

DYNAMIC ASSESSMENT OF HYDRO TURBINES FOR EFFECTIVE POWER UTILIZATION IN KAINJI AND JEBBA DAMS

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Abstract

This study investigates the dynamic assessment of hydro turbines for effective power utilization in Kainji and Jebba dams. Hydro power plant mainly consists of three sections, governor (controller), hydro servo system and hydro turbine. The hydro turbine governor is usually coupled to a synchronous generator to drive the shaft so that the mechanical energy of turbine is converted to electrical energy. Accurate modeling of hydraulic turbine and its governor system is essential to depict and analyze the dynamic system response. In this work, both hydraulic turbine and turbine governor system were modeled. The hydro turbine model is designed using penstock and turbine characteristic equations. The simulation model is developed using MATLAB/SIMULINK. The dynamic response of the governing system to the disturbances such as load variation on the generator parameter during fault was presented. The results graphically demonstrate the effect of load variation on generator parameters under a three phase to ground fault. The transient behavior of generator voltage, current and the rotor speed are also captured. Similarly, two hydropower dams along the River Niger (Kainji and Jebba dams) in Nigeria were analyzed for energy generation using multilayer perceptron artificial neural network. Total monthly historical data of Kainji and Jebba hydropower reservoirs' variables and energy generated were collected for a period of forty-two years (1980-2021) and (1994-2021) for the network training. These data were divided into training, testing and holdout data set. The neural network analysis yielded a good forecast for Kainji and Jebba hydropower reservoirs with correlation coefficients of 0.89 and 0.77 respectively. These values of the correlation coefficient showed that the networks are reliable for modeling energy generation as a function of reservoir variables for future energy prediction. Accordingly, the study recommended that Advanced Real-Time Controllers should be developed so as to reduce system oscillations and improve overall system stability, Parameter Tuning Methods should be implemented with the use of advanced optimization techniques, such as sensitivity analyses and automated parameter tuning algorithms, Hydro Turbine and Governor Models should be implemented with the use of real-time simulation tools, allowing for the integration of these models with other power systems, such as wind or solar power systems, Optimization Algorithms should be developed with the consideration of uncertainty in system parameters, operating conditions and Advanced Control Systems should be developed with the goal of improving grid resiliency and reliability..

Keywords: Dynamics, Assessment, Hydro Turbines, Effective, Power Utilization and Dams.

Introduction

As hydropower generation accounts for 75% of renewable sources in the world's electrical mix (Turgeon *et al.*, 2021), optimizing hydropower generation is crucial from an economic and environmental perspective. An optimized hydropower operation offers numerous benefits, including better use of water resources, increased renewable energy production, and mitigating growing energy demand. To achieve

this optimization, accurate inflow prediction is essential for hydropower generation forecasting, which involves estimating the power available to the grid using hydrological and climatic data. By adopting performance criterion and optimizing dispatch of generating units, hydropower plants can operate at their best efficiency, ultimately providing a reliable and cost-effective solution to meet rural energy demands (Bordin *et al.*, 2020). A hydropower plant's operation involves complex processes, including pre-operation, real-time, and post-operation stages. The pre-operation steps can be separated into long-term, medium-term, short-term, and real-time scheduling (Bordin *et al.*, 2020). Proper planning is essential, as hydropower offers the lowest cost among renewable energy sources, with low risk and a longer life span of up to 80 years (MAC, 2012).

Major decisions are made during the design process, and system design tradeoff studies are carried out to select an optimum design (Black, 98). Considerations in turbine design and plant operation are critical in achieving a viable hydroelectric system, which relies on hydro turbines to transfer kinetic energy from moving water to a rotating shaft, generating electricity. Notably, as energy demands continue to rise with global population growth, the need for reliable and sustainable energy sources becomes increasingly urgent (Kokubu *et al.*, 2012). Among the various forms of energy, electricity has become a key driver of development, with hydroelectric power (HPS) standing out as a particularly promising solution (Kumar & Saini, 2010). HPS offers a renewable, environmentally friendly, and cost-effective energy source with a higher capacity factor than wind energy, all while requiring minimal civil infrastructure (Liu *et al.*, 2017). The process of converting the kinetic energy of running water into electrical energy through a turbine is central to this technology (Mehr *et al.*, 2022). In cases of runoff, water is channeled through a penstock to the turbine and countries like Venezuela, Norway, and Brazil already generate the majority of their electricity from hydropower, further highlighting its reliability and potential for widespread adoption. Globally, hydroelectricity now accounts for a significant portion of energy production, with countries like Switzerland generating over half of their electricity from hydropower (BP, 2012). The ongoing push for increased use of renewable energy sources underscores the growing recognition of hydropower's role in meeting the global energy challenge (Fleischmann *et al.*, 2021).

The background to this research study sought to explore the feasible options available for parameter estimation of hydro-turbine plants using Artificial Intelligence (AI) neural network solutions since they offer a more promising solution compared to the conventional linear optimizers. Furthermore, the use of mathematical modeling and simulations are well-known established processes that have been successfully used to illustrate the dynamic behaviour of mechanical and electrical machines, therefore a comprehensive model of Hydro turbine and synchronous generator was presented under ideal condition and three-phase to ground faults to illustrate the responses due to the transient disturbance.

Statement of the Problem

Hydroelectric energy is generated through the natural cycle of water flow, where evaporation sends water upwards into the atmosphere, only to be pulled down by gravity. However, it is unimaginable that despite the abundance of water resources, the suitability of a body of water for hydroelectric power generation is

often limited by various factors. A mild climate, accessible surrounding area, and a body of water with a good head, sufficient volume, and strong flow are all necessary conditions, which are often difficult to find in conjunction. Furthermore, the high initial cost of building a hydroelectric plant is a significant obstacle, making it paradoxical that industrial-scale hydroelectric plants are considered a cost-effective source of energy in the long run. Additionally, the construction process is complex and may require the expertise of highly experienced engineers and architects, which can be a challenge in developing countries. It is also ironic that hydroelectric power plants, which are designed to harness the natural flow of water, can have devastating effects on the natural environment, disrupting the natural flooding process and affecting fish and other organisms that rely on the natural flow of the river. Moreover, dams can have significant social impacts, influencing the lives of people who live near them. In some cases, massive damming projects have resulted in the flooding of entire villages, evicting local populations and creating social tension. The failure of a large hydroelectric dam can also have catastrophic consequences, including widespread flooding, civilian deaths, and destruction of property. Hydroelectric plants are especially vulnerable to climate change and its resulting effects, such as extreme weather events like hurricanes and droughts. The future of hydroelectricity lies in the development of better technologies improving its efficiency, as well as in energy decentralization, building smaller, interconnected, and distributed hydroelectric plants equipped with battery storage. The statement of the problem is embedded in the followings:

- i. Cavitation: Which occurs due to the formation of the voids or bubbles where the pressure of the liquid changes rapidly. The bursting of such voids can cause strong shockwaves as a result of change in fluid pressure. Cavitation defects can be found at four places: leading edge, trailing edge, draft tube swirl and inter blade vortex.
- ii. Erosion: Erosion problem which reduces power generation. Erosion rate depends upon the silt size, concentration, hardness, velocity of striking particles with components and material of component.
- iii. Fatigue: This is a process which makes material weak by repeated cyclic stress. It is another problem which can become cause of turbine failure in case of hydro turbine assembly connected with number of components and welding joints. This process is noticed during the transition of load variation in hydro turbine and material of runner and other component.
- iv. Material defect: Maximum failure in hydro turbine is due to cavitation and silt erosion. Materials defects in turbines and other components are controlled during manufacturing, but at the time of installation some material defects can also generate causing failure of components.

Aim and Objectives of the Study

This study is aimed at optimizing the dynamic assessment of hydro turbines for effective power utilization in Kainji and Jebba Dams. The specific objectives of the study is to:

- i. Analyze two hydropower dams (Kainji and Jebba dams) in Nigeria for energy generation using multilayer perceptron artificial neural network.
- ii. Mathematically model the dynamics of hydro-power plant characteristics

How Hydropower Works

Hydroelectric is electricity generated from running water. The running water is directed to the turbine where it rotates the turbine shaft connected to the rotor of the generator. It's regarded as free energy as it's generated from running water, continuously running without human intervention. It's one of the oldest sources of energy, dating back to a thousand years back when it was used to turn paddle wheels used for grinding grains. Today, it's one of the most reliable green energy sources adopted in all parts of the world due to its environmental friendliness. A lot of improvement has been made to hydroelectric power design in a bid to achieve a more efficient system. Importantly, there are three main types of turbines that are used based on the capacity and weight difference of the water:

- i. Francis's turbine
- ii. Pelton turbine and,
- iii. Kaplan turban. The Francis Turbine was developed in 1848 by British American engineer James B. Francis, and it is the most used hydraulic turbine. A centripetal flow turbine, as the water reaches the impeller through a spiral conduit, adjustable palettes attached to the stationary part direct the flow so that it strikes the impeller blades. It is used for medium height differences from 10 up to 400meters, and from 2 to 100 cubic meters per second of water capacity.

Hydroelectric power is a renewable energy source that harnesses the energy of water in motion. This energy can be seen as a form of solar energy, as the sun powers the hydrologic cycle, which gives the Earth its water (Salihu, 2025). The hydrologic cycle is a complex process that involves the continuous movement of water on, above, and below the surface of the Earth. The hydrologic cycle begins with evaporation, where water from the oceans, lakes, and rivers is heated by the sun and turns into water vapor. This water vapor rises into the atmosphere and cools, condensing into clouds. When the clouds become saturated with water, they release their water content in the form of precipitation, which can be in the form of rain, snow, sleet, or hail (dos Santos Sousa et al., 2025). Once the precipitation reaches the Earth's surface, it can follow several paths. Some of it may evaporate, while some of it may percolate into the soil to become groundwater. Groundwater can eventually feed into streams, rivers, and lakes, where it can evaporate again and continue the cycle (Zvereva et al., 2025). The movement of water in the hydrologic cycle is what drives hydroelectric power generation. Hydroelectric power plants harness the energy of moving water by channeling it through a turbine, which converts the kinetic energy of the water into electrical energy (Liu et al., 2025).

The Effective Capacity of a Power Plant

Most power stations have instrumentation that measures such information as the line frequency, voltages, currents, power and energy generated. While all but the last two are helpful in the day-to-day running of the plant, the last provides the engineer with a useful basis for measuring the performance of the facility. Let $p(t)$ be the instantaneous power produced by the plant; then the energy can be expressed as follows:

$$\Delta(t) = p(t)\Delta t$$

Then the total energy over the time interval $[0, T_f]$ designated as (T_f) can be expressed as follows:

$$(Tf) = \int (t)t$$

The effective capacity of the plant is defined as the average power over the observation period and can be expressed as follows:

$$P = (Tf)/Tf$$

This definition has interesting ramifications. If a power plant has rated capacity of P MW, then if it is to be run as efficiently as possible, it will generate PTf MW-hr. which can be charged at some nominal tariff. This process effectively provides a benchmark against which to measure any other deviation from the ideal situation. Clearly for a plant that is 100% functional $P = P$. That is the upper limit of the effective capacity and should be the target for an ideal operation of such a facility especially where it is used to meet the base load demand. Otherwise, it is easy to show that if (t) is less than the above in parts of the closed interval with a nonzero measure, then;

$$P = \int (t) + \int (t) < P * T1 + \Omega 1 \Omega PPT$$

Where

P = Effective capacity,

P^* = Operating capacity when the system is operating at less than its rated value of P , and $T1$ is the total time during which the plant was operating at less than the rated capacity. $\Omega 1$ is the union of the segments on the interval $[0, Tf]$ where $p(t) \neq P_{rated}$, and $[0, Tf] = \Omega 1 \cup \Omega p$.

Seasonal effects like comparing performances during a season or weekly, monthly, tri-annual, biannual, quarterly etc. are relatively easy to determine and can be helpful in assessing how good the performance of the units is. In general, however, since the up-times and downtimes are stochastic processes, the effective capacity is also a stochastic process and will manifest a characteristic that reflects the statistical properties that determine the up-times/time-between failures of the specific unit. A useful analysis that can help in decision-making can be derived by considering the potential revenue generation and the actual for the unit. Loss of revenue can then be readily determined and used as a basis for arguments in favor of enhanced funding for repairs, maintenance and retrofitting. Assuming the cost of say $N \theta$ /MWhr., then the maximum revenue to be expected R_{max}

$$R_{max} = P \times \theta \times \Delta T$$

The loss due to failure to operate at a rated capacity can be determined as follows:

$$\Lambda = (P - P)\Delta T$$

In a rational decision-making context where revenue streams play a major role in allocation of resources, this analysis can provide a very detailed argument for boosting allocations to the often neglected and inarticulately represented engineering maintenance budget.

Theory of Francis Water Turbines

The Francis water turbine has a rich historical development that spans over two centuries. The turbine's evolution is a testament to human ingenuity and the quest for efficient and sustainable energy production (Lewis et al., 2014). The precursor to the Francis Turbine was the reaction turbine, developed by Jean-Victor Poncelet in the 1820s. Poncelet's design used a spiral casing to direct water into the turbine,

increasing efficiency. However, it was the mathematical foundations laid by Leonhard Euler that paved the way for the development of modern hydraulic turbines (Calinger, 2015). Euler's work on the theory of turbines and the concept of "reaction" versus "impulse" turbines laid the foundation for the development of modern hydraulic turbines, including the Francis turbine. Euler's equations, which describe the motion of fluids, are still widely used today in the design and analysis of hydraulic turbines. Building on Euler's work, Benoît Fourneyron, a French engineer, invented the first practical hydraulic turbine, known as the Fourneyron turbine (Lewis et al., 2014). Fourneyron's design, patented in 1832, used a spiral casing and a runner with fixed blades, similar to the Francis turbine.

Fourneyron's turbine was the first to achieve high efficiency and power output, paving the way for the development of more advanced hydraulic turbines. The success of Fourneyron's turbine sparked a wave of innovation in hydraulic turbine design, and it was during this period that James B. Francis, an American engineer, began working on his own turbine design. Francis's breakthrough came in 1849 when he designed the first Francis Turbine for the Lowell Machine Shop in Massachusetts (Lewis et al., 2014). His innovative design featured a spiral casing, a guide vane, and a runner with fixed blades. This configuration allowed for a significant increase in efficiency, making the Francis Turbine a game-changer in hydroelectric power generation. Samuel B. Howd, an American engineer, played a crucial role in the development and testing of the Francis Turbine. Howd's contributions helped to refine the design and improve its efficiency. The Francis Turbine's success was not limited to its efficiency; it also proved to be highly reliable and adaptable. Throughout the late 19th and early 20th centuries, the Francis Turbine underwent significant improvements (Ermenc, 2019). The introduction of the draft tube, which allowed for a more efficient use of the available head, was a major innovation. Additionally, advancements in materials and manufacturing techniques enabled the construction of larger, more efficient turbines. The 20th century saw the widespread adoption of Francis Turbines in hydroelectric power plants around the world. The turbines played a crucial role in meeting the increasing demand for electricity, particularly during the post-World War II period (Evans, 2017). The development of large Francis turbines, such as those used in the Hoover Dam and the Grand Coulee Dam, further solidified their position as a leading technology in hydroelectric power generation. Today, Francis turbines remain a dominant force in hydroelectric power generation, with ongoing research and development focused on improving efficiency, reducing environmental impact, and increasing reliability (Suhaime et al., 2023). Francis turbines are widely used over the world, operating under heads varying from 30 to 500m. A single unit can develop power as high as 750MW. The specific speed ranges from 60 to 400. Formerly, its specific speed was limited to about 60 and it was radial inward flow type, but at present, they are the mixed flow type with radial entry and axial exit. The versatility and adaptability of Francis Turbines have made them a popular choice for hydroelectric power plants worldwide. Below indicates the diagram of Francis water turbine, which illustrates its complex design and functionality.

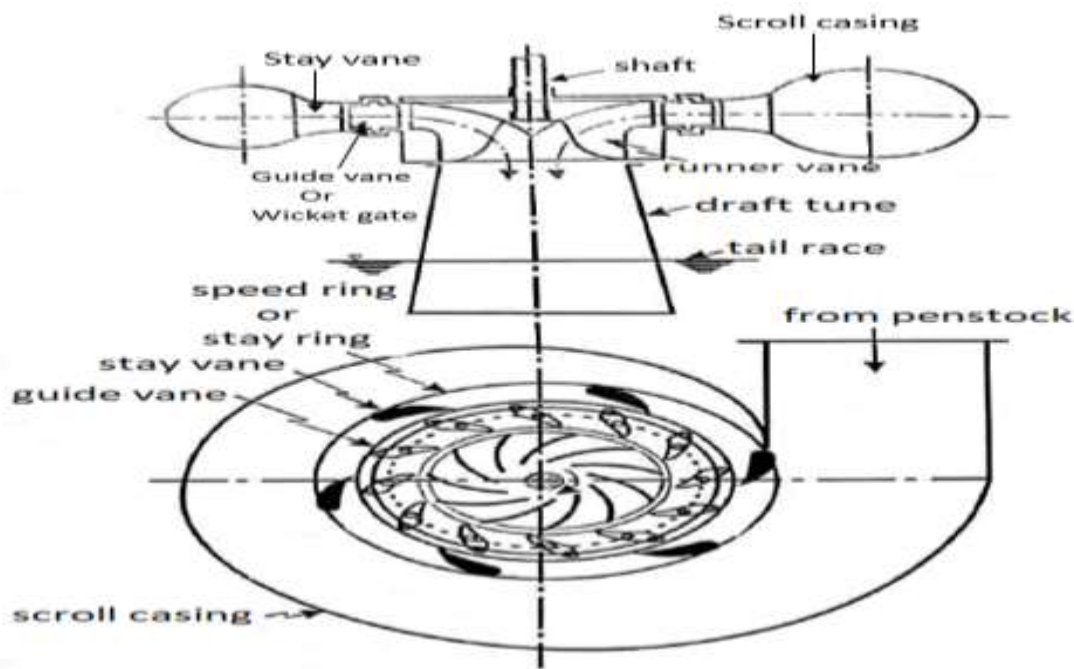


Figure 2.25: Diagram of Francis Water Turbine (Suhaime et al., 2023).

Advantages and Disadvantages of Hydroelectric Power Plant

The utilization of hydroelectric power has been a cornerstone of renewable energy production for decades, offering numerous advantages that have contributed to its widespread adoption. One of the primary benefits of hydroelectric power is its lack of fuel requirement, as it harnesses the energy of water to generate electricity, making it a perennially available source, as noted by Kirmani et al. (2021). This, in turn, leads to low operating costs, as there is no need to purchase fuel, making the cost of electricity per KWH significantly cheaper compared to thermal or nuclear power plants, a point emphasized by Bagher et al. (2015). Additionally, hydroelectric power plants do not produce any pollution, as they do not involve the combustion of fossil fuels, thereby eliminating the problem of ash disposal, as discussed by Das and Jena (2020). Moreover, hydroelectric power plants are simple in concept, self-contained, and reliable in operation, with a greater life expectancy of around 50 years, compared to thermal or nuclear power plants, which have a lifespan of approximately 30 years, according to Naranjo Silva and Álvarez del Castillo (2021). Furthermore, hydroelectric turbines can be easily switched on and off in a short period, making them highly flexible and adaptable to changing energy demands, a feature highlighted by Şahin et al. (2016). However, despite these advantages, hydroelectric power plants also have several disadvantages.

Related Works

A thorough analysis of the most current research reveals a wide range of studies targeted at improving turbine performance. Kokubu *et al.*, (2012), in their work on performance improvement of a micro eco crossflow hydro turbine, delve into the investigation of performance enhancements for a micro eco crossflow hydro turbine, aiming to bolster the efficiency and effectiveness of small-scale hydro-turbine

systems. The study focuses on optimizing the design and operational parameters of a micro eco crossflow hydro turbine to maximize energy extraction while minimizing losses and environmental impact. By exploring innovative approaches and technologies tailored for micro-scale hydro-turbine systems, Kokubu *et al.* aimed to address the challenges associated with sustainable energy production at smaller scales. Their research contributes valuable insights into the optimization of micro hydro-turbines, paving the way for enhanced performance and broader adoption of small-scale hydroelectric power generation solutions. However, it should be noted that the empirical study by Kokubu *et al.* (2012) is related to objective (ii) "Analyze the hydro turbine input-output Modeling Estimation" as it investigates the performance enhancements for a micro eco cross-flow hydro turbine, focusing on optimizing design and operational parameters to maximize energy extraction while minimizing losses and environmental impact. The study's emphasis on analyzing the input-output relationships of the micro hydro-turbine system demonstrates the importance of understanding the complex interactions between turbine design, operational parameters, and energy output. The point of departure between the empirically reviewed work and the current study is the recognition that existing research, such as Kokubu *et al.*'s study, has primarily focused on optimizing the performance of small-scale hydro-turbine systems, whereas the current study aims to address the broader challenge of optimizing the assessment and management of hydro turbines in general, encompassing a wider range of turbine sizes and configurations.

Tsuzuki *et al.*, (2015) completed a study on development of a complete methodology to reconstruct, optimize, analyze and visualize Francis turbine runners. The study introduced a meticulous methodology tailored to the intricate process of reconstructing, optimizing, analyzing, and visualizing Francis turbine runners. This holistic approach not only offers a deep dive into the intricacies of turbine design but also provides a systematic framework for enhancing performance and efficiency. By meticulously reconstructing the turbine runners, researchers and engineers gain a nuanced understanding of the underlying mechanisms governing their operation. Through optimization techniques embedded within the methodology, potential inefficiencies are identified and rectified, paving the way for improved turbine performance. Furthermore, the analytical tools integrated into the methodology allow for a thorough examination of various performance metrics, enabling researchers to pinpoint areas of improvement and refine turbine designs accordingly. Lastly, the visualization component of the methodology provides a tangible representation of the optimized turbine design, facilitating communication and decision-making among stakeholders. Notably, the empirical study by Tsuzuki *et al.* (2015) is related to objective (iii) "Derive and model the dynamic equations of a synchronous generator" as it introduces a comprehensive methodology for reconstructing, optimizing, analyzing, and visualizing Francis turbine runners, which is a crucial component of hydroelectric power plants that interacts with the synchronous generator. The study's focus on developing a systematic framework for enhancing turbine performance and efficiency demonstrates the importance of understanding the complex interactions between turbine design, optimization techniques, and performance metrics. The point of departure between the empirically reviewed work and the current study is the recognition that existing research, such as Tsuzuki *et al.*'s study,

has primarily focused on developing methodologies for optimizing turbine design and performance, whereas the current study aims to develop a more comprehensive understanding of the dynamic interactions between hydro turbines, generators, and power systems, requiring the derivation and modeling of dynamic equations that govern these interactions. Overall, Tsuzuki *et al.*'s methodology stands as a cornerstone in the quest for enhancing Francis turbine performance, offering a comprehensive approach that combines theoretical insights with practical applications.

Bahrami *et al.* (2016), in their research titled Multi-Fidelity Shape Optimization of Hydraulic Turbine Runner Blades Using a Multi-Objective Mesh Adaptive Direct Search Algorithm, concentrate on refining the design of hydraulic turbine runner blades through a multi-fidelity shape optimization approach employing a multi-objective mesh adaptive direct search algorithm. This research is centered on enhancing the efficiency and performance of hydraulic turbines by optimizing the geometric configuration of runner blades. By employing advanced computational techniques and optimization algorithms, the study aims to iteratively refine the blade shape to achieve multiple objectives, such as maximizing energy extraction, minimizing losses, and reducing flow disturbances. Through the integration of multi-fidelity modeling and adaptive search strategies, Bahrami *et al.* contribute to the advancement of optimization methodologies tailored specifically for hydraulic turbine applications. This research represents a significant step forward in the quest to enhance the efficiency and performance of hydraulic turbines, thereby facilitating the continued growth and sustainability of hydroelectric power generation.

He *et al.* (2019) delved into the investigation titled "Optimal impoundment operation for cascade reservoirs," where they focused on exploring advanced techniques to optimize impoundment operations. By employing a combination of parallel dynamic programming with importance sampling and successive approximation methods, their study aimed to enhance the operational efficiency and effective utilization of water resources in cascade reservoir systems. Through their research, He and colleagues sought to address the complex challenges associated with managing water resources across multiple reservoirs within a cascade system. Their innovative approach offered valuable insights into developing robust strategies for sustainable water management and enhancing the overall performance of cascade reservoir systems. As such, the empirical study by He *et al.* (2019) is related to objective (iii) "Derive and model the dynamic equations of a synchronous generator" as it investigates optimal impoundment operation for cascade reservoirs, which involves understanding the complex interactions between water resources, reservoir operations, and power generation. Although the study does not directly focus on synchronous generators, its emphasis on optimizing impoundment operations to enhance operational efficiency and effective utilization of water resources demonstrates the importance of understanding the dynamic interactions between hydro-power plant components. The point of departure between the empirically reviewed work and the current study is the recognition that existing research, such as He *et al.*'s study, has primarily focused on optimizing individual components of hydro-power systems, such as reservoir operations, whereas the current research has attempted to develop a more comprehensive understanding of the complex interactions between various components of hydro-power plants, including turbines,

generators, and power systems. By addressing this knowledge gap, the current research provides a more holistic understanding of hydro-power plant dynamics, contributing to the development of more efficient and sustainable hydro-power systems. The current research has attempted to derive and model the dynamic equations of a synchronous generator, which is a critical component of hydro-power plants, to optimize overall system performance and power generation.

Methodology

Hydro Power Plant Modelling

This section which is usually materials and methods is introduced in order to explain the mathematical modeling and the dynamics of hydro turbine governor. Figure 3.1a shows a block diagram of hydro power plant while the simplified diagram is illustrated in Figure 3.1b. The stored water at certain head (H) contains potential energy. This energy is converted to kinetic energy. When it is allowed to pass through the penstock, this kinetic energy is converted to mechanical energy (rotational energy) which allows water to fall on the runner blades of the turbine. As the shaft of the generator is coupled to the turbine, the generator produces electrical energy by converting the mechanical energy into electrical energy. The speed governing system of turbine adjusts the generator speed based on the feedback signals of the deviations of both system frequency and power with respect to their reference settings. This ensures power generation at synchronous frequency.

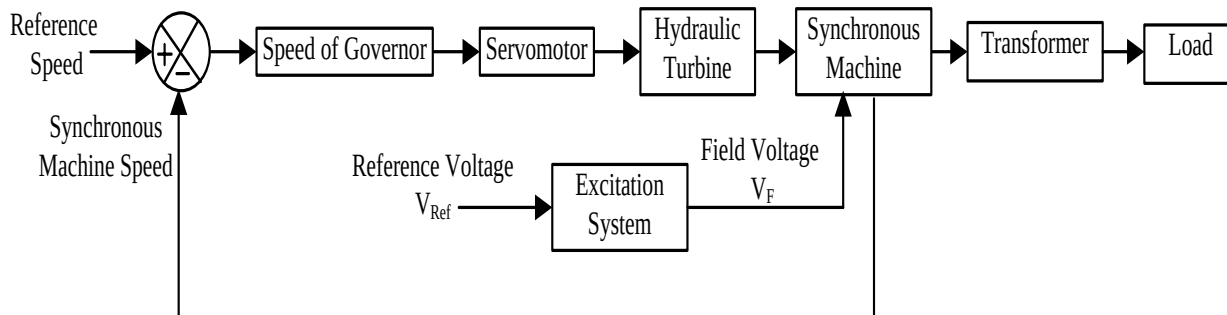


Figure 3.1a: Block Diagram of a Hydro Power Plant

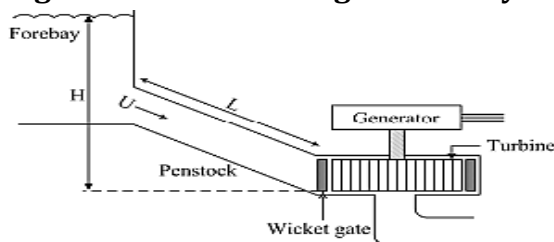


Figure 3.1: Simplified Block Diagram of a Hydro Power Plant

The hydro turbine governor is used to maintain a constant turbine speed hence the frequency and active power in response to load variation. The turbine governor regulates water input into a turbine, which in turn rotates the generator to produce electricity. This section details the mathematical modeling of the

mechanical-hydraulic turbine governing system. A mathematical representation of a hydraulic governing system including the turbine-penstock is introduced here. Hydro turbine governing systems are strongly influenced by the effects of water inertia. To adjust the gate opening of the wicket gate, the servomotor controls a pilot valve. The servomotor is activated by the signals generated from the turbine governor. Equation 3.1 is derived based on the assumption of short penstock, insignificant water hammer and incompressible flow of fluid through penstock. It defines the characteristics of per unit turbine flow in terms of water time constant and head.

$$\frac{dQ}{dt} = \frac{(h_s - h - h_1)g \times A}{L} \quad (3.1)$$

Where:

Q = Per-unit turbine flow,

h_s = Static head of the water column,

h = Head at the turbine water admission,

h_l = Per-unit conduit head losses,

L = Length of the conduit section,

A = Cross-section area of the penstock,

g = Gravitational acceleration.

The given equation (in 3.1) can be converted to per unit equation by dividing it with its base quantity which results to equation (3.2).

$$\frac{d \frac{Q_{base}}{Q_{base}}}{dt} = \frac{d\bar{q}}{dt} = \frac{(h_s - h - h_1)}{h_{base}} \times \frac{h_{base} \times gA}{L \times Q_{base}} = (h_s - h - h_1) \times \frac{1}{T_w} \quad (3.2)$$

$$T_w = \frac{L \times Q_{base}}{h_{base} \times gA} \quad (3.3)$$

Where:

h_{base} = Difference between Lake Head and Tail head.

Q_{base} = Maximum gate opening of the reservoir. $\bar{q}$ is the per unit water flow,

$\bar{h}_s$ = Per unit static head,

$\bar{h}$ = Per unit head at the turbine water admission.

$\bar{h}_1$ = Per unit head loss due to friction.

$\bar{T}_w$ = Water time constant or water starting time.

The block diagram for the above models is presented in Figure 3.2.

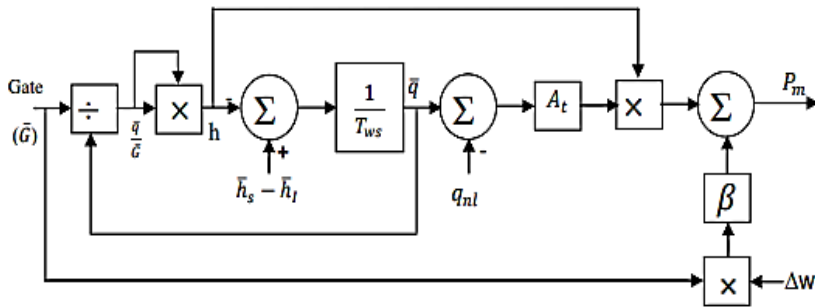


Figure 3.2: Block diagram of Penstock and turbine models

3.1.1 Hydro Turbine Input-Output Modeling Estimation

This section considered the equations describing the variation in flow rate, gate opening, runner blade movement of the hydro turbine and the mechanical power developed with respect to the turbine speed deviation and damping. Francis turbine is used in a wide range of application in the hydraulic industry because of its high efficiency of performance. As the developed power in the turbine varies with the flow rate, so does the system operate or attains a steady state when the flow through the penstock gets constant. The flow rate through turbine is a function of gate opening and head as presented in equation (3.4).

The equations governing the transient performance of the hydraulic turbines are based on the following assumptions:

- Frictional resistance of the hydraulic turbine is neglected which implies that the blade is considered smooth.
- The water hammer on penstock is neglected
- The fluid is considered to be incompressible
- The velocity of water in penstock varies directly with gate opening
- The developed power output of turbine is proportional to the product of head and velocity of flow.

$$q = F(\text{gate, head}) \quad (3.4)$$

The flow rate through turbine in per unit system is given by equation (3.5)

$$\bar{q} = \bar{G}\sqrt{\bar{h}} \quad (3.5)$$

The turbine model is based on steady state measurements of the output power and water flow and the relation is given by equation (3.6).

$$P_m = A_t h (q - q_{nL}) = \frac{1}{(\bar{G}_{max} - \bar{G}_{min})} \times h \times (q - q_{nL}) \quad (3.6)$$

$$A_t = \frac{1}{(\bar{G}_{max} - \bar{G}_{min})} \quad (3.7)$$

Where:

P_m = Per unit mechanical power,

q = Per unit water flow,

A_t = Turbine gain,

q_{nL} = Per unit no-load flow,

$\overline{G_{max}}$ = Maximum full load per unit gate opening and

$\overline{G_{min}}$ = No-load per unit gate opening.

Practical turbine has less than 100% efficiency. It has a small speed deviation and damping effect due to the water flow in the turbine. Therefore, during a transient disturbance due to speed deviation, a modified form of equation (3.6) in terms of speed deviation is presented in equation (3.8).

$$P_m = A_t h (q - q_{nL}) - \beta G \Delta \omega \quad (3.8)$$

$\Delta \omega$ = Speed deviation which defines the deviation of the actual turbine-generator speed from the normal speed.

$\beta G \Delta \omega$ = Speed deviation due to damping at the gate opening.

The hydraulic characteristics and mechanical power output of the turbine has been modeled here. The nonlinear characteristics of hydraulic turbine are neglected in this model. The complete MATLAB block diagram of hydro turbine model is shown in Figure 3.3. The actuator's (hydro-electric servo motor) output is the gate opening and it controls the valve to maintain a uniform speed by regulating the rate of water flow. The flow rate Q and net head H has been represented in equations (3.1)-(3.2). Here $(h_s - h - h_1)$ is entered as an input and the flow rate is the output signal. h_s has been assumed a static head with reference value of 1pu. Using a summation block, the signal $(h_s - h - h_1)$ is obtained. To find the actual water flow rate the no load flow is subtracted from Q using a sum block. Turbine frictional factor is neglected in this modeling. To get the value of mechanical power output P_m , equation 3.6 is used to establish the relation between the developed power at turbine, actual water flow rate and the Head.

Hydro turbine governor is a major part of hydro power plant. It is basically used for two purposes which are enumerated as follows:

- i. Firstly, it develops mechanical power at the shaft of the generator which is fed to the synchronous generator for production of electricity.
- ii. Secondly, it controls the variation of speed of the generator such that the generated frequency remains constant. The PID controller, hydroelectric servo system and hydraulic turbine are the main components of the hydro turbine governor. These block models of components are connected in such a manner that the generated frequency remains constant. The block diagram of hydro turbine governor is shown in Figure 3.4. The first element of the governor is PID controller. The error in speed and deviation of power is entered as input to the controller, which generate the position signal at the input of the hydro-electric servo motor. Furthermore, the servo motor responds by controlling the valve according to input signal to the servo mechanism. The valve is used to control the flow rate such that the generated frequency of the system remains constant.

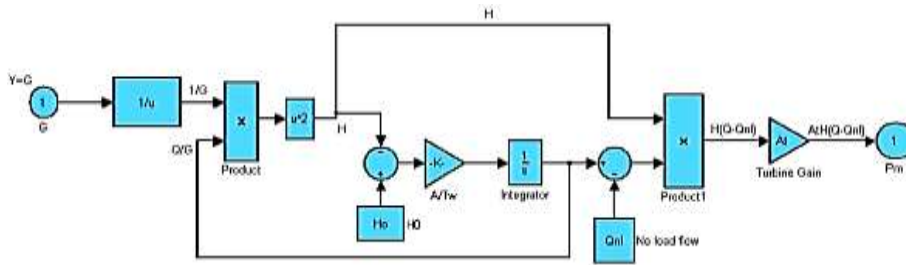


Figure 3.3. MATLAB/Simulink Block Diagram of Hydro Turbine Model.

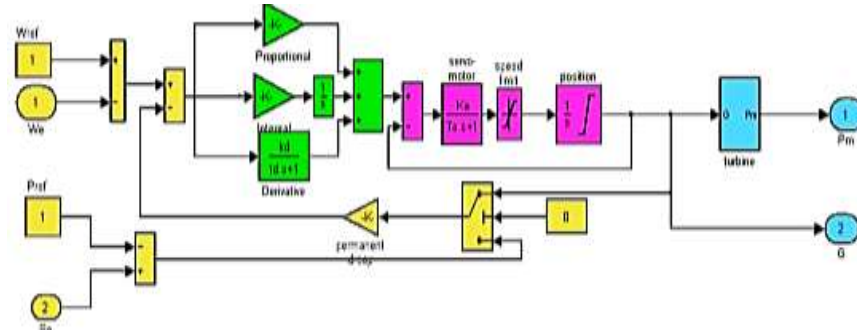


Figure 3.4. MATLAB/Simulink Model of Hydro Turbine Governor.

Mathematical modeling of a Synchronous Generator

This section presents the dynamic equations of three phase salient pole synchronous machine applied in the computer simulation. The electrical and electromechanical behaviour of most synchronous machines can be predicted from the dynamic equations that describe the three phase salient pole synchronous machine. The qdo voltage equations of a synchronous machine are clearly presented in equations (3.21) – (3.27).

$$V_{qs} = r_s i_{qs} + P\lambda_{qs} + \omega_r \lambda_{ds} \quad (3.21)$$

$$V_{ds} = r_s i_{ds} + P\lambda_{ds} - \omega_r \lambda_{qs} \quad (3.22)$$

$$V_{os} = r_s i_{os} + P\lambda_{os} \quad (3.23)$$

$$V'_F = r'_F i'_F + P\lambda'_F \quad (3.24)$$

$$V'_{kd} = r'_{kd} i'_{kd} + P\lambda'_{kd} \quad (3.25)$$

$$V'_g = r'_g i'_g + P\lambda'_g \quad (3.26)$$

$$V'_{kq} = r'_{kq} i'_{kq} + P\lambda'_{Fq} \quad (3.27)$$

The flux linkages equations are presented in equations (3.28) – (3.34).

$$\lambda_{qs} = L_q i_{qs} + L_{mq} i'_g + L_{mq} i'_{kq} \quad (3.28)$$

$$\lambda_{ds} = L_d i_{ds} + L_{md} i'_F + L_{md} i'_{kd} \quad (3.29)$$

$$\lambda_o = L_{Ls} i_o \quad (3.30)$$

$$\lambda'_F = L_{md} i_{ds} + L_{md} i'_{kd} + L'_{FF} i'_F \quad (3.31)$$

$$\lambda'_{kd} = L_{md} i_{ds} + L_{md} i'_{kd} + L'_{kdkd} i'_{kd} \quad (3.32)$$

$$\lambda'_g = L_{mq} i_{qs} + L_{mq} i'_{kq} + L'_{gg} i'_g \quad (3.33)$$

$$\lambda'_{kq} = L_{mq}i_{qs} + L_{mq}i'_g + L'_{kqkq}i'_{kq} \quad (3.34)$$

The various leakage inductances and the mutual inductances are related by equations (3.35) – (3.40).

$$L_q = L_{Ls} + L_{mq} \quad (3.35)$$

$$L_d = L_{Ls} + L_{md} \quad (3.36)$$

$$L'_{FF} = L_{LF} + L_{md} \quad (3.37)$$

$$L'_{kdkd} = L_{Lkd} + L_{md} \quad (3.38)$$

$$L'_{gg} = L_{Lg} + L_{mq} \quad (3.39)$$

$$L'_{kqkq} = L_{Lkq} + L_{mq} \quad (3.40)$$

Substituting equations (3.35) – (3.40) into equations (3.28) – (3.34) gives rise to the modified flux linkage equations represented in (3.41) – (3.46).

$$\lambda_{qs} = L_{Ls}i_{qs} + L_{mq}(i_{qs} + i'_g + i'_{kq}) \quad (3.41)$$

$$\lambda_{ds} = L_{Ls}i_{ds} + L_{md}(i_{ds} + i'_F + i'_{kd}) \quad (3.42)$$

$$\lambda'_F = L'_{LF}i'_F + L_{md}(i_{ds} + i'_F + i'_{kd}) \quad (3.43)$$

$$\lambda'_{kd} = L'_{Lkd}i'_{kd} + L_{md}(i_{ds} + i'_F + i'_{kd}) \quad (3.44)$$

$$\lambda'_g = L'_{Lg}i'_g + L_{mq}(i_{qs} + i'_g + i'_{kq}) \quad (3.45)$$

$$\lambda'_{kq} = L'_{Lkq}i'_{kq} + L_{mq}(i_{qs} + i'_g + i'_{kq}) \quad (3.46)$$

The electromechanical power output developed by the machine is given by equation (3.47).

$$P_{em} = \frac{3}{2}(\omega_r(\lambda_d i_{qs} - \lambda_q i_{ds})) \quad (3.47)$$

Where ω_r stands for the electrical speed which is related to the mechanical speed by equation (3.48).

$$\omega_r = \left(\frac{P}{2}\right) \omega_m \quad (3.48)$$

Substituting equation (3.48) into (3.47) gives rise to equation (3.49)

$$P_{em} = \frac{3}{2} \times \frac{P}{2} \times \omega_m (\lambda_d i_{qs} - \lambda_q i_{ds}) \quad (3.49)$$

For computer simulation purposes, the real and reactive power developed by the machine is given by equations (3.50) and (3.51).

$$P = V_{qs}i_{qs} + V_{ds}i_{ds} \quad (3.50)$$

$$Q = V_{qs}i_{ds} - V_{ds}i_{qs} \quad (3.51)$$

The electromechanical torque developed is given by equation (3.53).

$$T_{em} = \frac{3}{2} \times \frac{P}{2} (\lambda_d i_{qs} - \lambda_q i_{ds}) \quad (3.52)$$

Motor speed is derived from the motional torque and represented in (3.53) while the angular position is given by (3.54).

$$\frac{d\omega_{mr}}{dt} = \frac{1}{J}(T_{em} - T_{Load} - B\omega_{mr}) \quad (3.53)$$

$$\theta_r = \int_0^t \omega_{mr} dt \quad (3.54)$$

The above modeled equations for the hydro turbine plant and the synchronous generator were simulated in a MATLAB/SIMULINK environment. The Simulink models of the different stages with the respective subsystems and overall block diagrams are presented in Appendixes 1-3 while the simulation parameters are presented in appendix 4-5.

Table 3.1 Feature of Kainji and Jebba Hydropower Reservoirs

Reservoir Features	Kainji	Jebba
First year of operation	1968	1984
Installed capacity (MW)	760	540
Design power plant factor	0.86	0.70
Number of generators	8	6
Reservoir flood storage capacity (Mm ³)	15,000	4,000
Reservoir flood level (m)	143.50	103.55
Maximum operating reservoir elevation (m.a.s.l)	141.83	103.00
Minimum operating reservoir elevation (m.a.s.l)	132.00	99.00
Maximum storage (active storage capacity), (Mm ³)	12,000	3,880
Minimum storage (Dead storage capacity), (Mm ³)	3,000	2,880

Source: Ifabiyi, I. P. (2021)

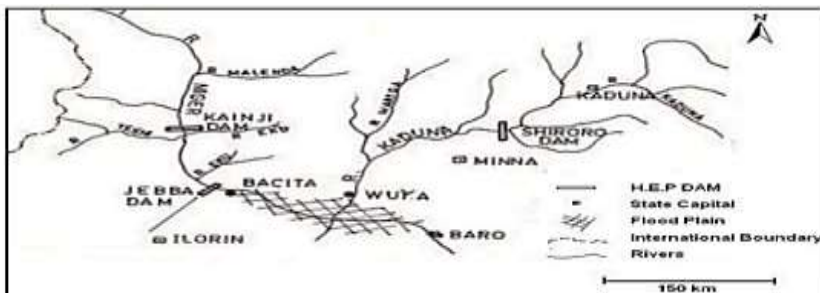


Figure 3.4: Location Map of the Kainji and Jebba Hydropower Reservoirs on Niger River

Source: Salami, A. W *et al* (2012)

3.3 Statistical Sampling of Hydro power reservoir variables for Kainji and Jebba Dam.

Total monthly historical data of Hydro Power reservoir variables for Kainji and Jebba stations were analyzed. The data include reservoir inflow (Mm³), storage (Mm³), reservoir elevation (m), turbine release (Mm³), net generating head (m), plant use coefficient, tail race level (m), evaporation losses (Mm³) and energy generation (MWh). These data were collected from Power Holding Company of Nigeria (PHCN) for a period of forty two years (1980-2021) for Kainji and twenty eight years (1994-2021) for Jebba station. The summary of the statistical analysis is presented in Tables 3.2 and 3.3 for Kainji and Jebba Hydro Power reservoirs. The following statistical equations were used to realize the values presented in Tables 3.2 and 3.3 respectively.

$$\text{Mean} = \bar{x} = \frac{\sum fx}{\sum f} \quad (3.55)$$

$$\text{Standard deviation} = S.D = \sqrt{\frac{\sum fd^2}{\sum f}} = \sqrt{\frac{\sum f(x - \bar{x})^2}{\sum f}} \quad (3.56)$$

$$\text{Spearman coefficient of variation} = CV = 1 - \frac{6 \sum d_i^2}{N(N-1)} \quad (3.57)$$

Where: d_i = Maximum – minimum value and N = number of years in review.

Table 3.2: Summary of Statistical Analysis of the Kainji Hydro Power Data (1980 - 2021)

Reservoir Elements	Mean	Median	S.D	C.V	Minimum	Maximum	Skew
Reservoir Inflow (Mm ³)	2504.35	2408.77	632.93	0.25	1396.93	3653.04	0.44
Reservoir Storage (Mm ³)	8058.58	8088.18	722.04	0.09	6654.53	9258.92	-0.17
Reservoir Elevation (m)	138.17	138.12	0.67	0.00	136.86	139.34	0.00
Turbine Release (Mm ³)	1881.96	1880.54	419.47	0.22	1131.05	2806.00	0.18
Net Generating Head (m)	38.57	38.48	0.59	0.02	37.63	39.90	0.41
Energy Generation (MWh)	178570.26	158016.25	73090.93	0.41	81553.53	378612.85	1.13
Plant Use Coefficient	0.39	0.35	0.15	0.39	0.17	0.80	1.06
Tail Race Level (m)	100.97	100.37	1.92	0.02	98.02	103.83	0.26
Evaporation Loss (Mm ³)	145.20	146.00	5.30	0.04	138.52	152.10	-0.09

Note: S.D = Standard deviation, C.V = Coefficient of variation

Table 3.3 Summary of Statistical Analysis of the Jebba Hydro Power Data (1994 - 2021)

Reservoir Elements	Mean	Median	S.D	C.V	Minimum	Maximum	Skew
Reservoir Inflow (Mm ³)	2647.90	2474.85	729.23	0.28	1588.86	4154.26	0.51
Reservoir Storage (Mm ³)	3595.74	3594.00	79.81	0.02	3423.55	3751.58	0.13
Reservoir Elevation (m)	102.01	101.99	0.34	0.00	101.22	102.60	-0.17
Turbine Release (Mm ³)	2182.05	2186.21	297.70	0.14	1566.66	2572.62	-0.37
Net Generating Head (m)	28.15	28.22	0.54	0.02	26.61	29.07	-1.05
Energy Generation (MWh)	175134.17	163525.08	54346.26	0.31	103542.36	282039.95	0.77
Plant Use Coefficient	0.47	0.45	0.15	0.33	0.26	0.72	0.20
Tail Race Level (m)	73.69	73.61	0.40	0.01	73.09	74.54	0.64
Evaporation Loss (Mm ³)	49.28	49.30	1.90	0.04	45.57	51.27	-0.77

Note: S.D = Standard deviation, C.V = Coefficient of variation

Source: Power Holding Company of Nigeria (PHCN), 2012

Artificial Neural Network (ANN) Data Analysis of Kainji and Jebba HP Station

The data sets were partitioned into three; training, testing and holdout samples for each of the stations. The training data records were used to train the neural network in order to obtain a model. The testing sample is an independent set of data records used to track errors during training in order to prevent overtraining. The holdout sample is another independent set of data records used to assess the final neural network; the error for the holdout sample gives an estimate of the predictive ability of the model. In this study, multilayer perceptron (MLP) was adopted with sigmoid activation function both at hidden and output layers. A normalized method of rescaling was used for scaling the Hydro Power reservoir variables. The neural network was trained with 504 data for Kainji station and 336 data for Jebba station. The data for each of the stations include reservoir inflow (Mm³), storage (Mm³), reservoir elevation (m), turbine release (Mm³), net generating head (m), plant use coefficient, tail race level (m) and evaporation losses (Mm³) as input layers and energy generation (MWh) as output layer. In the training process, the weights of input layer and hidden layer nodes are adjusted by checking the training and testing stage performances of neural networks. The coefficient of correlation and the mean square error are the performance criteria for the testing stage.

Results and Analysis

The ANN generated network structure is presented in Figure 4.1 while a plot of predicted value against the energy generated for Kainji Hydro power is represented in Figure 4.2 respectively.

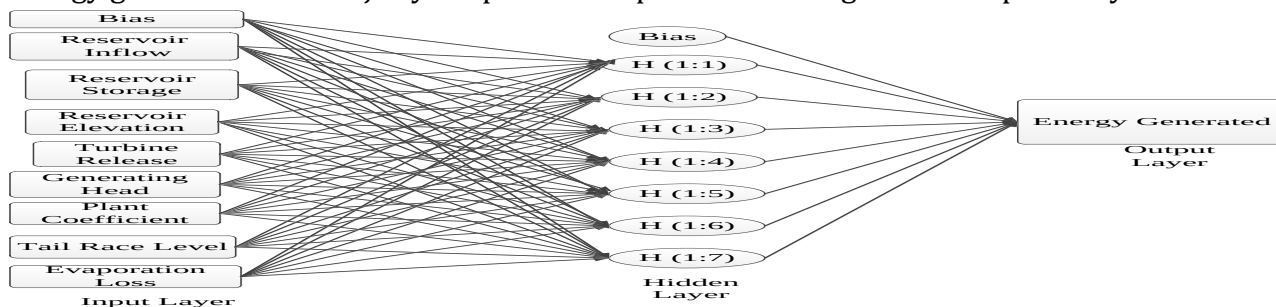


Figure 4.1: Generated Network Structure

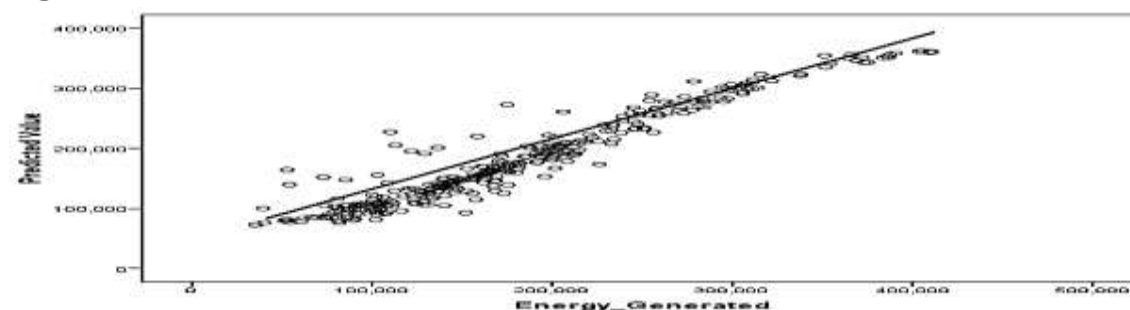


Figure 4.2: Scatter Plot of Predicted and Observed Energy Generated for Kainji HP

Similarly, the scatter plot of the predicted value against the Energy generated for Jebba hydro power plant is presented in Figure 4.3.

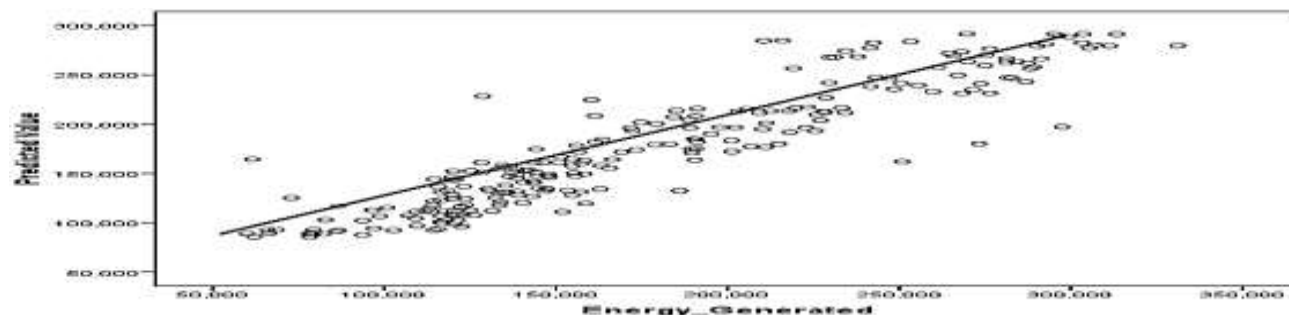


Figure 4.3 Scatter Plot of Predicted and Observed Energy Generated for Jebba HP.

The waveforms of the dynamic characteristics of the three phase synchronous generator and the hydro-turbine operated machine are presented in Figures 46-4.12 under ideal operational condition and under a three phase to ground fault.

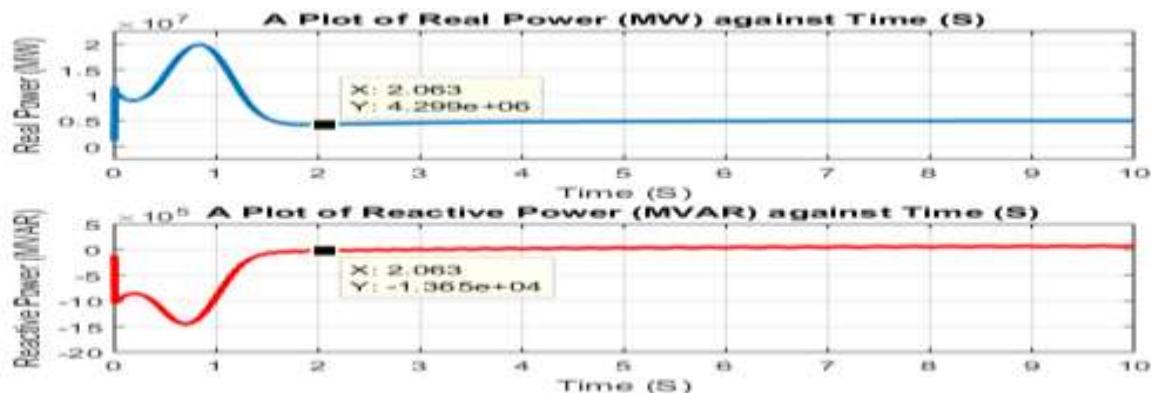


Figure 4.6. A Plot of Real & Reactive Power against Time

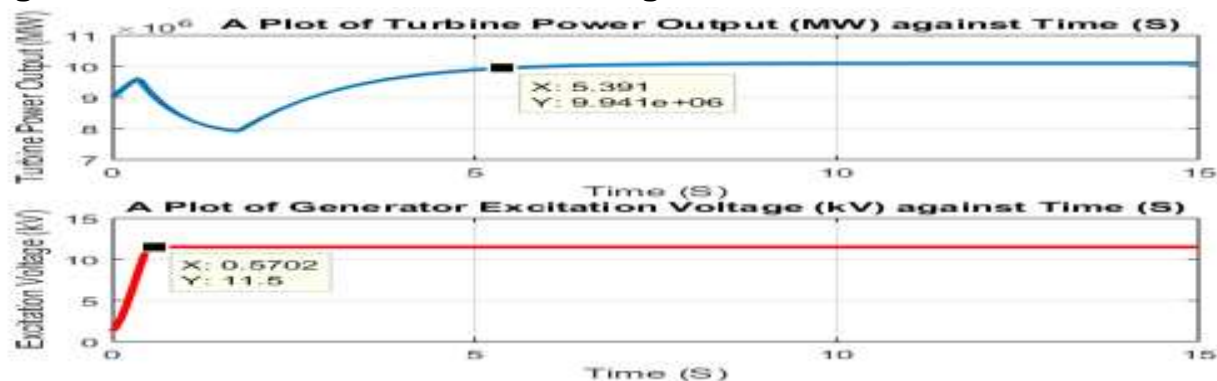


Figure 4.7 A Plot of Turbine Output Power & Excitation Voltage against Time



Figure 4.8. A Plot of Generator Speed, Power Output & Torque against Time

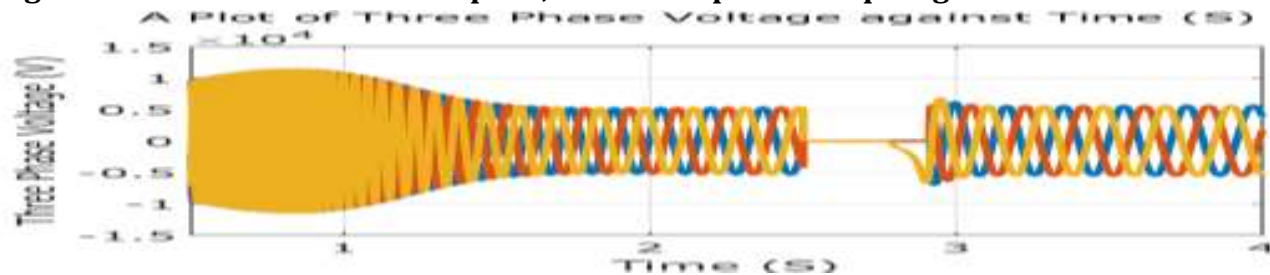


Figure 4.9. A Plot of Three Phase Voltage against Time under 3LG-Fault

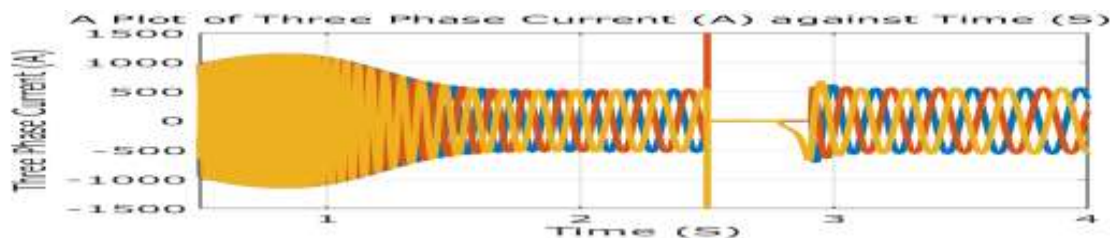


Figure 4.10. A Plot of Three Phase Current against Time under 3LG-Fault

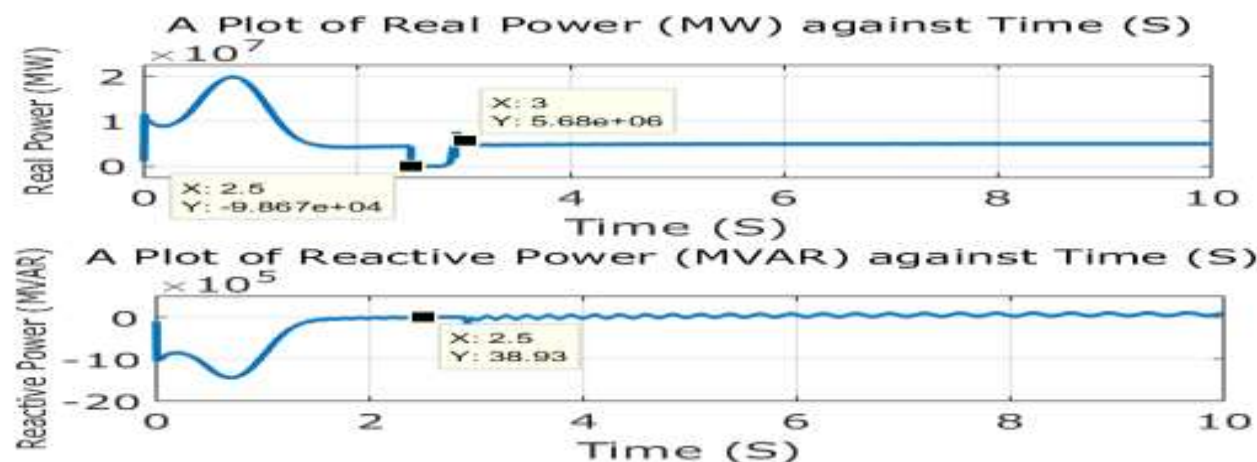


Figure 4.11. A Plot of Generator Real & Reactive Power against Time under 3LG-Fault

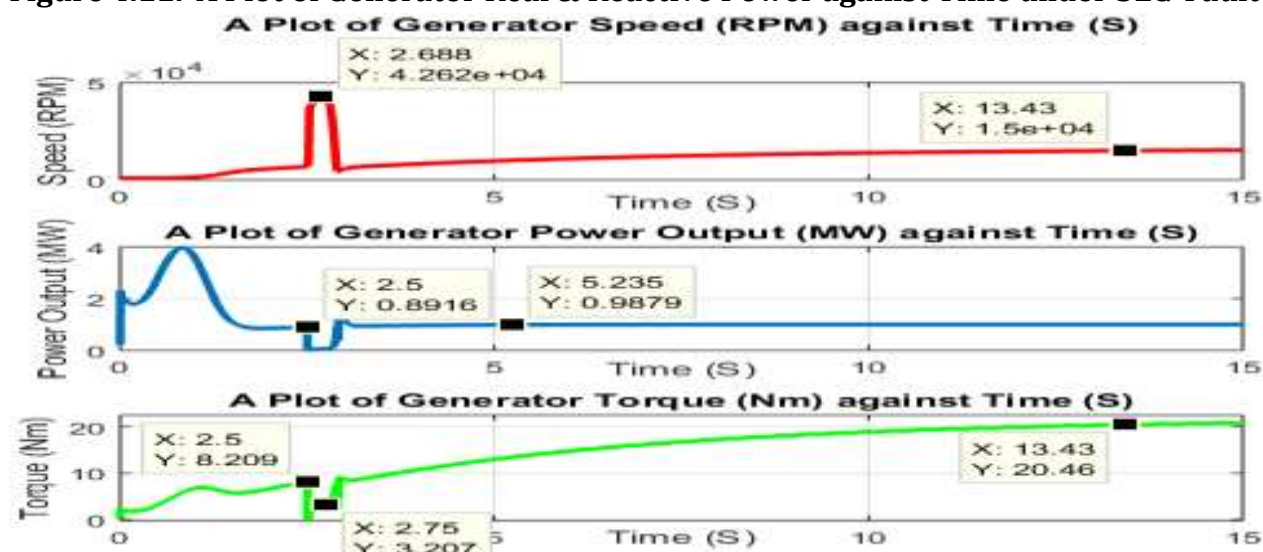


Figure 4.12 Plot of Generator Speed, Power Output & Torque against Time under 3LG-Fault

Discussion of Findings

The findings of this study also suggest that the restoration of eutrophicated reservoirs can be facilitated through the use of model approaches that assess the propagation of water quality improvements downstream along a cascade system. This is in line with Soares *et al.* (2022), who employed a model

approach to assess the restoration from eutrophication in interconnected reservoirs. Furthermore, the use of statistical analysis has provided a comprehensive understanding of the reservoirs' behavior, including the computation of statistical parameters such as mean, median, and standard deviation for each variable. This training involves estimation of main controlling parameters called network weights. A supervised training algorithm, otherwise known as feed-forward back propagation or Mackquard Lederberg Propagation algorithm, was adopted to optimize the neural network model. The application of this algorithm is supported by Bhattarai *et al.* (2019), who employed novel trends in modeling techniques of Pelton Turbine bucket for increased renewable energy production. Their study highlighted the importance of optimizing turbine performance to enhance energy generation. Similarly, Kokubu *et al.* (2012) demonstrated the performance improvement of a micro eco crossflow hydro turbine, emphasizing the need for efficient turbine design. The use of multiobjective optimization techniques, as employed by Liu *et al.* (2017) in their parametric design of an ultrahigh-head pump-turbine runner, can also enhance turbine performance. The achievement of synchronous speed and stable power output observed in this study is consistent with the findings of the study by He *et al.* (2019), highlighting the effectiveness of modeling and optimization techniques in achieving efficient hydro turbine performance. When a severe three-phase to ground fault was introduced on the machine at 2.5-2.75 seconds, it was observed that the generator voltage and current value were completely grounded to a zero value within the fault region, as shown in Figures 4.9 and 4.10. This condition is usually not allowed to be prolonged to avoid downtime and machine breakdown. This finding is consistent with the study of Soares *et al.* (2022), who employed a model approach to assess the restoration from eutrophication in interconnected reservoirs, demonstrating the importance of accurate modeling in predicting reservoir behavior and ensuring reliable operation.

Summary of Findings

Energy generation from hydro power reservoir relies essentially on the adequate planning and operation of the reservoir and this can be achieved through modeling of its variables in relation to energy generation. Kainji and Jebba hydropower reservoir variables were modeled for energy generation using neural network multilayer perceptron with sigmoid function as activator. Neural network model yielded a good forecast for Kainji and Jebba hydropower reservoirs with correlation coefficients of 0.89 and 0.77 respectively. These values showed strong linear relationship between the observed and predicted energy generation and this is an indication that the Artificial Neural Network model is reliable for modeling of hydropower reservoirs for energy generation. The dynamic characteristics of the turbine and the synchronous generator were obtained through mathematical modeling and simulation processes. The results obtained showed that the turbine and the generator performance are affected by parameter variation such as the governor settings and controller adjustments. The simulation results equally indicated that during a three phase to ground fault, rapid changes were observed in the turbine and generator speed, real and reactive power which is very vital for design engineers in averting the downtime of composite system operation failure.

Conclusion

The general non-linear mathematical models of hydraulic turbine have been presented in this thesis. This model is suitable for dynamic studies of hydro power plant. At the same time, it also focused on how to implement the developed mathematical models into a simulation process to showcase the physical characteristic performance of the composite system. Severe disturbances were examined on dynamic model of the power plant and power systems. Results showed sufficient accuracy of the model for the whole working range. The current turbine models with minor refinements will improve accuracy over the entire operating range. Kainji and Jebba hydropower reservoir variables were modeled for energy generation using neural network multilayer perceptron with sigmoid function as activator. Neural network model yielded a good forecast for Kainji and Jebba hydropower reservoirs with correlation coefficients of 0.89 and 0.77 respectively. These values showed strong linear relationship between the observed and predicted energy generation and this is an indication that the NN model is reliable for modeling of hydropower reservoirs for an efficient energy generation.

Contributions to Knowledge

This work serves as a useful guide for power engineering experts and research students who want to use an appropriate hydro power plant model including the penstock, turbine, governor, and generator for stability studies. Development of a Mathematical model of the dynamics of a hydro-power plant and a synchronous generator. The analysis of two hydropower dams (Kainji and Jebba dams) in Nigeria for energy generation using a multilayer perceptron artificial neural network. This thesis provides required background knowledge for studying the effect of actual data on the model parameters and behavior of a hydro turbine performance method. The review and comparison of different models help the electrical engineers to choose the best model for specific studies. Furthermore, the appropriate tuning of the conventional controller and governor using a simple approach has been presented which is very useful for educational purposes and real time applications for efficient power generation.

References

- Bagher, A. M., Vahid, M., Mohsen, M., & Parvin, D. (2015). Hydroelectric energy advantages and disadvantages. *American Journal of Energy Science*, 2(2), 17-20.
- Bahrami, S., Tribes, C., Devals, C., Vu, T. C., & Guibault, F. (2016). Multi-fidelity shape optimization of hydraulic turbine runner blades using a multi-objective mesh adaptive direct search algorithm. *Applied Mathematics and Modelling*, 40, 1650–1668.
- Bhattarai, S., Vichare, P., Dahal, K., Al Makky, A., & Olabi, A. G. (2019). Novel trends in modelling techniques of Pelton Turbine bucket for increased renewable energy production. *Renewable and Sustainable Energy Reviews*, 112, 87-101.
- Bordin, C.; Skjelbred, H.I.; Kong, J.; Yang, Z. Machine learning for hydropower scheduling: State of the art and future research directions. *Procedia Comput. Sci.* **2020**, 176, 1659–1668

- Calinger, R. S. (2015). Leonhard Euler: *Mathematical genius in the enlightenment*. Princeton University Press.
- dos Santos Sousa, R., Dewes, J. J., Rauch, H. P., Sutili, F. J., & Hörbinger, S. (2025). First results of soil and water bioengineering interventions to stabilise and control erosion processes in hydroelectric power plant reservoirs in Brazil. *Ecological Engineering*, 211, 107458.
- Ermenc, J. J. (2019). Small Hydraulic Prime Movers for Rural Areas of Developing Countries: A Look at the Past. In *Renewable Energy Resources And Rural Applications In The Developing World* (pp. 89-113). Routledge.
- Evans, P. S. (2017, January). Water turbines of the woods point goldfield 1866–1867. In *19th Australasian engineering heritage conference: Putting water to work: Steam power, river navigation and water supply* (pp. 76-89). Engineers Australia Mildura, VIC.
- Fleischmann, A. S., Brêda, J. P. F., Passaia, O. A., Wongchuig, S. C., Fan, F. M., Paiva, R. C. D., ... & Collischonn, W. (2021). Regional scale hydrodynamic modeling of the river-floodplain-reservoir continuum. *Journal of Hydrology*, 596, 126114. Monitored reservoirs in Brazil. *Environmental Modelling & Software*, 134, 104803.
- He, S., Guo, S., Chen, K., Deng, L., Liao, Z., Xiong, F., & Yin, J. (2019). Optimal impoundment operation for cascade reservoirs coupling parallel dynamic programming with importance sampling and successive approxim
- Kirman, F. A. H. I. M., Pal, A., Mudgal, A., Shrestha, A., & Siddiqui, A. (2021). Advantages and disadvantages of hydroelectric power plant. *International Journal of Innovative Science and Research Technology*, 6(7), 715-718.
- Kokubu, K., Kanemoto, T., Son, S. W., & Choi, Y. D. (2012). Performance improvement of a micro eco cross-flow hydro turbine. *Journal of Advanced Marine Engineering and Technology (JAMET)*, 36(7), 902-909.
- Kumar, P., & Saini, R. P. (2010). Study of cavitation in hydro turbines—A review. *Renewable and Sustainable Energy Reviews*, 14(1), 374-383.
- Lewis, B. J., Cimbala, J. M., & Wouden, A. M. (2014, March). Major historical developments in the design of water wheels and Francis hydroturbines. In *IOP Conference Series: Earth and Environmental Science* (Vol. 22, No. 1, p. 012020). IOP Publishing.

- Liu, J., Zhang, J., Huang, Z., Xu, H., Bai, Y., & Wang, G. (2025). Modeling the hydraulic roughness of a movable flatbed in a sand channel while considering the effects of water temperature. *International Journal of Sediment Research*, 40(1), 31-44.
- Liu, L., Zhu, B., Bai, L., Liu, X., & Zhao, Y. (2017). Parametric design of an ultrahigh-head pump-turbine runner based on multiobjective optimization. *Energies*, 10(8), 1169.
- Naranjo Silva, H. S., & Álvarez del Castillo, J. (2021). An approach of the hydropower: Advantages and impacts. A review. *Journal of Energy Research and Reviews*, 8(1), 10-20.
- Şahin, M., Güven, Y., Oğuz, Y., & Şahin, E. (2016). Importance of Hydroelectric Power Plants In Terms of Environmental Policy. *El-Cezeri*, 3(3).
- Salihu, I. (2025). Design and Implementation of a Prototype Micro Hydropower System Utilizing Jaffi Waterfalls, Nigeria. *International Journal*, 11(1).