

# Himalayan Run-Off River Power Generation Modelling for Power Security in Evolving Weather Conditions

Swaechchha Dahal <sup>a,b,\*</sup>, Thomas Øyvang <sup>b</sup>, Gunne John Hegglid <sup>b</sup>, Shailendra Kumar Jha <sup>a</sup>  
Bhupendra Bimal Chhetri <sup>a</sup>

<sup>a</sup> Department of Electrical and Electronics Engineering, Kathmandu University, Nepal, <sup>b</sup> Department of Electrical Engineering, Information Technology and Cybernetics, University of South Eastern Norway, Norway, sdahall13@gmail.com

## Abstract

Extreme black-swan occurrences like earthquakes, glacial lake outbursts, flash floods, landslides, etc. are important concerns in Himalayan countries like Nepal, which are highly susceptible, geologically active, and exquisitely fragile. Nepal generates 97 percent of its electricity from hydropower, where 56.08 percent of it is coming from seasonal run-off-river (RoR) hydro plants. Landslides and mudflows are common in the monsoon, and low discharge is common in the winter season. These RoR plants must be able to withstand high-impact events like earthquakes and lengthy droughts in order for the Nepalese grid to remain secure. This study gives a presentation and overview of previously occurred natural hazards in Nepal related to hydropower plants. In particular, the 2014 Sunkoshi landslide and the 2021 Melamchi flood are evaluated as extreme events and their impacts on hydropower plant has been studied. In addition, an in-depth investigation on a ROR plant is carried out. Moreover, the water discharge and extreme rainfall peaks in time series data is evaluated using an ARIMA-based model. This paper shows the feasibility of predicting the energy produced by a run-off river hydropower plant. The purpose is to forecast discharge and hence the ROR power generation with the aim to facilitate the hydropower operators for their availability declaration which will again help in the overall energy planning. The results are discussed together with performance metrics, and indicates that the implemented technique is promising. These predictions can be further used for planning and estimating the power generation on a more complex level.

## 1. Introduction

### 1.1. Background

The electrical power system supports a variety of important infrastructures in today's world, including transportation, communication, health, and education. Countries, on the other hand, are subjected to severe exigencies and natural disasters that directly or indirectly damage electricity systems. The rising expense of power outages caused by natural disasters or climate fluctuations, as well as the devastating impact on different fields of security and personnel security, cannot be overlooked. Power outages over extended periods of time, substantial and important equipment failures in the system, cascading failures, load-shedding, and even system blackouts are all possible outcomes. For the power system to run smoothly, it is important to keep the system in balance while keeping its security and economic limits.

Extreme weather events, as well as climatic differences, are becoming more common in many countries throughout the world. As a result, today's electricity system must be resilient in this area. Power system engineers face a difficult task in designing a resilient power system that can resist climate change and extreme occurrences. After all, weather is stochastic, unexpected, and difficult to anticipate. Figure 1 depicts an overview of climate influences on the electricity system based on a number of papers. The globe is currently confronted with the issues of climate change and global warming; the primary fo-

cus has been on clean energy and the decarbonization of global energy systems. The movement toward a flexible electrical system based on renewables is gaining traction (Mitchell, 2016). Hydropower is the world's greatest renewable energy source, and it contributes significantly to global power system balance and regulation (Yang et al., 2018). Hydropower is not only needed for electricity; it also helps to balance the intermittent renewable energy supply. The relevance of hydropower to the reliability, sustainability, and economy of energy systems is addressed in Europe's 2050 Energy Strategy (Roadmap, 2011). The backbone for connecting multiple renewable energy systems is more flexible in a hydro-dominated power system. However there are still challenges with a power system that are heavily dependant on hydropower mainly due to natural events, for instance, scheduling the right amount of reserve capacity, the possibility of frequency oscillations in the system, and the overall quality, security, and dependability of the power system.

### 1.2. Nepalese Power System and the impacts of natural disaster

The Nepalese grid, known as the Integrated Nepal Power System (INPS), is one of the hydro-dominated electric grid systems in the Himalayan region. Currently, Nepal generates 97% of total electricity from hydropower; 56.08% of it from Run-Off-River (RoR) plants. These RoR plants are subject to a large discharge variation between wet and dry seasons. Also, the catchment area faces land-

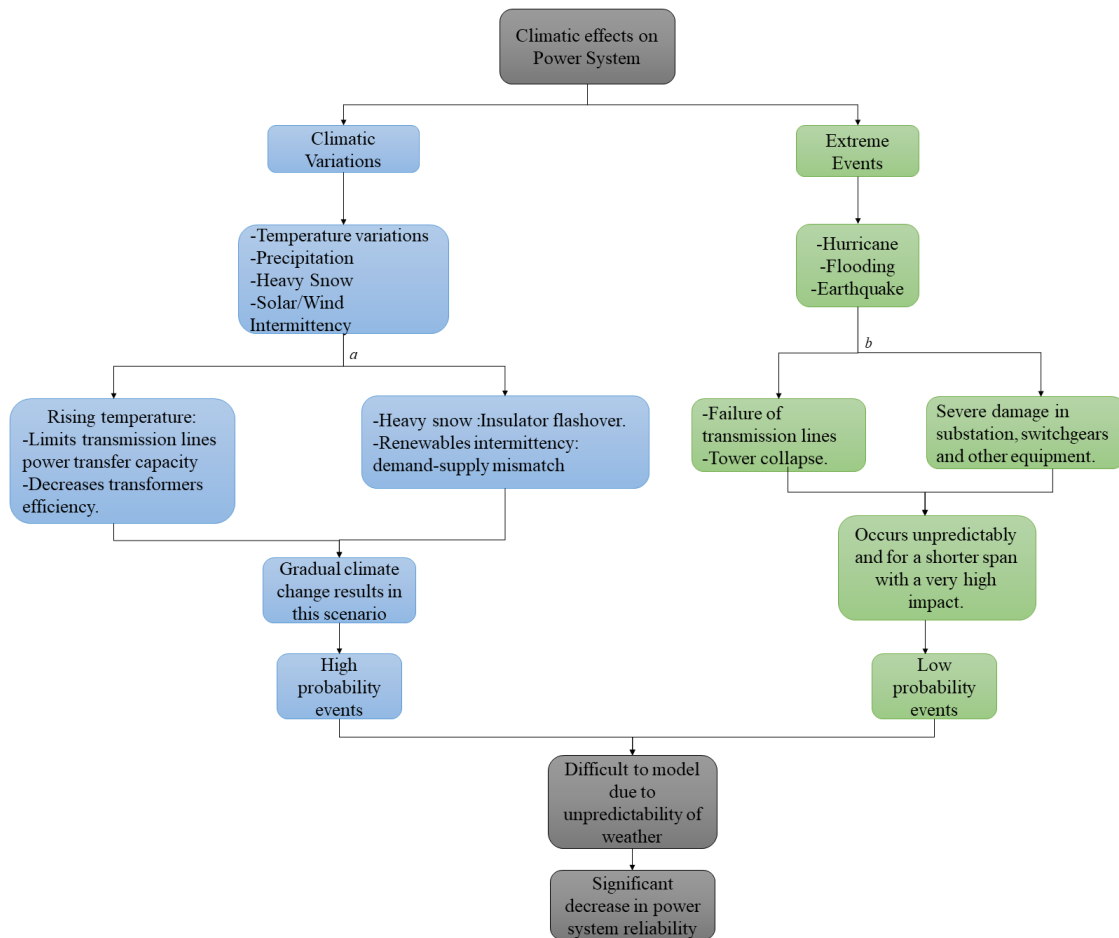


Figure 1: The figure presents the impact of climatic effects on the electric power system distinguished between climate variations and extreme events.

*a* represents climatic variation and their effects on power system

*b* represents effects of extreme events on power system

slides and heavy mudflow conditions in monsoon, and prolonged periods of low discharge in the winter. Typical generation capacity of a RoR plant is roughly 100% for 6 wet months, when it is most vulnerable to landslides and floods, 80% for 2 months, 50-30% for 4 months of winter when any form of energy is highly precious to the livelihood. Therefore, the power system operational security of the Nepalese grid is heavily dependent on how these RoR plants respond to winter demands. RoR should safeguard itself during the monsoon floods and landslides, and be resilient to other high impact events such as earthquakes and prolonged drought. Moreover, concerns with the Nepalese grid have posed a threat to INPS's reliability and security. Until 2017, Nepal was subjected to up to 18 hours of load shedding during the dry season. Although load shedding has been officially resolved, there is still a problem with INPS' power supply quality and reliability. In INPS, the existing transmission lines are mostly working at full capacity. In all existing high voltage lines, there is no sufficient provision for n-1 contingency. As a result of this and inappropriate contingency analysis, the INPS reliability is compromised.

River flow and hydropower are inextricably linked, and rainfall has a considerable impact on both. Because rainfall is influenced by a multitude of factors, hydropower

generation is highly seasonal. Nepal is also at risk from earthquakes, flooding, landslides, and a variety of other natural disasters. In Table 1, the effects of a few natural risks on Nepal's power generators and system over the last decade are presented. It is clear from this table that the Nepalese power infrastructure is extremely sensitive to weather and natural disasters.

### 1.3. Contribution of the work

Having a good grasp of the trends and behavior of river discharge is critical for an effective power/energy management, especially in the hydropower-dominated power system. The amount of rain, temperature, and other environmental factors influence how much water is discharged. Reliably predicting hydropower generation under certain operational conditions is essential to making the most of hydropower's advantages as a clean and inexpensive energy source. Economic and societal gains can be gained through its use. It is also possible to perform some preventative measures if the serious condition is anticipated. Consequently, this research focuses on analyzing the river discharge and hydroelectric output of one of the hydropower facilities in Nepal. The following points will serve as a reminder of the study's contributions during the discussion:

- Extreme events including floods, landslides, and

Table 1: Natural hazards in Nepal in the last decade.

Event	Major Effect
Flash Flood-Seti River-2012	Damage to infrastructure and livelihood including water supply systems and electric poles (Ojha, 2018)
Landslide-Jure-2014	Damage of more than 1.5 million USD in Sunkoshi HPP (Liu et al., 2020)
Earthquake-Gorkha- 2015	Severe damage to infrastructure and livelihood including significant damage in Sunkoshi HPP (Liu et al., 2020)
Glacial Lake Outburst Flood (GLOF)- Bhotekoshi- 2016	Damage to infrastructure and livelihood including damage in intake dam of Upper Bhotekoshi HPP (Action, 2018)
Terai Flood-2017	The financial loss of 584.7 million USD including damages in the energy sector as well ( <i>First Tornado in Nepal – March 2019</i> , 2019)
Tornado-Bara/Parsa-2019	Damage to infrastructure and many livelihoods leaving affected places without electricity and communication (Service, 2020)
Landslide-Sindhupalchok-2020	Loss of many lives and houses and other infrastructure (Samiti, 2020)
Flash flood-Melamchi-2021	Swept houses, bridges, and severe damage to infrastructure and livelihoods including hydropower plants (Debnath and Mourshed, 2018)

earthquakes have all been researched in relation to the discharge statistics of the rivers.

- It is the goal of this work to analyze weather, discharge, and extreme events connected to time series data, and to estimate their effects on power generation using a modeling approach. The Auto-Regressive Integrated Moving Average modeling approach is used for the forecasting of time series data on discharge and power generation.

#### 1.4. Structure of the paper

This paper opens by describing the setting in which the study is being conducted, as well as the reasons for doing so. Section 2 presents the assumptions and strategies utilized to tackle these problems. In the third section, the study's results are presented, and the conclusions taken from them are discussed in Section 4.

## 2. Methodology

For the investigation of underlying forecasting methods, a systematic review of published literature's was conducted. A number of literature's have shown that linear time series models, such as the Auto-Regressive Integrated Moving-Average (ARIMA) model, are among the most popular statistical models used to forecast time series based on historical data. It owes its reliability for this sort of data (Debnath and Mourshed, 2018). In (El Desouky and Elkateb, 2000), an Artificial Neural Networks (ANN) and ARIMA modeling were used to forecast electric load where both strategies were implemented to reduce forecasting mistakes, and they found that both techniques produce lower errors as compared to similar predictions obtained using the established time-series method. (Erdogdu, 2007) implemented ARIMA modeling technique for studying energy demand in Turkey and obtained results with very small error. Similarly, (Wang et al., 2011) employed a seasonal decomposition approach with vector regression to forecast hydropower usage in China and demonstrated that the method they utilized for time series forecasting was accurate. Likewise, (Cassiano et al., 2013) established an ARIMA model for forecasting effluent flow in a hydroelectric facility in Brazil by merging hierarchical clustering and Principal Component Analysis (PCA).

Forecasting, in general, refers to making future predictions based on the analysis of current and historical trends, with three primary components: input variables (historical and

current data), prediction methods (trend analysis), and output variables (future predictions), as illustrated in Figure 2.

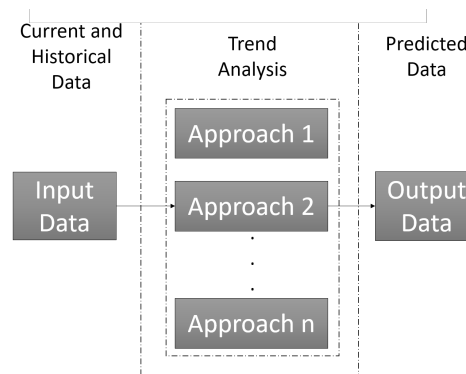


Figure 2: General forecasting model structure.

In this study, the prediction method used is the ARIMA modeling approach. The input variable is the river discharge (cubic meter per second/cumecs), and the output variable is the forecasted average discharge values. The ARIMA modeling technique is one of the efficient time-series forecasting model for hydropower generation forecast along with the prediction in the river discharge (Polprasert et al., 2021). Hence, the study has considered the implementation of ARIMA model in case of hydropower in Nepal which has not been done in the previous literature. Nepal is a developing country with huge potential in hydropower generation and it is very important to ensure a balance between the generation and consumption in order to make the grid secure. This study aims in contributing to this fact by analyzing ARIMA time-series modeling approach for investigating the behavior of Runoff River (RoR) hydropower plant subject to seasonal river discharge and its power generation. This will aid in further study of various other hydropower plants in case of Nepal to ensure power security in INPS.

The ARIMA model has the format of ARIMA (p, d, q), where p is the Auto-Regressive term, d is the order of differencing required for the data to make it stationary and q is the Moving-Average term. The established model is identified through the data of sample autocorrelation function (ACF) and partial autocorrelation function (PACF). Box and Jenkins presented a complete stepwise approach

for analysis and forecasting of a time series using ARIMA models in 1976 (Box et al., 2015). Because of the popularity of its methodology, ARIMA models are frequently referred to as Box-Jenkins models (Jamil, 2020).

The ARIMA model is a type of Box-Jenkins series analysis. The prediction value is viewed as a function defined by the time sequence. Integrated autoregressive and moving average models are used to model the data. These are regression models that include delays in the dependent variable as well as delays in the error term.

The ARIMA (p, d, q) model is decomposed into three parts (Polprasert et al., 2021).

The part (p) is AR part which represents the dependent variable regressed on its own lagged values as shown in equation 1.

$$X_t = \alpha_0 + \alpha_1 X_{t-1} + \dots + \alpha_t X_{t-p} + \epsilon_1 \quad (1)$$

where,

$\alpha_0$  = constant

$X_t$  = interpreted variable

$\alpha_1, \dots, \alpha_t$  = coefficients or AR model parameters

$X_{t-p}$  = pre-stage data

$t$  = periodic time

$\epsilon_1$  = error term

Similarly, the part (q) is MA part which shows that the regression error is a linear combination of error terms whose values occurred simultaneously and at various times in the past as shown in equation 2.

$$X_t = u_t + \beta_1 u_{t-1} + \dots + \beta_q u_{t-q} \quad (2)$$

where,

$\beta_1$  = coefficient of MA model which is the weight

$X_t$  = interpreted variable

$t$  = periodic time

$u_{t-q}$  = error term

Finally, the part (d) is the I part that indicates that the data values have been replaced with the difference between their current values and the previous values.

A general ARIMA model can be written as shown in equation 3.

$$X_t = \alpha_0 + \alpha_1 X_{t-1} + \dots + \alpha_t X_{t-p} + \epsilon_1 + u_t + \beta_1 u_{t-1} + \dots + \beta_q u_{t-q} \quad (3)$$

Before building ARIMA model, it is necessary to check the stationarity of the data. The first step is to analyze the data-time plot to examine whether it is covariance stationary. The time series is subjected to a unit root test to determine its stationarity. The unit root test regresses the time series  $X_t$  on its lag value  $X_{t-1}$ , and the results reveal the data's nature in respect of stationarity (*First Torнадо in Nepal – March 2019*, 2019). If the data is non-stationary, after basic first-order or second-order differencing, the ARIMA model is still suitable to nonstationary time series. At this stage, the level of differentiation i.e., the number of times the data is differenced for its stationary is (d). Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Kwiatkowski et al., 1992) test was used in the research as a unit root test for testing a null hypothesis that the observable time series is stationary around a deterministic trend. The KPSS test is a linear regression-based statistical test for determining if a time series is stationary. The test's null hypothesis is that the time series is stationary, whereas the alternative hypothesis is that the time series has a unit root. (Kwiatkowski et al., 1992) provides a detailed mathematical formulation behind the KPSS test.

The study is carried out using EXPLORATORY tool (Exploratory, Inc., n.d.). The software builds an ARIMA time series model and performs forecast based on input time series data. The model parameters p,d,q are selected on the basis of ACF and PACF plots. The effectiveness of the model is observed from three performance metrics: Root Mean Square Error (RMSE) which gives the root of mean of squares between the forecasted and actual value, Mean Absolute Error (MAE) which is the mean of absolute differences between forecasted and actual value and Mean Absolute Percentage Error (MAPE) which is the mean of absolute differences in percentage of actual value (Exploratory, Inc., n.d.).

### 3. Results and Discussion

The efficacy of the presented approach has been tested on a RoR Hydropower Project test case. The salient features of the project is shown in table Table 2.

Table 2: Salient features of the test case project

Particulars	Features
Location	Pyuthan District, Central / West Nepal
Intake River	Jhimruk Khola
River Training	2 km Canal, Gabion Mattresses
Dam	300m Curvilinear with desilting basin and intake, 10,000m <sup>3</sup> Concrete
Tunnels	Headrace 1100m x 8.5m <sup>2</sup> , fully lined Inclined Shaft (45 degree) 280m x 9/3.5m <sup>2</sup> , fully lined (Steel, Concrete)
Powerhouse	Semi-underground, Steel Trusses, 8m x 20m x 18m
Rated power	12,6 MW
Head	201,5 m
Flowrate	12 m <sup>3</sup> /s (4m <sup>3</sup> /s each turbine)
Turbines	3 units, Francis, Kvaerner
Speed	1000 rpm

The two years daily average discharge and power generation data collected are presented in Figure 3a. The data shows the daily variations of average discharge from 2017 to 2019. It is evident that the average discharge shows a seasonality trend with high discharge during wet seasons and low discharge in dry months. Moreover, there is an abundant water supply, typically from July to October.

It can be seen that the hydropower plant can not generate more than the rated maximum even at the times of maximum discharge. However, there is a substantial difference in the values of maximum and minimum energy production, which indicates the significant dependence of hydropower generation on discharge, water quality and operational constraints.

Ideally, in a hydropower plant, the abundance water suggests high hydropower generation. Therefore, a flat hydropower generation plot with maximum rated value could be expected during the times of high discharge. But, contrary to the ideal assumption, it can be observed that the hydropower generation seems to decrease when the river discharge spikes as shown in Figure 3b which is a zoomed in view of Figure 3a. This is because the selected site and the rivers of Nepal in general also face the challenges of high sediment issues which results in shut down/rescheduling of the generation units in order to prevent the sediment erosion in a turbine to ensure its durability when the river discharge increases during monsoon season. The generation plot is almost flat post monsoon season as seen in Figure 3b as the sediment is less during that period.

To understand the correlation between variables and the trend in decrease/increase of data, the raw data along with its trend line is illustrated in the following Figure 4.

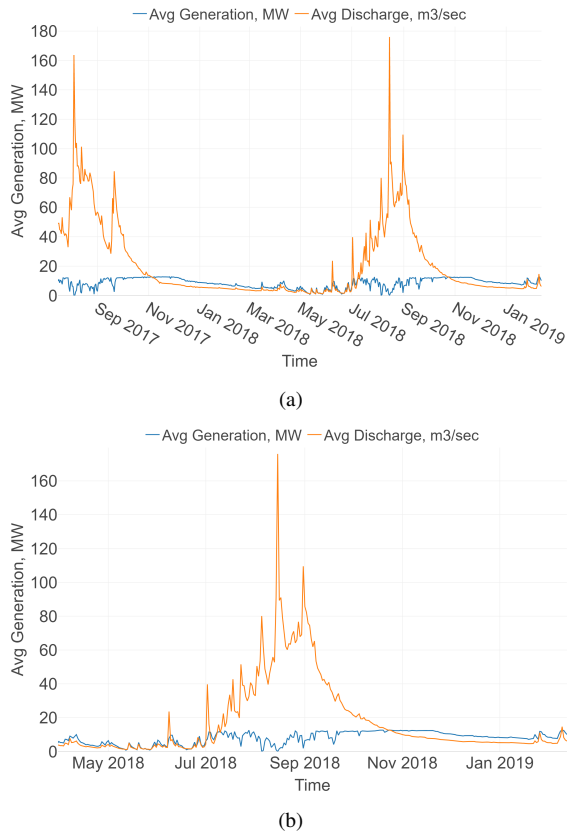


Figure 3: The figure presents the average discharge and average generation plot. (a) represents the overall plot of the input data for two years (b) represents a zoomed version of (a) from May 2018 for a better analysis of the plot

The trend change lines represent the points in a year where the river discharge is either changed to increasing or decreasing flow. The major rate of change in the trend line is observed around September, where the discharge sharply decreases from that month onward.

The predicted average discharge from ARIMA model as compared to the actual average discharge is shown in Figure 5a.

There was a considerable increase in average discharge around August 2017 as shown in Figure 5b, resulting in a significant difference between predicted and actual values. However, the model fit improves significantly after that, as the predicted and observed values nearly perfectly overlap.

The performance metrics RMSE, MAE and MAPE from the study was obtained as shown in Table 3. In general, a lower value yields a better prediction. It is evident from

Table 3: Performance Metrics

Metric	Value
RMSE	8.04
MAE	2.8
MAPE	0.12

the results that the RMSE value (squared error) is significant larger than the approaches for average error estimations. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. The RMSE is most useful when large errors are par-

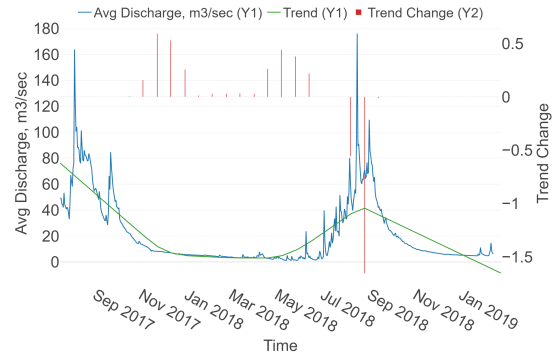


Figure 4: Change in the Average Discharge Trend.

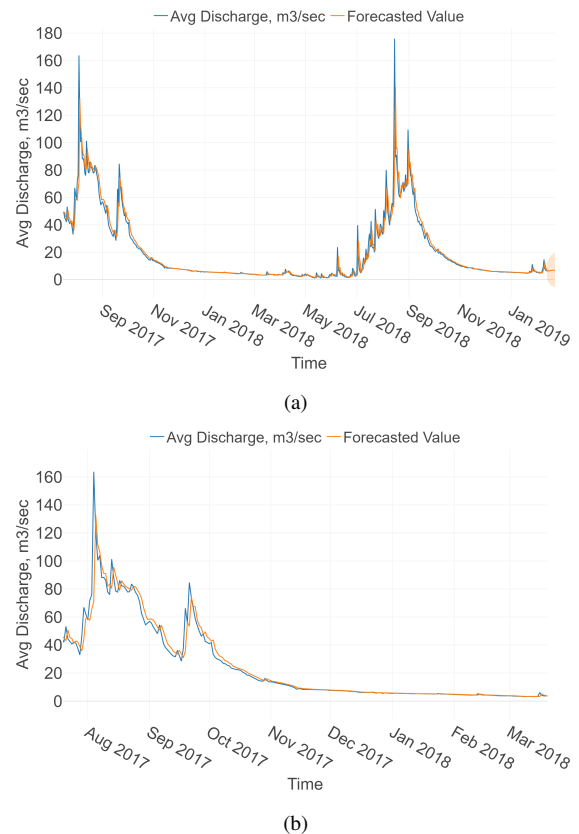


Figure 5: The figure presents the ARIMA model for average discharge. (a) represents the overall plot of the model for entire input data (b) represents a zoomed version of (a) for a better analysis of the model

ticularly undesirable. From the figures it can be seen that the difference between actual and forecasted values at the discharge peaks (rainfall) are significant. Hence, all three methods should be used together to diagnose the variation in the errors in a set of the forecasts. As the ROR plant has large seasonal variation and different magnitude, a mix of these methods should be considered in the forecasting evaluation. An ideal model should have the lowest error metrics. However, the results show a good fit of the developed model as compared to the previous literature in the relevant domain (Jamil, 2020), (Polprasert et al., 2021).

Figure 6 shows the short-term forecasting result obtained from the ARIMA model for average discharge. The forecasting for immediate 10 days has been obtained from the model. In the historical data, average discharge plot during January-March is almost flat which is reflected in the forecasted data for February as well. As the input data for only two years has been used in the modeling, the forecasted data tends to follow the trend shown by the historical data. The model do not seem to forecast the sudden events such as increment in discharge and the peak it causes. A minimum sample size of 50 is required for a reliable statistical analysis of a time series using the ARIMA method, which indicates that data for at least 50 years should be available (Box and Tiao, 1975). The intent of this work is to analyze and forecast annual generation based on discharge and other operation or maintenance variables; which is expected to show an annual trend but not the monthly or weekly or daily trend. As the data for large number of years was not available, the model accuracy is compromised. The model would have been more effective if larger volume of historical data was available as input for the model.

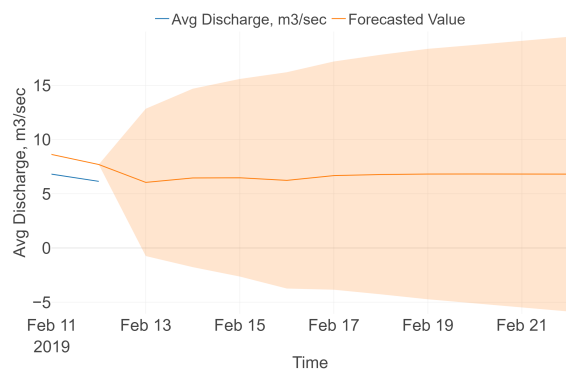


Figure 6: The figure represents the forecasting part of average discharge with ARIMA modeling as seen in bottom right part of Figure 5(a).

Proper energy planning is a crucial factor to ensure power security. There are several cases of power cut and unreliable power supply due to mismatch in the energy production capacity and its consumption. The scenario gets worse because of evolving climatic variations which has affected the power systems all over the world. Nepal, being a rich country in hydropower generation potential, is also a victim of seasonality leading to frequent power cuts and low power quality in various parts of the country. Several studies are being conducted to estimate the power system parameters subject to changing climatic conditions but the study in case of Nepal is very limited. Therefore, as a small step in ensuring power security for INPS, this study has applied ARIMA forecasting model for varying seasonal discharge to make it easy for the electricity regulators to conduct proper energy planning amidst the fluctuating river discharge.

The study, till this point, is done for average river discharge by fitting an ARIMA model. River discharge is a natural process which can be accurately modeled. Therefore, preliminary investigation to study and forecast has been obtained in this study. Further, the implications of weather events on hydropower production, as mentioned in Section 1, is yet to be addressed. Correlating weather events and actual hydropower generation and its modeling is a complex process as generation is affected by operational constraints such as operator's instructions as well. This is yet to be incorporated in the model. Although the aim is to incorporate extreme events such as GLOF, landslide, flooding, etc., the modeling of these events in relation to a hydropower production is a complex methodology which is yet to be addressed.

The major challenge during the study was the availability of the data from hydropower in Nepal. There was lack of proper record maintenance and also the power plants were reluctant to provide data. The study was performed with the daily discharge and generation data for two years. Results from modelling could be improved if more observations were available e.g., either hourly data or if data for a larger period of time was available.

#### 4. Conclusions

This paper presents a study that investigates the historical and future trends of energy produced by a hydropower plant of Nepal, taking into account its historical average discharge conditions. Forecasting studies play a significant role in resource planning and management in the future. The gathered historical data was statistically analyzed, and ARIMA modeling was used to forecast Nepal's future average discharge impacting hydroelectricity generation. From the research investigation, it is concluded that the proposed model can be utilized to better understand the trend in discharge and generation of a ROR hydropower plant and as a reference for energy planning. However, when utilizing the model to anticipate electricity generation from green energy, which is based on natural resources, additional care must be taken because environmental circumstances and climate fluctuation might have a significant impact.

The major findings of the paper can be summarized as:

- It is evident that ROR hydropower plants have large natural yearly variations following the rainfall seasons. Future climate variations may further impact this variation, demanding good statistical models for discharge and power generation forecasting.
- An effective forecasting model demands more observations e.g., several years of discharge data to give a satisfying prediction.
- The ARIMA modeling approach is an effective method for predicting river discharge. The model follows the river discharge trend in mostly of the study and gives a short-term forecasting result. However, seasonal rainfall peaks are rather challenging to track.

Future work will focus to enhance the modelling framework and environment. More sophisticated data-driven models e.g., Long short-term memory (LSTM), and other artificial neural network and deep learning will be explored. A novel architecture such as Temporal Fusion Transformer (TFT) which is also being used in time-series forecasting and gives globally important variables, sustaining temporal patterns and significant events in the dataset is of interest. The proposed approach can be an improved decision tool for power producers for planning

and revenue. In addition, government officials in the energy industry can make informed energy production decisions and develop a long-term strategic plan to keep up with economic growth in Nepal.

## References

- Action, P. (2018), 'Nepal flood 2017 wake up call for effective preparedness and response'.  
**URL:** <https://reliefweb.int/sites/reliefweb.int/files>
- Box, G. E., Jenkins, G. M., Reinsel, G. C. and Ljung, G. M. (2015), *Time series analysis: forecasting and control*, John Wiley & Sons.
- Box, G. E. and Tiao, G. C. (1975), 'Intervention analysis with applications to economic and environmental problems', *Journal of the American Statistical association* **70**(349), 70–79.
- Cassiano, K., Junior, L., Souza, R., Menezes, M., Pessanha, J. and Souza, R. (2013), 'Hydroelectric energy forecast', *International Journal of Energy and Statistics* **01**. doi: 10.1142/S2335680413500142.
- Debnath, K. B. and Mourshed, M. (2018), 'Forecasting methods in energy planning models', *Renewable and Sustainable Energy Reviews* **88**, 297–325. doi: <https://doi.org/10.1016/j.rser.2018.02.002>.  
**URL:** <https://www.sciencedirect.com/science/article/pii/S1364032118300200>
- El Desouky, A. and Elkateb, M. (2000), 'Hybrid adaptive techniques for electric-load forecast using ann and arima', *Generation, Transmission and Distribution, IEE Proceedings-* **147**, 213 – 217. doi: 10.1049/ip-gtd:20000521.
- Erdogdu, E. (2007), 'Electricity demand analysis using cointegration and arima modelling: A case study of turkey', *Energy Policy* **35**(2), 1129–1146. doi: <https://doi.org/10.1016/j.enpol.2006.02.013>.  
**URL:** <https://www.sciencedirect.com/science/article/pii/S030142150600098X>
- Exploratory, Inc. (n.d.), 'Exploratory'.  
**URL:** <https://exploratory.io>
- First Tornado in Nepal – March 2019* (2019).  
**URL:** <https://www.inf.org.uk/first-tornado-in-nepal/>
- Jamil, R. (2020), 'Hydroelectricity consumption forecast for pakistan using arima modeling and supply-demand analysis for the year 2030', *Renewable Energy* **154**, 1–10. doi: <https://doi.org/10.1016/j.renene.2020.02.117>.  
**URL:** <https://www.sciencedirect.com/science/article/pii/S0960148120303128>
- Kwiatkowski, D., Phillips, P. C., Schmidt, P. and Shin, Y. (1992), 'Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?', *Journal of econometrics* **54**(1-3), 159–178.
- Liu, M., Chen, N., Zhang, Y. and Deng, M. (2020), 'Glacial lake inventory and lake outburst flood/debris flow hazard assessment after the gorkha earthquake in the bhote koshi basin', *Water* **12**(2). doi: 10.3390/w12020464.  
**URL:** <https://www.mdpi.com/2073-4441/12/2/464>
- Mitchell, C. (2016), 'Momentum is increasing towards a flexible electricity system based on renewables', *Nature Energy* **1**(2), 15030. doi: 10.1038/nenergy.2015.30.  
**URL:** <https://doi.org/10.1038/nenergy.2015.30>
- Ojha, S. (2018), 'Rehabilitation of sunkoshi small hydropower plant (2.6 mk), nepal after sequences of natural disaster', *INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY AND SCIENCES (IJETS)*. doi: <https://doi.org/10.15282/ijets.v5i2.1398>.
- Polprasert, J., Nguyen, V. A. H. and Charoensook, S. N. (2021), Forecasting models for hydropower production using arima method, in '2021 9th International Electrical Engineering Congress (iEECON)', IEEE, pp. 197–200.
- Roadmap, E. (2011), '2050, impact assessment and scenario analysis', *European Commission, Brussel* **15**. doi: 10.2833/10759.  
**URL:** <https://ec.europa.eu/energy/sites/ener/files/documents>
- Samiti, R. S. (2020), 'Flood sweeps houses, bridges in melamchi'.  
**URL:** <https://thehimalayantimes.com/nepal/flood-sweeps-houses-bridges-in-melamchi>
- Service, H. N. (2020), '75 killed, 40 missing in sindhupalchowk floods, landslides'.  
**URL:** <https://thehimalayantimes.com/nepal/75-killed-40-missing-in-sindhupalchowk-floods-landslides>
- Wang, S., Yu, L., Tang, L. and Wang, S. (2011), 'A novel seasonal decomposition based least squares support vector regression ensemble learning approach for hydropower consumption forecasting in china', *Energy* **36**(11), 6542–6554. doi: <https://doi.org/10.1016/j.energy.2011.09.010>.  
**URL:** <https://www.sciencedirect.com/science/article/pii/S0360544211006074>
- Yang, W., Norrlund, P., Saarinen, L., Witt, A., Smith, B., Yang, J. and Lundin, U. (2018), 'Burden on hydropower units for short-term balancing of renewable power systems', *Nature Communications* **9**(1), 2633. doi: 10.1038/s41467-018-05060-4.  
**URL:** <https://doi.org/10.1038/s41467-018-05060-4>