Integrated Analysis of Reservoir Dynamics, Water Discharge and Hydroelectric Power Generation Using Daily Operational Data

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Abstract

Hydroelectric power is one of the most reliable renewable energy sources, and its efficient operation depends on optimal reservoir management and effective utilization of available water resources. However, comprehensive data-driven studies integrating reservoir dynamics, stage-wise electricity generation, and water discharge for large multi-stage hydropower systems remain limited. This study presents a detailed operational performance assessment of the Hydroelectric Complex, using daily operational data collected over the 2020–2021 water year. The analysis utilizes **365 daily observations** comprising reservoir water levels, daily reservoir rise/fall, stage-wise electricity generation, turbine water discharge, and overall power production. A comprehensive analytical framework incorporating descriptive statistics, monthly operational assessment, stage-wise performance evaluation, reservoir behavior analysis, and water–energy relationship assessment was developed. During the study period, the Koyna Hydroelectric Complex generated a total of **3184.47 million units (MU)** of electricity, with Stage I & II contributing **1227.84 MU (38.56%)**, Stage IV contributing **1200.55 MU (37.70%)**, Stage III generating **590.62 MU (18.55%)**, and KDPH producing **165.48 MU (5.19%)**. The combined turbine water discharge through Stage I, II and IV was **1886.18 million cubic meters (Mm³)**, while Stage III discharged **1058.68 mm³**, indicating efficient utilization of stored water resources. Monthly electricity generation varied considerably from **163.09 MU** in September 2020 to a peak of **386.77 MU** in March 2021, demonstrating strong seasonal variability in plant operation. Similarly, reservoir elevation increased from approximately **641.8 m** during the monsoon recharge period to **659.4 m** at full reservoir level before gradually declining during the dry season.

The results reveal a strong positive relationship between turbine water discharge and electricity generation, highlighting the effectiveness of coordinated multi-stage operation and reservoir regulation. The proposed analytical framework provides valuable insights for improving operational planning, reservoir scheduling, and water-use efficiency in large hydroelectric systems. The findings contribute to sustainable hydropower management and offer a practical decision-support approach for optimizing renewable energy generation under varying hydrological conditions.

Keywords: Hydroelectric Power, Reservoir Operation, Multi-Stage Hydropower, Electricity Generation, Water Discharge, Reservoir Dynamics, Operational Performance, Renewable Energy, Water–Energy Nexus, Data Analytics.

1. Introduction and Background

Hydropower is one of the most reliable and sustainable renewable energy sources, contributing significantly to electricity generation, flood control, irrigation, and water resource management worldwide. The performance of hydroelectric power plants is strongly influenced by reservoir storage conditions, hydraulic head, water discharge, turbine efficiency, and operational policies. Efficient utilization of available water resources has therefore become a critical requirement for maximizing energy production while ensuring long-term sustainability and operational reliability [1]. Traditionally, hydropower system performance assessment has relied on deterministic formulations and physical models derived from the fundamental hydropower equation. Although these approaches provide valuable engineering insights, they often fail to adequately represent the nonlinear relationships among reservoir dynamics, water utilization, and energy generation observed under actual operating conditions. The rapid advancement of digital monitoring systems, sensor technologies, and computational capabilities has consequently accelerated the transition from conventional analytical methods toward data-driven modelling approaches [2,3].Data-driven models have gained considerable attention in dam engineering due to their ability to capture complex system behavior using historical operational data. Salazar et al. [2] reported that data-based predictive models have become increasingly important for understanding dam behavior and supporting operational decision-making. Similarly, Hariri-Ardebili et al. [3] highlighted the growing role of soft computing and machine learning techniques in dam engineering, emphasizing their capability to model nonlinear interactions more effectively than traditional statistical methods. A substantial body of research has focused on deformation monitoring and structural behavior prediction of concrete dams. Classical Hydrostatic–Seasonal–Time (HST) models and their variants have long been used for monitoring dam displacement and structural responses [1]. However, these approaches exhibit limitations when applied to highly nonlinear operational conditions. To overcome these limitations, researchers have proposed advanced machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, Gaussian Process Regression (GPR), and Long Short-Term Memory (LSTM) networks for deformation prediction and structural health monitoring [4-11]. Recent studies have demonstrated that hybrid and ensemble learning models frequently outperform conventional statistical methods in terms of prediction accuracy and robustness [12,13].

The integration of physical principles with data-driven methods has emerged as a promising research direction in dam engineering. Song and Hu [12] proposed a data–physics-driven hybrid deformation monitoring model based on Bayesian optimization and Light Gradient Boosting Machine (LightGBM), while Yao et al. [13] developed a multisource data-driven framework for comprehensive assessment of dam behavior. These studies indicate that combining operational data with physical understanding can significantly improve model interpretability and predictive performance. Machine learning techniques have also been extensively applied in reservoir management and hydropower forecasting. Various researchers have investigated Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines, Random Forests, and deep learning architectures for reservoir level prediction, inflow forecasting, and hydropower generation estimation [14-21]. Üneş et al. [15] demonstrated that ANFIS models outperform conventional approaches for reservoir level prediction, while Almubaidin et al. [16] reported the effectiveness of machine learning techniques for daily forecasting of dam water levels. Villeneuve et al. [19] further highlighted the growing importance of artificial intelligence in hydropower scheduling, optimization, and energy forecasting.

Recent studies have also emphasized the role of digitalization, Industry 4.0 technologies, and digital twins in enhancing hydropower system efficiency and operational performance [21]. Digital twin frameworks facilitate real-time monitoring, predictive analytics, and decision support by integrating operational data with computational models. These developments have significantly improved the capability of hydropower operators to manage complex reservoir systems under dynamic environmental conditions.

Despite these advances, existing research primarily focuses on structural health monitoring, deformation prediction, seepage assessment, reservoir level forecasting, and hydropower scheduling. Limited attention has been given to the development of integrated energy flow models that explicitly quantify the relationships among reservoir storage conditions, water utilization, and electrical energy generation using actual operational plant data. Most available studies investigate either hydrological forecasting or structural behavior independently, without establishing a comprehensive framework linking reservoir dynamics directly to energy generation performance [14-21]. The Koyna Hydroelectric Complex, located in Maharashtra, India, is one of the largest multi-stage hydroelectric generation systems in the country. While the Koyna Dam has received significant research attention due to the historic 1967 reservoir-induced earthquake and subsequent seismic investigations [22, 23-26], relatively few studies have focused on operational energy flow analysis and performance assessment using actual reservoir and generation data. Existing Koyna-related research has predominantly addressed seismic safety, fracture mechanics, dam–reservoir interaction, and structural reliability [27-30]. Consequently, a substantial research gap exists in developing operationally oriented data-driven models capable of explaining and predicting energy generation behavior within the Koyna Hydroelectric Complex.

Furthermore, recent review studies have identified several unresolved challenges in dam engineering research, including the need for physically interpretable machine learning models, integrated operational frameworks, climate-resilient reservoir management strategies, and real-time decision-support systems [31,32]. Current hydropower performance studies rarely establish direct quantitative relationships among reservoir storage, water discharge, and generated energy while simultaneously providing practical performance assessment indicators suitable for operational planning and management. To address these research gaps, the present study develops and validates a data-driven mathematical framework for energy flow analysis and performance assessment of the Koyna Hydroelectric Complex. Daily operational data consisting of reservoir levels, reservoir fluctuations, water discharge, and energy generation records are utilized to establish mathematical relationships governing hydroelectric performance. Three modelling approaches are investigated, namely a Multiple Linear Regression Model, a Nonlinear Energy Flow Model, and a novel Integrated Energy Flow Model (IEFM). In addition, performance indicators are proposed to evaluate water-to-energy conversion effectiveness and overall hydropower system efficiency.

The primary contribution of this study lies in the development of a comprehensive energy flow modelling framework capable of linking reservoir dynamics and operational variables with electrical energy generation in a multi-stage hydroelectric power generation system. The proposed methodology provides a practical decision-support tool for hydropower operators while contributing to the growing body of knowledge on data-driven modelling and performance assessment of large-scale hydroelectric systems.

2. Research Methodology

This study adopts a data-driven analytical approach to investigate the energy flow characteristics and operational performance of the Koyna Hydroelectric Complex, India.

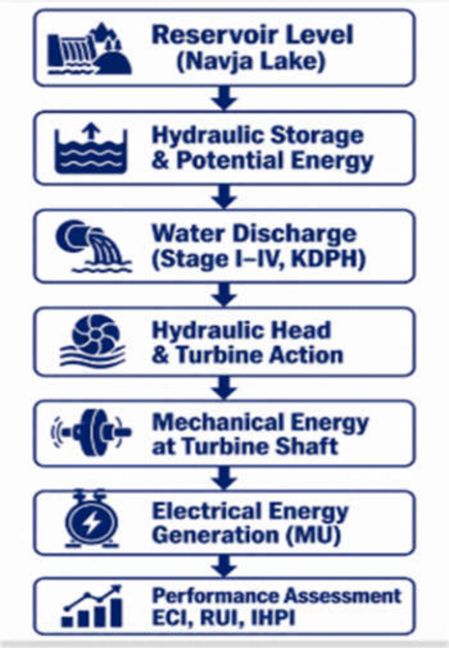

Figure 2. Energy flow framework illustrating the transformation of reservoir water potential into electrical energy and subsequent performance assessment in the Koyna Hydroelectric Complex.

The methodology integrates reservoir operational parameters, water utilization data, and electricity generation records to establish quantitative relationships governing hydropower production. The overall framework aims to evaluate the effectiveness of water-to-energy conversion within a multi-stage hydroelectric generation system and identify operational factors influencing energy production. The study was conducted using operational data from the Koyna Hydroelectric Complex located in Maharashtra, India. The Koyna project is one of the largest hydroelectric generation systems in the country and consists of multiple generating stages operating under varying hydraulic heads and reservoir conditions. The complex includes Stage I, Stage II, Stage III, Stage IV, and KDPH generating units. Energy generation is primarily governed by reservoir water availability, operating head, turbine discharge, and plant operating conditions. The study utilizes daily operational records obtained from the Koyna Generating Station Complex (KGSC). The dataset contains information related to reservoir conditions, hydraulic operations and electricity generation from multiple generating stages. The collected data represent the complete operational behavior of the hydroelectric system under varying hydrological and reservoir conditions. The collected daily records were screened for consistency and completeness. Data cleaning procedures were performed to remove duplicate entries and identify missing values. For each observation, total daily energy generation and total water discharge were computed by combining the generation and discharge values from all operating stages. The processed dataset was organized into a structured database suitable for statistical and mathematical analysis.

3 Data Collection

The present study utilizes operational data collected from the **Koyna Hydroelectric Generating Station Complex (KGSC), Maharashtra State Power Generation Company Limited (MAHAGENCO), India**. The dataset comprises authenticated daily operational records maintained by the station control room and represents actual plant performance under varying hydrological and operational conditions. The information was extracted from the Daily Progress Reports (DPRs), which are routinely generated for monitoring reservoir conditions, water utilization, and electricity generation across all generating stages.

The analysis presented in this research focuses on the **Water Year 2020–2021**, beginning with operational records from **June 2020**, marking the onset of the southwest monsoon season. Daily observations were recorded at **07:00 hours**, providing a consistent temporal reference for all hydrological and generation-related measurements. The collected data serve as the primary input for statistical analysis, mathematical modelling, and energy forecasting.

The dataset integrates both **hydrological variables** and **power generation parameters**, thereby enabling comprehensive evaluation of reservoir dynamics, water-energy relationships, and operational efficiency of the hydroelectric complex. Since Koyna is a multi-stage hydroelectric power station, generation data from individual stages as well as combined generation have been incorporated to accurately represent the complete energy production system.

Table 1 Operational variables collected from the Koyna Generating Station.

Variable	**Description**	**Unit**
Date	Daily observation date	Day
Navja Lake Level	Reservoir water level recorded at 07:00 hrs.	Feet (ft.) and Meter (m)
Rise/Drop	Daily variation in reservoir level	Feet
Stage I & II Generation	Daily electricity generated by Stage I and II	Million Units (MU)
Stage I & II Water Discharge	Water utilized for Stage I & II generation	mm^3 / TMC
Stage IV Generation	Daily electricity generated by Stage IV	MU
Stage IV Water Discharge	Water released through Stage IV turbines	mm^3 / TMC
Combined Stage I+II+IV Generation	Total generation from operating surface power stations	MU
Combined Water Discharge	Total water utilized by Stages I, II and IV	mm^3 / TMC
Stage III Generation	Underground power station generation	MU
KDPH Generation	Generation from Koyna Dam Power House	MU
KGSC Total Generation	Total electricity generated by the complete Koyna Generating Station Complex	MU

The June 2020 operational dataset consists of **30 consecutive daily observations**, representing the transition from the pre-monsoon to early monsoon period. During this month, reservoir levels varied between **2080.2 ft. and 2084.3 ft.**, reflecting the combined influence of power generation releases and initial monsoon inflows.

The total electricity generated during June 2020 by the Koyna Generating Station Complex was **249.20 Million Units (MU)**. The combined generation from **Stage I, II, and IV** contributed **188.305 MU**, while **Stage III** produced **45.93 MU** and **KDPH** contributed **14.965 MU**. Correspondingly, the total water discharged through Stages I, II, and IV amounted to **154.617 mm^3 (5.4595 TMC)**.

The observed operational data demonstrate significant day-to-day variability due to reservoir operation policies, electricity demand, and rainfall events. For example, maximum daily generation exceeded **25 MU** on high-discharge days, whereas minimum generation was below **3 MU** during reduced operational schedules. Such variability provides an ideal dataset for developing predictive models capable of capturing nonlinear relationships between reservoir storage, water discharge, and hydroelectric power generation.

Table 2 Monthly Statistics (June 2020)

Parameter	**Value**
Observation Period	1 June – 30 June 2020
Number of Daily Records	30
Reservoir Level Range	2080.2–2084.3 ft.
Stage I & II Generation	108.475 MU
Stage IV Generation	79.830 MU
Combined Stage I+II+IV Generation	188.305 MU
Stage III Generation	45.930 MU
KDPH Generation	14.965 MU
Total KGSC Generation	**249.200 MU**
Combined Water Discharge	154.617^3 (5.4595 TMC)

4 .Results and Discussions

For this research paper the details of June 2020 are described. June 2020 represents a transition period between the dry summer season and the onset of the southwest monsoon in the Koyna catchment. During the first half of the month, reservoir inflows remained limited, and hydroelectric generation continued to rely primarily on the stored water available in the Shivaji Sagar Reservoir. However, during the latter half of June, the commencement of monsoon rainfall gradually increased reservoir inflows, resulting in stabilization of reservoir levels and improved water availability for power generation. This transition significantly influenced the operational strategy of the Koyna Generating Station Complex (KGSC), as reservoir management shifted from conservation of stored water to the utilization of incoming inflows while maintaining optimum reservoir storage.

The operational performance of the generating station during June 2020 was analysed using the Daily Progress Reports maintained by Maharashtra State Power Generation Company Limited (MAHAGENCO). The analysis includes daily reservoir levels, reservoir rise and fall, electricity generation by different generating stages, turbine water discharge, and overall monthly generation. The observations provide valuable insight into the operational behavior of the hydroelectric system during changing hydrological conditions.

Table 3 Monthly Operational Summary for June 2020

Parameter	**Stage I & II**	**Stage IV**	**Stage I+II+IV**	**Stage III**	**KDPH**	**KGSC Total**
Electricity Generation (MU)	**108.475**	**79.830**	**188.305**	**45.930**	**14.965**	**249.200**
Water Discharge (Mm³)	**92.536**	**62.081**	**154.617**	**114.481**	–	**269.098**
Water Discharge (TMC)	**3.267**	**2.192**	**5.460**	**4.042**	–	**9.502**

4.1 Reservoir Behaviour

The reservoir exhibited two distinct operational phases during June 2020. During the first fifteen days, reservoir levels continued to decline gradually from **2083.80 ft.** on 1 June to approximately **2080.20 ft.**, reflecting continuous utilization of stored water under limited inflow conditions. Following the commencement of monsoon rainfall, reservoir inflows increased and reservoir levels began recovering, reaching **2084.30 ft.** on 21 June before gradually stabilizing near **2080.20 ft.** by the end of the month.

Unlike April and May, several days recorded **positive reservoir rise**, including **+1.10 ft. on 16 June** and **+1.40 ft. on 19 June**, indicating the arrival of substantial inflows into the reservoir.

These observations clearly demonstrate the transition from reservoir depletion to reservoir replenishment, which is characteristic of the early monsoon period in western Maharashtra.

Overall, reservoir operation during June reflects careful balancing between incoming water, electricity generation, and storage conservation, ensuring optimum utilization of available water resources.

4.2 Electricity Generation Analysis

Table 4. Daily Electricity Generation by Stage during June 2020

Date	Stage I & II (MU)	Stage IV (MU)	Stage III (MU)
01-Jun	3.595	1.017	0.518
02-Jun	2.125	0.192	0.688
03-Jun	2.345	0.269	0.884
04-Jun	2.440	1.625	1.246
05-Jun	2.875	1.496	0.724
06-Jun	2.530	1.335	0.882
07-Jun	3.050	0.532	0.662
08-Jun	4.810	6.159	2.242
09-Jun	6.755	12.312	4.652
10-Jun	3.830	6.128	2.586
11-Jun	2.405	0.000	0.346
12-Jun	4.345	2.859	1.212
13-Jun	2.730	1.169	1.488
14-Jun	2.525	0.000	0.488
15-Jun	2.835	0.295	0.768
16-Jun	2.640	0.315	1.432
17-Jun	2.290	0.000	0.422
18-Jun	1.095	0.144	0.940
19-Jun	3.295	1.533	1.056
20-Jun	2.705	1.446	0.974
21-Jun	2.395	0.351	1.296
22-Jun	5.090	6.363	2.296
23-Jun	5.905	6.499	3.206
24-Jun	8.935	11.715	4.408
25-Jun	7.960	9.283	3.758
26-Jun	4.245	2.866	1.816
27-Jun	4.095	3.164	1.840
28-Jun	2.935	0.091	1.240
29-Jun	3.065	0.015	0.834
30-Jun	2.630	0.657	1.026

Electricity generation during June decreased compared with the previous two months because the operational focus gradually shifted toward reservoir replenishment rather than maximum energy extraction.

Stage I & II generated **108.475 MU**, whereas Stage IV contributed **79.830 MU**, resulting in a combined generation of **188.305 MU**. Stage III produced **45.930 MU**, while KDPH generated **14.965 MU**, giving a total monthly generation of **249.200 MU**.

Daily generation varied considerably throughout the month. Lower generation was observed during the first week because of limited water availability, whereas higher generation occurred during the last week as monsoon inflows increased. The highest daily generation occurred on **24 June**, when the total KGSC generation reached **25.754 MU**, while the minimum generation of **2.851 MU** was recorded on **18 June**.

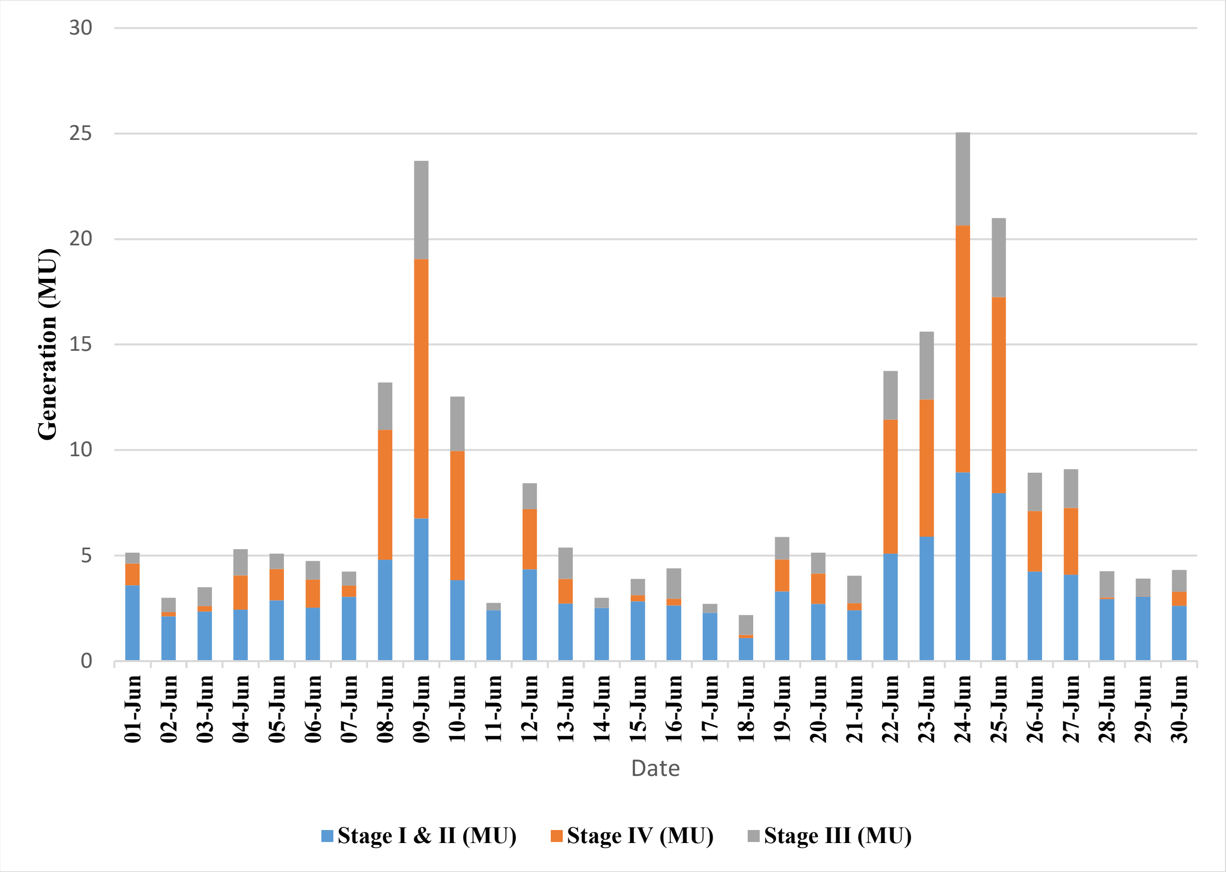

Figure 2 Daily Electricity Generation by Stage During June 2020

Stage I & II remained the major contributors to generation throughout the month, while Stage IV generation increased significantly during periods of higher inflow. The coordinated operation of all generating stages enabled continuous and reliable electricity production despite changing hydrological conditions.

4.3 Water Discharge Analysis

Water discharge during June followed the daily electricity generation pattern. Stage I & II utilized **92.536 Mm³ (3.267 TMC)** of water, whereas Stage IV discharged **62.081 Mm³ (2.192 TMC)**. The combined discharge through these generating stations amounted to **154.617 Mm³**, equivalent to **5.460 TMC**. Stage III discharged an additional **114.481 Mm³ (4.042 TMC)**, resulting in a total water utilization of approximately **269.098 Mm³** during the month.

Table 5 Daily Water Discharge During June 2020

Date	Stage I & II (mm³)	Stage IV (mm³)	Combined Stage I+II+IV (mm³)	KDPH (mm³)
01-Jun	3.067	0.778	3.844	5.301
02-Jun	1.813	0.145	1.958	5.301
03-Jun	2.000	0.206	2.206	5.301
04-Jun	2.081	1.266	3.348	3.534
05-Jun	2.452	1.158	3.610	1.933
06-Jun	2.158	1.039	3.197	0.000
07-Jun	2.602	0.413	3.015	0.000
08-Jun	4.103	4.749	8.852	0.000
09-Jun	5.762	9.573	15.335	1.049
10-Jun	3.267	4.768	8.035	5.301
11-Jun	2.052	0.000	2.052	5.301
12-Jun	3.706	2.227	5.933	3.921
13-Jun	2.331	0.905	3.236	2.583
14-Jun	2.156	0.000	2.156	2.583
15-Jun	2.421	0.222	2.643	1.076
16-Jun	2.252	0.248	2.500	0.000
17-Jun	1.953	0.000	1.953	3.228
18-Jun	0.934	0.112	1.046	5.301
19-Jun	2.811	1.189	4.000	5.301
20-Jun	2.305	1.121	3.426	5.301
21-Jun	2.041	0.274	2.314	5.301
22-Jun	4.337	4.953	9.290	5.301
23-Jun	5.037	5.063	10.100	5.301

24-Jun	7.622	9.143	16.764	5.301
25-Jun	6.790	7.240	14.030	5.301
26-Jun	3.621	2.230	5.851	5.165
27-Jun	3.493	2.470	5.963	5.165
28-Jun	2.507	0.069	2.575	5.165
29-Jun	2.618	0.011	2.629	5.004
30-Jun	2.246	0.510	2.756	5.165

The gradual increase in water discharge observed after the middle of June corresponds closely with increasing reservoir inflows due to monsoon rainfall. This relationship demonstrates the adaptive operational strategy adopted by the generating station, wherein turbine discharge is adjusted according to reservoir storage, inflow conditions, and electricity demand.

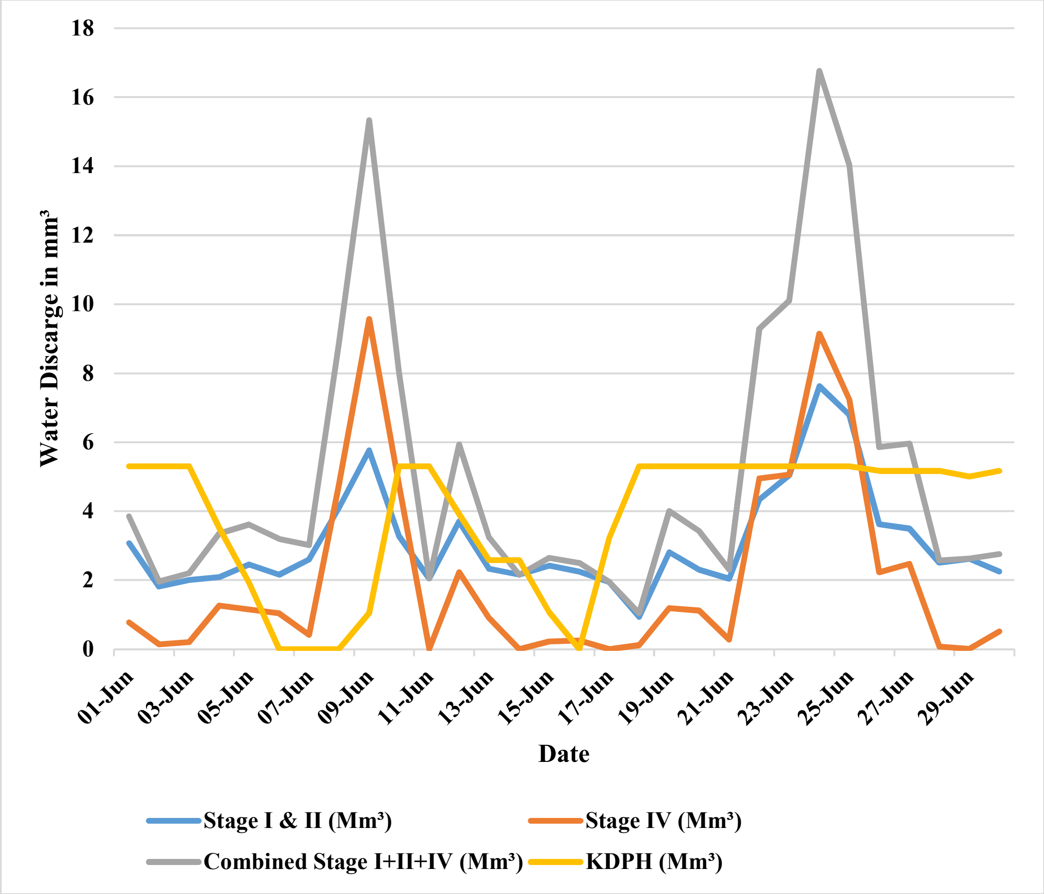

Figure 3 Daily Water Discharge During June 2020

4.4 Operational Performance Assessment

June 2020 marks the beginning of the hydrological recovery period for the Koyna reservoir. The operational data indicate that the generating station successfully adapted to changing inflow conditions by balancing electricity generation with reservoir replenishment.

Compared with April and May, electricity generation was intentionally reduced during several days to facilitate storage recovery. The occurrence of positive reservoir rise during the second half of the month confirms the effectiveness of reservoir operation under early monsoon conditions.

The coordinated operation of Stage I & II, Stage III, Stage IV, and KDPH ensured uninterrupted electricity supply while preserving reservoir storage for the subsequent monsoon months. No significant operational abnormalities or prolonged shutdowns affecting overall system performance were observed during the study period.

5. Conclusions

The following significant observations were obtained from the operational analysis of June 2020:

1. June represented the transition from the dry season to the southwest monsoon.
2. Reservoir levels initially declined but began recovering after mid-June because of increasing inflows.
3. Positive reservoir rise recorded during the latter half of the month confirmed the onset of monsoon recharge.
4. Total electricity generation of the Koyna Generating Station Complex during June was **249.200 MU**.
5. Combined generation from Stage I & II and Stage IV reached **188.305 MU**.
6. Total turbine water discharge from Stage I & II and Stage IV was **154.617 Mm³**, equivalent to **5.460 TMC**.
7. The highest daily electricity generation (**25.754 MU**) was recorded on **24 June**, whereas the lowest (**2.851 MU**) occurred on **18 June**.

8. Reservoir operation during June successfully balanced electricity generation with increasing inflows, preparing the reservoir for the peak monsoon season.

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