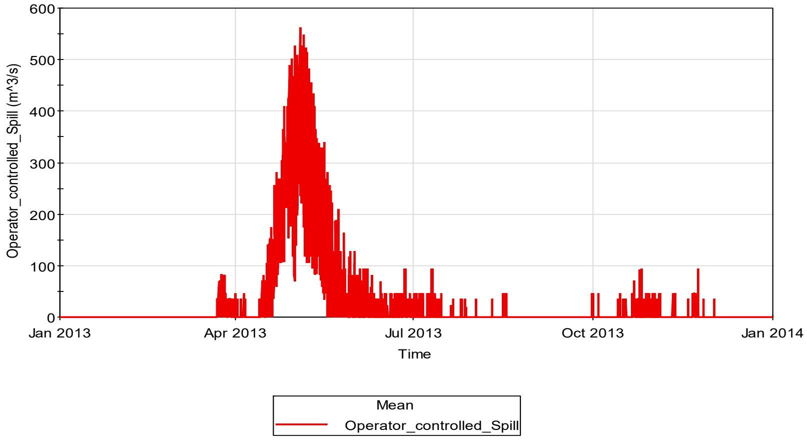


*Figure 8.32 Plot of mean Operator Controlled Spill as a function of time*

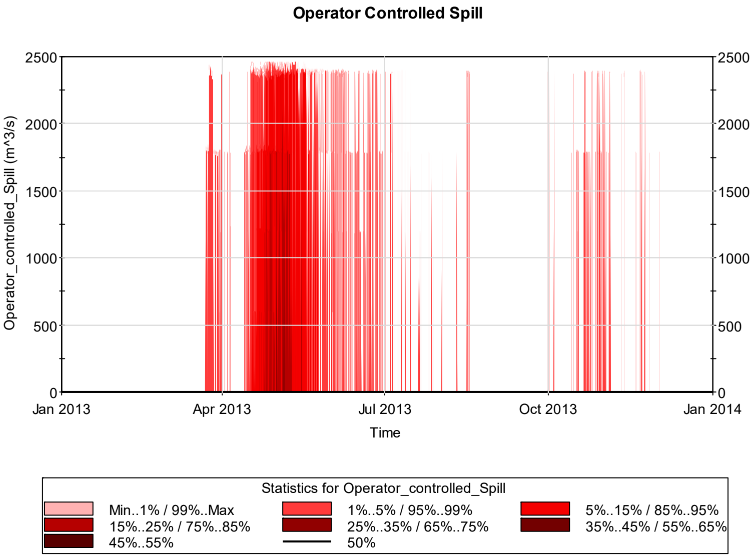


*Figure 8.33: Probability statistics for Operator controlled spill*

Figure 8.32 is a plot of the mean operator Spill over the 51 years of historic data from start of January to end of December. It can be inferred from this plot that Operators must be on standby during the start of freshet to travel to the site and operate the additional gates if need be. It's important for management to ensure that from the start of April to August ending, all roads to the control center are cleared of any snow etc. and be accessible to human operators on demand to enable swift response to signals to operate the additional four gates during high inflow periods. Figure 82 also shows that based on historical data, the requirement for operators to be dispatched to the site through the year is below the 50th percentile with the annual peak flows having annual probability of about .45 to require human operators.

Figure 8.33 shows a plot of the Probability of Spill into the main Dam. This is important in order to prepare for the consequences of Spilling into the main dam. Over the years, the probability of Spill into the main dam has been rare with a mean probability (50th percentile) of zero cubic meters year on year. All though this indicates that Spill into the Mattagami is rare, contingencies must be put in place to ensure that when it occurs, its consequences are mitigated.

Figure 84 shows the mean  of operator controlled spill and total spill from start of year to end of year for 51 replications. The difference between these plots-although they both follow the same profile- is the operator-controlled spill. This plot demonstrates the importance of human operators in safely routing out excess inflows from the lower Mattagami reservoir. Hence hindrance to their operations or errors by them could be catastrophic in the events of high inflows.

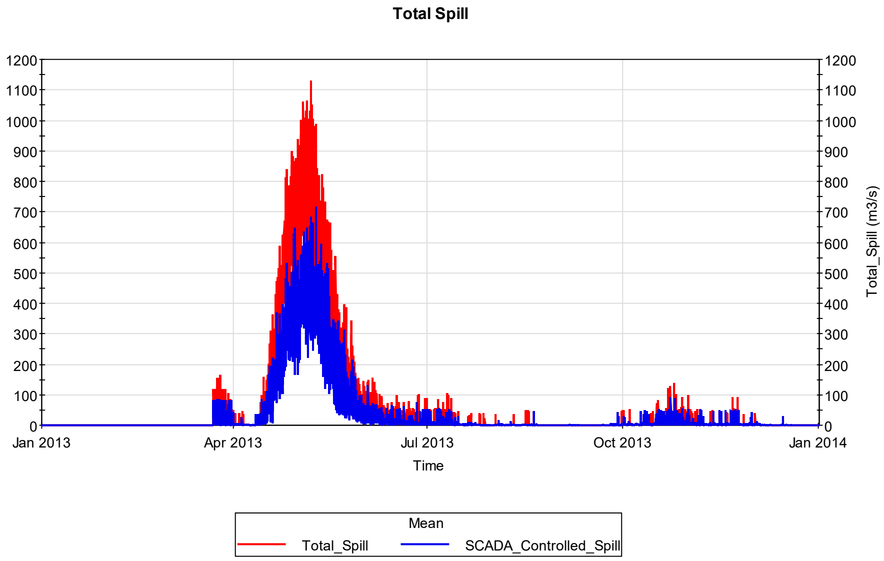


*Figure 8.34: Operator Controlled Spill Vs Total Spill*

Figure 8.34 shows the annual probabilities for Spillway overflows and from the plot we can infer that until the start of April, there is generally no Spillway flow. The month of May seems to have the highest demand for Spillway activities with probability of Spillway flows in the 50th percentile.

# CHAPTER 9: CONCLUSIONS AND FUTURE WORK

## *9.1. Summary*

The framework and techniques presented in this thesis provide the foundation for Simulation based Systems reliability approach to analyzing operational risks in complex engineered systems. Systems engineering and systems thinking represents a new dimension in risk analysis for hydrosystems and has built on the advancements made using contemporary methodologies such as event trees and fault tree analysis. The contemporary methods clamp different aspects of dam performance into separate failure modes and treat these failure modes separately. The history of dam safety suggests that accidents and failures occur in more complex ways, mostly due to systems and human interactions, and need to be addressed accordingly. The systems reliability approach addresses these flaws from the first generation/contemporary methods. It does so by approaching dams as engineered systems and dam operations as an integral part of safety. Modeling these systems quantitatively is highly more complex than first generation analyses. Models of physical systems differ fundamentally from models of sensor and SCADA systems or from models of human operator actions or operational rules. Additionally, the systems being modelled are complex and exhibit non-linear behavior, from interacting components, often involving sub-systems that are themselves complex. Data mining the outputs of the simulation runs enables us to also identify and examine the build-up of conditions leading to accidents or failures, the structure and nature of dependency among failure modes and the nature of interactions among failure mechanisms. The framework and the tools to support the systems reliability approach to modeling operational risks in hydrosystems is presented in this thesis.

### *9.2. Contributions*

The argument made in this thesis is that systems reliability approach to analyzing operational risks—precisely because it treats systems interactions—cannot be based on the decomposition, linear methods of contemporary practice. These methods cannot logically capture the interactions and feedback of complex systems. Analyzing operational risks in engineered systems using the proposed systems reliability approach is very promising. There are many factors leading to this conclusion, among them,

- The importance of emergent behaviors, which cannot be enumerated *ex anti;*
- The need to account for time in failure analysis;
- The feedback of operating procedures and human reliability in systems function;
- The need to fuse models across different technological and human systems;
- The chaining of precursors in accident sequences.

These have not usually been accounted for in operational risk analysis in dam safety and the proposed systems simulation approach in this thesis doe accounts for systems interactions and feedback loops that are generally unaccounted for in the contemporary methods. Examples of how the presented systems reliability framework incorporates these and the implications of these factors for moving to simulation-based approaches is presented in this thesis.

### *9.3. Recommendations for Future Work*

Systems reliability models do not perfectly characterize a system, thus no matter how well a model is constructed, there will always be some discrepancy between the real system and the simulation model. Inescapably, there will be simplifications in the physics, based on features that are too complicated to be included in the model, features omitted due to lack of knowledge, disparities between the scales on which the model and the system operate, and simplifications and approximations in solving the mathematical equations underlying the system. Thus, understanding structural uncertainty and how to accommodate it into the systems model is one of the most challenging aspects of the systems reliability framework which requires further research. Another challenging aspect of structural uncertainty is the quantification of the uncertainty that arises due to the parametrization of only the salient aspects of the system; resulting in unmodelled physical processes. In model development, certain physical processes will inevitably be neglected if there's a belief that these processes have little to no effect on the model's accuracy yet adds complexity to the mathematical description. Moreover, during model development, there may be a failure to include certain physical processes due to a lack of knowledge about those processes. Other uncertainties such as observational uncertainty— which arises due to errors in the measurement of natural systems—and uncertainties about the Initial Boundary conditions need to be explored and accounted for in the systems reliability modeling framework.

Additionally, although the influence of disturbances external or internal to the system is considered in this thesis, further work needs to be done to explore the complexities inherent in such disturbances. Most natural hazard disturbances such as earthquakes, forest fires and lightning strikes occur not only in time but also in space (spatio-temporal processes). A significant strength of the systems modeling approach to flow-control reliability is the multi-physics framework in which disturbances such as seismic events, lightning strikes or grid unavailability can be accommodated. Further research needs to be performed on mathematical characterization of such disturbances, so they may be incorporated into the systems model where present. The possibility of one or more combinations of both external and internal disturbances, ranging from those that occur essentially simultaneously to those that occur at different times but in ways that the effects of the disturbances combine, also need to be considered.

Going forward, a full understanding of human errors in flow control systems and the development of a proper methodology for human reliability analysis is important to incorporate into the proposed systems modeling framework. The development of a new holistic HRA model is a critical task for the future of dam and levee safety risk assessment. The general trend today in incorporating human errors in Dam safety risk analysis is to treat humans as machines with failure rates. The behavior of human operators in fault situations is, of course, more complex than modeling operators as behaving as error-prone equipment. The state of information available to the operator is critical, as are his or her detection, situation analysis, and problem-solving skills to assess that information. Thus, the influence of operator behavior is more complex than may easily be captured via traditional reliability modeling. For hydropower systems, many of the human errors are focused during the operations phase but they are also frequently found in design deficiencies, maintenance practices or strategies, lack of updated safety manuals and upper management decisions regarding such systems. Accidents and failures occur not just because hazard loads are high and dam components are fragile, but through the interactions of physical systems, sensor and SCADA systems, operating policies, human factors, and other aspects of dams. The concept of model integration is central to all systems modelling. Hence, it is imperative that the interaction of the various systems is key to understanding how the whole responds to changing conditions and disturbances in human operation. Additionally, the documentation of existing HRA methods is very important in understanding the human performance functions from both the cognitive and physical perspective. These performance functions are critical to developing a realistic framework that can be used to understand the human failure events and estimate the Human Error Probabilities for the system.

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