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Simulating hydropower reservoir operations of the Yamula Dam with machine learning

Yamula Barajının hidroelektrik rezervuar işletiminin makine öğrenimi ile simülasyonu

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Abstract

Large-scale reservoirs provide operational flexibility to water managers by storing water during times with higher surface water availability and releasing water when it is most needed. Most large-scale reservoirs serve for multipurpose demands, such as water supply for agricultural, urban and environmental users, hydropower, recreation, fisheries and transportation. Due to its low operating cost, hydropower generation is often maximized in energy systems with mixed hydro and thermal sources. Hydropower generation is also used to meet peak demand by advantage of operating in short notice. This study aims to simulate reservoir operations, including release schedule and hydropower operations of the Yamula Dam and hydropower plant using machine learning. Located on the Kızılırmak River, the Yamula Dam is a large-scale multipurpose reservoir with its 3476 million cubic meters of storage capacity. Turbine release decisions are learned with Random Forests algorithm using only reservoir inflow and upstream streamflow conditions. The developed model successfully predicts reservoir releases between 2006 and 2015, with a coefficient of determination value of 0.87. Model prediction results are provided, and then hydropower load, generation and revenue are calculated and results are presented. Based on simulation results, the Yamula Dam generates about 362.3 gigawatts hour of energy per year, with an annual average revenue of 14.1 million Dollars. With the developed model, reservoir operations under different upstream hydrological conditions can also be simulated.

Keywords: Reservoir operations, Water management, Hydropower, Machine learning, Random forests

Öz

Büyük depolama kapasiteli rezervuarlar yüzey suyunun fazlaca bulunduğu zamanlarda suyu depolayarak ve su ihtiyacının en yüksek olduğu zamanlarda bu depolanan suyu sisteme vererek suyu yönetenlere işletim esnekliği sağlar. Büyük kapasiteli rezervuarlar çoğunlukla tarımsal, kentsel ve çevresel su ihtiyaçlarının temini, hidroelektrik, rekreasyon, balıkçılık ve ulaşım gibi birden çok amaca hizmet ederler. Düşük işletim maliyetinden dolayı hidroelektrik üretimi, hidro ve termik karışık enerji sistemlerinde genellikle maksimize edilir. Hidroelektrik üretim kısa sürede işletime alınma avantajından dolayı pik saatlerdeki talebi karşılamak için de kullanılır. Bu çalışma Yamula Barajı ve hidroelektrik santralinin türbin akış zamanlaması ve hidroelektrik operasyonlarını içeren rezervuar işletimini makine öğrenimini kullanarak simüle etmeyi amaçlamaktadır. Kızılırmak Nehri üzerinde yer alan Yamula Barajı 3476 milyon metreküp depolama kapasitesiyle birden çok amaca hizmet eden büyük ölçekli bir barajdır. Rastgele Karar Ormanları algoritması ile sadece rezervuara giren akım ve memba akım koşullarına göre türbin akımı kararları öğrenilmiştir. Geliştirilen model 2006 ve 2015 yılları arasındaki türbin akımlarını, 0.87 korelasyon katsayısı ile, başarılı bir şekilde tahmin edebilmektedir. Model tahmini sonuçları gösterilmiş ve ayrıca hidroelektrik enerjisi üretimi ve getirisi hesaplanmış ve sonuçlar sunulmuştur. Simülasyon sonuçlarına göre Yamula barajı yılda yaklaşık 362.3 gigawatt saat enerji üretmekte ve 14.1 milyon dolar gelir sağlamaktadır. Geliştirilen model ile farklı memba hidrolojik durumlarına göre rezervuar işletim simülasyonları da yapılabilmektedir.

Anahtar kelimeler: Rezervuar işletimi, Su yönetimi, Hidroelektrik, Makine öğrenimi, Rastgele karar ormanları

1 Introduction

Small to large-scale reservoirs are used for a variety of purposes, such as water supply, flood mitigation, environmental protection, transportation, recreation, and hydropower. Reservoirs store water, and with their controlled releases, various demands, such as agricultural water demand during dry season or power demand during peak energy hours, are met [1]. Reservoirs store energy as higher-elevation water for hydropower. Power is produced by the vertical flow of water using the potential energy difference, or 'water head,' between reservoir intake and tailwater levels. In a power system with mixed hydro-thermal production sources, hydropower generation is often maximized due to its lower operating cost than the majority of other power sources [2, 3]. Hydropower also offers operational flexibility by rapidly producing energy [4, 5] and by providing extra ancillary services, such as peak and frequency management, and spinning reserve [6].

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The controlled reservoir releases, especially for hydropower generation, are highly dependent on decisions of reservoir operators rather than natural hydrological processes [7], while flood control may affect reservoir releases depending on reservoir storage and upstream flow conditions. Reservoir operating policy is either obtained from rule curves or from data-driven methods [8, 9]. Simulation models are commonly used for determining reservoir storage and release decisions [10], driven by prescribed operating rule curves [11, 12]. These reservoir operating rules depend on empirical relationship between reservoir storage and release, which can be derived from optimization models [12, 13]. While simulation models are helpful, reservoir operator's knowledge and experience are of great importance that sometimes operating rules need to be adapted to specific conditions, objectives or constraints [7, 11].

Data-driven methods, such as Machine Learning Algorithms (MLA) can extract the optimal decision information from operations to understand reservoir operator's release decisions under various conditions, such as specific month of a year, reservoir inflow or upstream flows. MLAs mathematically relate inputs and outputs without requiring explicit physical system representation [14]. Although MLAs are widely used to estimate streamflow [15-23] or forecast reservoir inflow [24-26], the number of studies on using MLAs to simulate reservoir operations is limited, especially for hydropower decisions. In literature, Yang et al. [7] simulated reservoir operations in California using decision trees and Random Forests algorithm. Khalil et al. [27] used Support Vector Machines for real-time management of reservoir releases. Gangrade et al. [28] employed Long-Short Term Memory for long-term reservoir operations. Qie et al. [29] compared different MLAs for simulating reservoir outflow and showed that MLAs are promising tools in reservoir management. Herman and Giuliani [30] used Decision Trees to obtain optimal reservoir operation policies. Özdoğan-Sarıkoç et al. [31] used several MLAs to forecast volumes of small reservoirs.

Data-driven reservoir simulation tools are useful tools for reservoir planners and operators, yet their developments are inadequate, especially for reservoirs in Turkey. This paper develops a model with Random Forests algorithm, one of commonly used MLAs, to simulate hydropower reservoir operations of the Yamula Dam and Hydroelectric Power Plant (HEPP), for a period between October 1, 2005 and September 30, 2015. The developed model is easy-to-use and depends only on reservoir inflow and upstream conditions to predict controlled reservoir releases. Hydropower load, generation and revenue calculated with predicted reservoir releases are presented. Specific objectives include:

1) Effectiveness of data-driven methods on simulating hydropower reservoir operations.

2) Use of Random Forests algorithm to learn and predict reservoir releases.

3) Input parameter selection to build a data-driven model.

4) Presenting a case study of the Yamula Dam operations with a comparison to observed values.

2 Material and methods

2.1 *Study area*

The Yamula Dam and HEPP is one of major reservoirs located on the Kızılırmak River near the city of Kayseri (Figure 1). The Yamula Dam is rock-filled with a clay core and has a volume of about 1.6 million cubic meters. The reservoir has a drainage area of about 15582 square kilometers [32]. Three stream gauge stations are identified to simulate the Yamula operations, shown in Figure 1. Station #1501 is located downstream of the dam, and its streamflow records represent reservoir releases. Station #1543 is located upstream of the dam, and its streamflow records are assumed to represent reservoir inflows. Station #1535 is located far upstream of the dam near the city of Sivas representing the upper basin conditions, whose records are used by the developed machine learning model along with other two stream gauge stations.

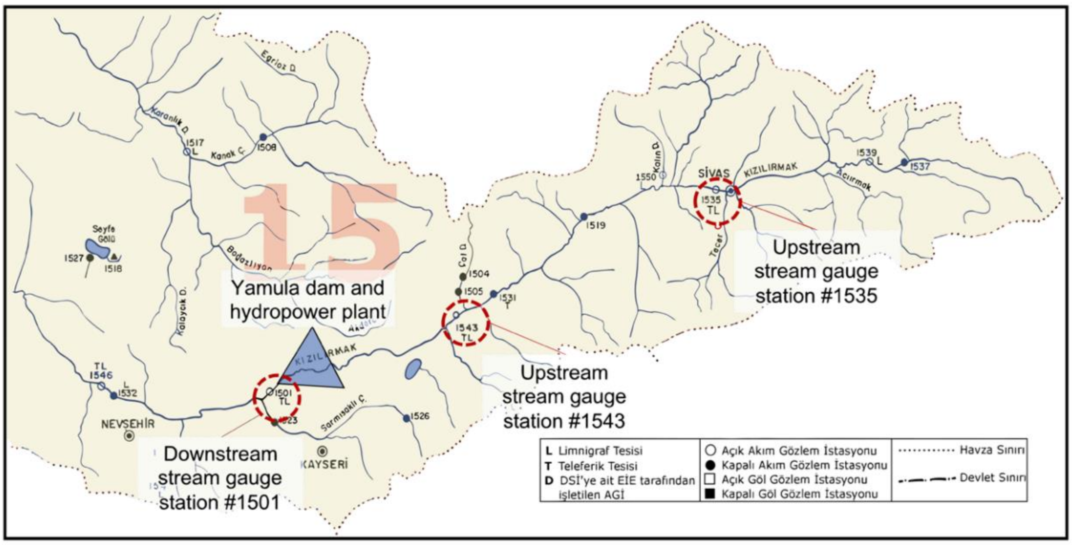


Figure 1. Study area: the Yamula Dam and HEPP and stream gauge stations (Image source: DSI [33]).

The Yamula Dam and HEPP is a multipurpose reservoir, including water supply for irrigation and urban users, hydropower generation and recreation. Table 1 shows characteristics of the reservoir and the hydroelectric power plant. The reservoir has a storage capacity of 3476 million cubic meters, 2025 million cubic meters of which is active storage, and has an area of 85.3 square kilometers. The Kızılırmak River at this location has an average natural flow of 67.7 cubic meters per second with annual average water volume of 2135 million cubic meters. The hydroelectric power plant has two Francis turbines with a total capacity of 100 megawatts (MW). The plant has a design head of 96.47 meters and overall efficiency of 0.85. The reliable power is estimated as 35.3 megawatts with an annual average reliable generation of 309.23 gigawatts hour (GWh) per year [32].

Table 1. The Yamula Dam and HEPP characteristics.

Plant characteristics	Value
Storage capacity (10^6 m^3)	3476
Total installed capacity (MW)	100
Average natural flow (m^3/s)	67.7
Net design head (m)	96.47
Overall efficiency	0.85
Reliable power (MW)	35.3
Reliable generation (GWh/year)	309.23

2.2 Streamflow Dataset

The dataset includes observed streamflow values from three stream gauge stations. The streamflow dataset is obtained from DSİ [33]. Target and input variables are derived from this streamflow dataset. In this study, the target variable is Yamula Dam daily outflows ($Q_{1501,d}$) measured at streamflow station #1501, and 18 input variables are used to predict this target variable. Input variables and their data range, mean (μ) and standard deviation (σ) are shown in Table 2. These input variables are day of a month (T_d), month of a year (T_m), year (T_y), water year (T_{wy}), daily ($Q_{1543,d}$), monthly maximum ($Q_{1543,m,max}$), monthly average ($Q_{1543,m,mean}$), monthly minimum ($Q_{1543,m,min}$), water year maximum ($Q_{1543,wy,max}$), water year mean ($Q_{1543,wy,mean}$) and water year minimum ($Q_{1543,wy,min}$) of streamflow station #1543, and daily ($Q_{1535,d}$), monthly maximum ($Q_{1535,m,max}$), monthly average ($Q_{1535,m,mean}$), monthly minimum ($Q_{1535,m,min}$), water year maximum ($Q_{1535,wy,max}$), water year mean ($Q_{1535,wy,mean}$) and water year minimum ($Q_{1535,wy,min}$) of streamflow station #1535.

2.3 Random Forests machine learning model

Random Forests (RF) is one of machine learning algorithms designed for classification and regression problems proposed by Breiman [34] and commonly used in hydrology and water resources [7]. The key concept of the RF algorithm is that it combines ensemble approach with a random selection of decision variables [24]. Different from Artificial Neural Networks, the RF is a nonparametric, whitebox classification and regression algorithm [24]. The RF algorithm also has lower runtime and less prediction error for water resources problems compared to other machine learning algorithms, such as Extreme Gradient Boosting, Support Vector Regressor and Artificial Neural Networks [7, 23].

Table 2. Input variables of the training and test sets for the period from October 1, 2005 to September 30, 2015.

	Data range	μ	σ
Input variable			
T_d	[1, 31]	-	-
T_m	[1, 12]	-	-
T_y	[2005, 2015]	-	-
T_{wy}	[2006, 2015]	-	-
$Q_{1543,d}$ (m^3/s)	[1.3, 546]	55.9	67.4
$Q_{1543,m,max}$ (m^3/s)	[8.7, 546]	91.2	108.4
$Q_{1543,m,mean}$ (m^3/s)	[11.2, 166.8]	55.9	50.7
$Q_{1543,m,min}$ (m^3/s)	[1.3, 175]	34.2	38.5
$Q_{1543,wy,max}$ (m^3/s)	[70.6, 546]	323	138.2
$Q_{1543,wy,mean}$ (m^3/s)	[19.4, 83.8]	55.9	19.3
$Q_{1543,wy,min}$ (m^3/s)	[1.3, 14.7]	7.7	4
$Q_{1535,d}$ (m^3/s)	[2.4, 301]	33.3	41.8
$Q_{1535,m,max}$ (m^3/s)	[4.9, 301]	57.8	70.1
$Q_{1535,m,mean}$ (m^3/s)	[6.4, 102.1]	33.3	31.4
$Q_{1535,m,min}$ (m^3/s)	[2.4, 91.8]	20	22.3
$Q_{1535,wy,max}$ (m^3/s)	[34.1, 301]	206	78.4
$Q_{1535,wy,mean}$ (m^3/s)	[9.6, 45.4]	33.2	10.8
$Q_{1535,wy,min}$ (m^3/s)	[2.4, 6.2]	4.6	1
Target variable			
$Q_{1501,d}$ (m^3/s)	[0.4, 176]	50.5	30.4

Therefore, RF is employed in this study for release schedule prediction. Similar to other machine learning algorithms, RF operates based on relationship between input and target variables. For regression problems, the machine learning model is trained and tested on a historical dataset and predictions are made for periods where target variable data are assumed unavailable. In the RF algorithm, many binary regression decision trees are randomly grown and ensemble average is taken for the final decision. Binary decision trees operate based on true or false decisions. Input variables are compared to split thresholds, and if comparison decision is true, then the left side, if false, then the right side of the tree branch is followed [23]. For each decision tree, optimal splits in the set of input variables are determined [35]. The optimal split point (j) minimizes the mean squared error, expressed in Equation (1).

$$\min_{k,j} \frac{1}{n} \sum_{i=1}^{n} \left(y_{observed} - y_{predicted}\right)^2 \qquad (1)$$

where $y_{observed}$ is observed value, $y_{predicted}$ is predicted value, k is split variable and n is the length of training set.

The number of trees in ensemble and maximum tree depth are calibrated hyper parameters for RF algorithms. The number of trees determines the size of forest and tree depth determines the size and branches of each individual tree. Having larger trees and forest sizes are preferred, however after a certain point, they do not improve results and increase runtime. Figure 2 shows calibrated hyper parameters that minimize root mean squared error. Calibrated parameters are as follows: the number of trees is 30 and maximum tree depth is 15.

The streamflow dataset covers the period from October 1, 2005 to September 30, 2015. 70% of the historical data is used to train, and remaining 30% is used to test and validate the developed RF model. Thus, the test set, consisting of observed reservoir releases, is randomly selected and unseen by the model. Figure 3 compares the predicted and observed reservoir releases of the test set. The model better predicts especially high reservoir releases, while some low releases are overpredicted between 0 and 25 m^3/s. This is partly because only upstream conditions are used as inputs. Large releases occur during wet times, which can be learned by the model from upstream records. Overall, the coefficient of determination r^2 (Equation (2)) value of 0.87 highlights the successful prediction capability of the developed model.

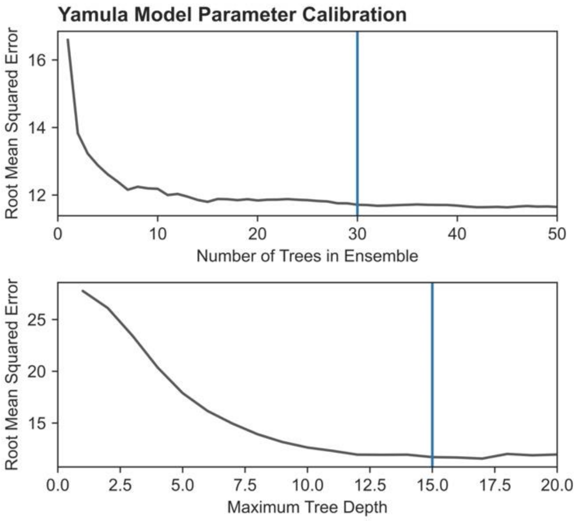


Figure 2. Model hyper parameter calibration.

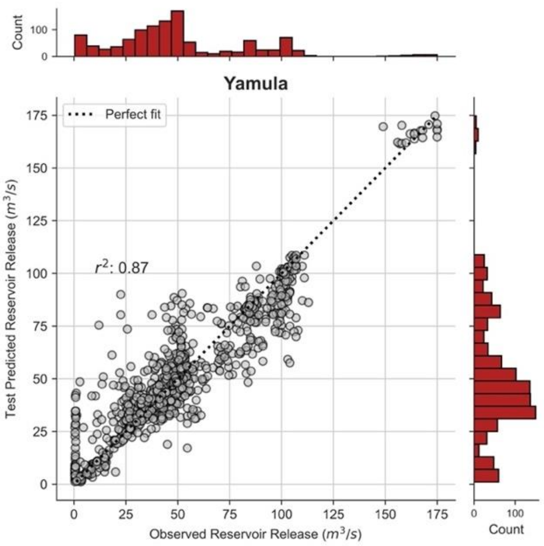


Figure 3. Test predicted and observed reservoir release (m^3/s) comparison for model validation with 30% of randomly selected and withheld data.

$$r^2 = \left[\frac{\sum_{i=1}^{n} (y_{observed,i} - \mu_{observed})(y_{predicted,i} - \mu_{predicted})}{\sqrt{\sum_{i=1}^{n} (y_{observed,i} - \mu_{observed})^2} \sqrt{\sum_{i=1}^{n} (y_{predicted,i} - \mu_{predicted})^2}} \right]^2 \qquad (2)$$

where $y_{observed}$ is observed value, $\mu_{observed}$ is the mean of observed test set, $y_{predicted}$ is predicted value, and $\mu_{predicted}$ is the mean of predicted set.

3 Results and discussion

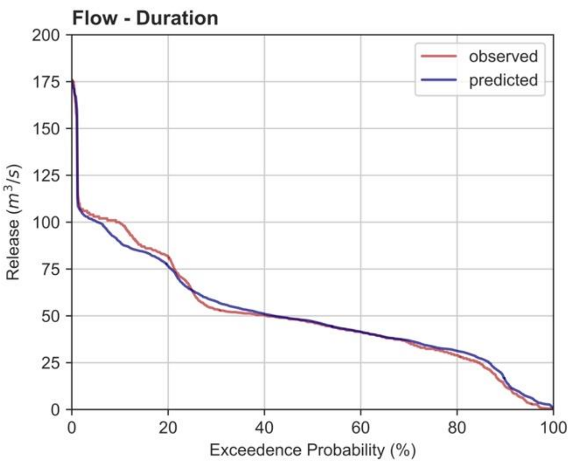
The Yamula Dam and HEPP operations are simulated between October 1, 2005 and September 30, 2015 at daily time-steps. Reservoir releases are predicted with Random Forests machine learning model. Using reservoir releases, power load, generation and revenue are calculated, and results are presented.

3.1 Reservoir release

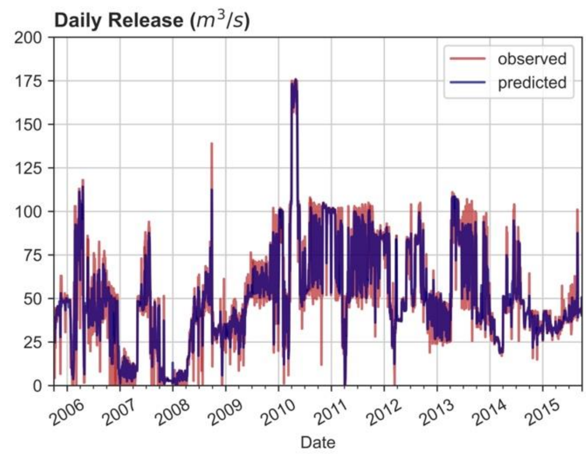
Reservoir releases are predicted with the developed RF machine learning model and compared to observed releases of the Yamula dam, shown in Figure 4. The model slightly underpredicts high releases, and overpredicts low releases, as seen in the flow duration curves (Figure 4-a). This commonly occurs in RF predictions as taking ensemble average for the final decision reduces variance. However, daily release time-series are shown in Figure 4-b. The RF model is able to follow low and high release trends. Monthly and water year average releases are shown in Figure 4-c and Figure 4-d. Water year is between October 1 and September 30 of a given year. While differences between monthly and annual average predicted and observed releases are small, the developed model tends to underpredict peak flows of May and June. Overall, the RF model can successfully predict reservoir releases given input conditions. As a typical large-scale reservoir, The Yamula stores water during wet months and releases mostly during dry months, between April and September, when demand is high. While releasing water, hydropower energy is generated, considering peak energy demand hours in a given day.

3.2 Power load and generation

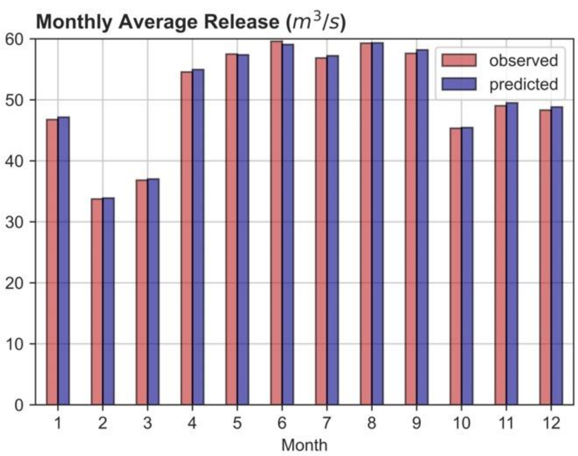
Hydropower is generated from vertical movement of water. Intakes divert water into penstocks, and water flow through turbines generate energy. The amount of power to be generated P depends on turbine discharge Q and water head H, which is a potential energy difference between intakes and tailwater (Equation (3)). The water head of the Yamula dam changes between 74.4 m and 105.5 m, depending on reservoir storage. Water head can be represented as a time dependant function of reservoir storage, however, due to lack of data availability, the constant net design head of 96.47 m is used in calculations.



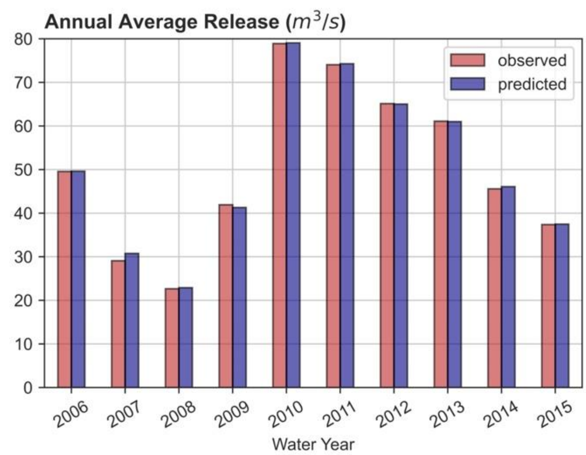
(a) Flow-duration curve of daily releases



(b) Daily time-series of releases



(c) Monthly average releases



(d) Annual average releases

Figure 4. Predicted and observed reservoir releases (m^3/s) of Yamula between 1/10/2005 and 30/09/2015.

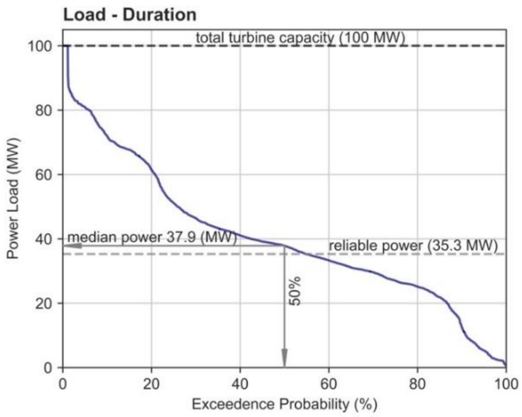
There are also other constant parameters that affect power, which are plant efficiency η, density of water ρ, and gavitational constant g. Integrating power over time t yields generation G, and multiplying generation with wholesale energy prices p results in hydropower revenue, shown in Equation (4) and Equation (5), respectively.

$$P = \eta \cdot \rho \cdot g \cdot Q(t) \cdot H \tag{3}$$

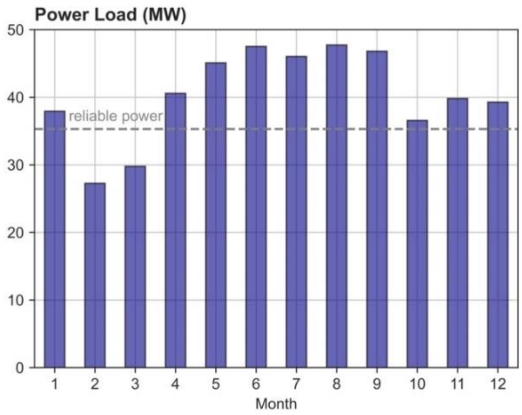
$$G = \eta \cdot \rho \cdot g \int_0^T Q(t) \cdot H \cdot dt \tag{4}$$

$$R = p \cdot \eta \cdot \rho \cdot g \int_0^T Q(t) \cdot H \cdot dt \tag{5}$$

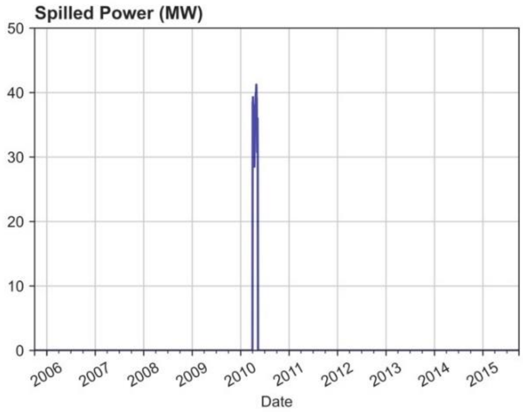
where P is power (W), G is generation (Wh), R is revenue ($), η is overall plant efficiency, ρ is density of water (kg/m^3), g is gravitational constant (m/s^2), Q is release (m^3/s), H is water head (m), T is time (hour), and p is wholesale energy market price ($/Wh).



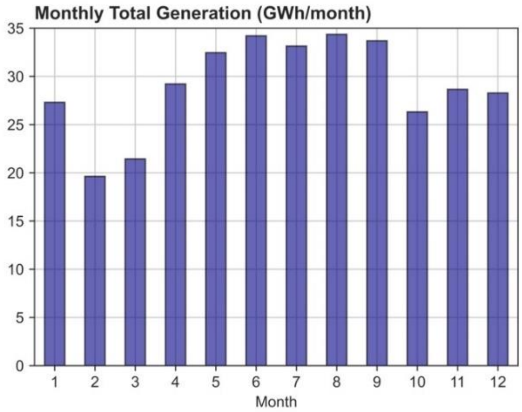
(a) Probability exceedance of daily power (MW)



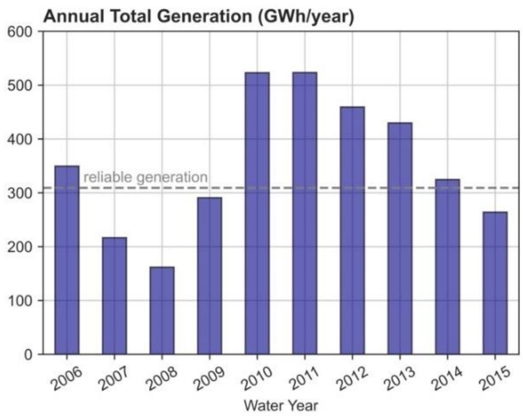
(b) Monthly average power (MW)



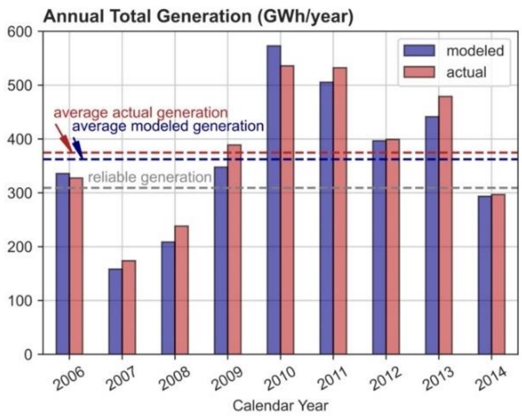
(c) Spilled power (MW)



(d) Monthly average hydropower generation (GWh/month)



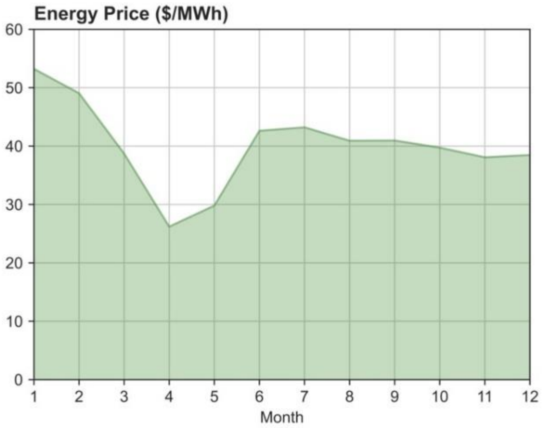
(e) Annual total hydropower generation (GWh/year) by water year



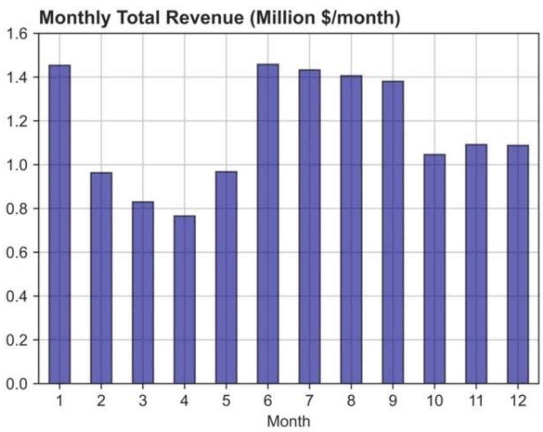
(f) Annual total hydropower generation (GWh/year) by calendar year

Figure 5. Power (MW) and generation (GWh) between 1/10/2005 and 30/09/2015.

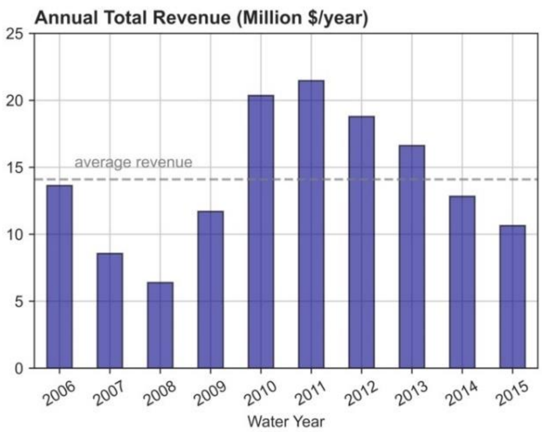
Figure 5 shows probability the distribution of daily power load, monthly average power, spilled power, and monthly and annual average hydropower generations with a comparison to actual annual average generation. The Yamula has two turbines with a combined capacity of 100 MW. The plant hits that capacity during only less than 1% of days in a ten-year period between October 1, 2005 and September 30, 2015. Reliable power load of the plant (35.3 MW) is slightly less than median power load (37.6 MW), corresponding to 50% exceedance probability (Figure 5-a). Monthly average power load is higher in April through September, as a result of high releases during these months. The peak power load of 47 MW is observed in June and August. Except for February and March, the monthly average power load is greater than reliable power in all other months (Figure 5-b). During the modeled period between October 1, 2005 and September 30, 2015, the reservoir spills between April 1 and May 11, 2010. This is because, the upper Kızılırmak River basin received 100% more precipitation than normal in 2010 water year [36]. Spills are not desired in hydropower reservoir operations, since hydropower is not generated when water flows through spillways instead of turbines. Due to spilling, power load between 30 to 40 MW in April and May of 2010 is lost (Figure 5-c). Following a similar trend as power load, monthly total generation is higher in April through September because of scheduled irrigation and water supply deliveries. Monthly total generation is lower in February and March since water demand and wholesale energy prices are low in these months (Figure 5-d). Between 2006 and 2015 water years, annual total hydropower generations in 2006, and 2010 through 2014 water years are higher than annual total reliable generation of 309.2 GWh/year. Annual total generation is less than reliable generation in remaining years (2007 through 2009, and 2015), shown in Figure 5-e. Peak annual total generations of 522.6 and 525.3 GWh/year are observed in water years 2010 and 2011, respectively. Calendar year total annual modeled generation is compared to actual generation in Figure 5-f. A calendar year is between January 1 and December 31. Actual annual total generation is obtained from Enerji Atlası [37]. Except for years 2006 and 2010, modeled annual total generation is slightly greater than actual generation. Assumptions, such as constant head and constant efficiency, can result in these differences. Nonetheless, annual average modeled generation of 362.3 GWh/year is close to annual average actual generation of 374.7 GWh/year between 2006 and 2014.



(a) Monthly average wholesale energy prices ($/MWh)



(b) Monthly total hydropower revenue (million $/month)



(c) Annual total hydropower revenue (million $/year)

Figure 6. Monthly average wholesale energy prices (a), monthly average (b) and annual total hydropower revenue (c).

3.3 Revenue

Hydropower revenue is obtained from the sale of generated energy in an energy market. Revenue is calculated by multiplying generation with wholesale energy prices. Energy prices can be determined in a deregulated energy market or based on fixed contract prices between retailers and generators. Monthly average energy prices of the year 2020 in $/MWh are gathered from EPİAŞ [38], shown in (Figure 6-a). Wholesale energy prices peak in January and remain lower April and May, when energy generation from relatively cheaper run-of-river hydropower plants reduces energy prices. Monthly and annual total hydropower revenue is calculated using 2020 energy prices (Figure 6-b and Figure 6-c). Peak monthly total hydropower revenue of about 1.4 million $ is obtained in January, when energy prices peak. Monthly revenue is also high in June through September with greater generation and also energy prices. The lowest monthly total revenue (0.77 million $) occurs in April, while the lowest hydropower generation is in February. The water year of 2008 has the lowest annual release and hydropower generation since it was a drought year. The total revenue in this year is 6.4 million $. While annual total generations in 2010 and 2011 are close, annual total revenue in 2011 water year (21.5 million $) is noticeably greater than total revenue in 2010 (20.3 million $). This is mostly because more hydropower is generated in months with higher energy prices in 2011 compared to 2010, resulting in higher annual total hydropower revenue. Annual average revenue between 2006 and 2015 is calculated as 14.1 million $ per year.

4 Conclusions

Reservoir operations of the Yamula Dam and HEPP were modeled with Random Forests machine learning algorithm. Daily reservoir releases are predicted with various input variables derived from reservoir upstream and upper basin stream gauge stations. These variables include time components of date, and minimum, mean and maximum flows in a given month or year, in addition to daily stream gauge observations. With a coefficient of determination r^2 value of 0.87, the developed model successfully estimates reservoir releases. Then, power load, generation and revenue results with predicted reservoir releases are presented. The Yamula's median power load of 37.6 MW exceeds its reliable power load value of 35.3 MW. The hydropower plant generates annual average of about 362 GWh of energy per year, gaining a revenue of 14.1 million $ per year. The developed simulation model is easy-to-use and requires minimal data. With only reservoir inflow and upstream streamflow dataset, the model makes controlled release predictions. The developed model also can be applied periods where input variables are known but reservoir releases unknown or to simulate different upstream conditions and their effects on hydropower reservoir operations of the Yamula. A similar methodology can also be applied to other reservoirs in order to learn their daily release schedules and simulate reservoir operation.

Conflict of interest

The authors declare there is no conflict.

Similarity rate (iThenticate): 6%

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