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Changing the World's Energy Future

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ABSTRACT

Revenue estimation for integrated renewable energy and energy storage systems is important to support plant owners or operators' decisions in battery sizing selection that leads to maximized financial performances. A common approach to optimizing revenues of a hybrid hydro and energy storage system is using mixed-integer linear programming (MILP). Although MILP models can provide accurate production cost estimations, they are typically very computationally expensive. To provide a fast yet accurate first-step information to hydropower plant owners or operators who consider integrating energy storage systems, we propose an innovative approach to predicting optimal revenues of an integrated energy generation and storage system. In this study, we examined the performance of two prediction techniques: Generalized Additive Models (GAMs) and machine learning (ML) models developed based on artificial neural networks (ANN). Predictive equations and models are generated based on optimized solutions from a market participation optimization model, the Conventional Hydropower Energy and Environmental Resource System (CHEERS) model. The two predicting techniques reduce the computational time to evaluate annual revenue for one set of battery configurations from 3 h to 1 to 4 min per run while also being implementable with significantly less data. The model validation prediction errors of developed GAMs and ML models are generally below 5%; for model testing predictions, the ML models consistently outperform the regression equations in terms of root mean square errors. This new approach allows plant owners, operators, or potential investors to quickly access multiple battery configurations under different energy generation and market scenarios. This new revenue prediction method will therefore help reduce the barriers, and thereby promoting the deployment of battery hybridization with existing renewable energy sources.

1. Introduction

The U.S. electricity system is rapidly evolving, bringing both opportunities and challenges to electricity market participation. Increasing deployment of variable renewable generation resources, such as wind and solar power, has enabled low-cost clean energy in many regions of the U.S. This change is also creating a need for resources that can store energy or quickly change their operations to ensure system reliability and resilience [14,16]. The convergence of the need for increased flexibility and reduced revenue for baseload resources is necessitating consideration of new paradigms for asset owners and project operators. For instance, integrating energy storage systems such as lithium-ion batteries, flywheels, and ultracapacitors in exiting hydropower plants can enable them to participate in the grid market in new ways such as ancillary service markets [2,17]. Pairing an appropriate energy storage system (e.g., considering type, sizing and control) with specific generation assets in a particular market can increase benefits and financial performance of the resulting integrated generation and storage system. This hybridization also has costs that need to be considered in optimizing the investment in new components of the system, such as the energy storage device.

A straightforward and computationally efficient tool for estimating revenue and optimizing energy storage sizing is useful to help interested parties consider appropriate energy storage systems to invest in for maximizing the benefits of their generation assets. This paper focuses on the revenue estimation portion of such as tool. It also focuses on renewable energy generation assets because a significant number of

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Nomenclature

E	Energy rating of battery (MWh)
Cap	Power capacity of battery (MW)
Min_chrg	Minimum charge (%)
Max_chrg	Maximum charge (%)
TE	Total round-trip efficiency (%)
Max_chrg_rate	Maximum charge rate for battery (MW)
P_E	Energy prices ($/MWh)
P_UP	Regulation up prices ($/MWh)
P_DN	Regulation down prices ($/MWh)
P_S	Spinning service prices ($/MWh)
P_NS	Non-spinning service prices ($/MWh)
Hydro_total	Total hydropower generated in each time interval (MW)
Hydro_cal	Generated hydropower that is not available to battery (larger than battery's maximum charging rate) (MW)
Total_Rev_cal	Revenue from selling Hydro_cal to energy market ($)
Hydro_left	Generated hydropower that is available to battery (MW)
Total_Rev_left	Potential revenue that can be produced from Hydro_left ($)
E_Norm	Energy rating of battery normalized by maximum plant capacity (MWh/MW)
Cap_Norm	Capacity rating of battery normalized by maximum plant capacity

renewable energy power plants exist today and their owners are interested in understanding how to maximize the benefits, and corresponding revenue, for their facilities. Yet, similar technoeconomic considerations apply for other types of generation assets participating in electricity markets.

Revenue optimization of integrated generation and energy storage systems has been widely studied using a plethora of existing tools [1]. For example, the Revenue, Operation and Device Optimization (RODeO) model developed by the National Renewable Energy Laboratory (NREL) is a price-taker model that has been implemented to optimize net revenue for integration of wind or PV solar with batteries [3]. Another example is the CHEERS model developed by the Argonne National Laboratory (ANL), which is a PC-based multi-objective network optimization tool that calculates the optimal market dispatch of integrated hydropower and energy storage systems including battery and flywheels [8]. The CHEERS model represents hydropower plant operations and participation in competitive markets in a 5 min time resolution. CHEERS and RODeO are fundamentally similar models, which both utilize MILP as the optimization technique to optimize revenue; CHEERS is used as an element of the current methodology.

MILP optimization model formulations are a proven technique, which often require a large number of inputs and have a large number of variables in the objective function. This both requires users to have a high degree of specialization and results in a long simulation computational time for each model run. Therefore, it is challenging to use these models to quickly estimate and analyze costs, benefits and trade-offs of various energy storage system designs and configurations. Based on these characteristics, there is a need for a methodology that can both reduce the required level of user specialization (i.e., be implemented easily by industry decision makers) and are more computationally efficient for the task of estimating revenue as a function of a large set of possible energy storage devices and configurations.

When selecting the ML techniques to build the predictive model, flexibility and interpretability of the techniques are our key consideration. Generally, regression models are easier to interpret from coefficient and intercept of variables, but can be less efficient facing complex dataset, while ML models are black-box models but can better approximate complex relationship [[18]]. Linear regression models, such as generalized linear models (GLMs) assume a linear relationship between the dependent and independent variables; these also tend to overfit data when training data are limited. In contrast, GAMs that are proposed by [[27]] can be flexibly applied to modeling complex and nonlinear relationship by fitting smoothing functions to covariates. GAMs have been successfully applied in complex time-series modeling problems such as grid load prediction [[19,26]], wind and solar power forecasting [[24]], and electricity price forecasting [[25]]. Therefore, GAMs are considered in this study as a prediction technique for predicting daily optimized revenue.

Machine Learning is an advanced mathematical tool that can be used to approximate relationships between decisions and their impacts on highly complex engineering system, where existing processes or physics-based models are computationally expensive [5,12]. For example, Xavier et al. [11] utilized ML to extract information from previously solved instances and to reduce unnecessary constraints in power system optimization problems. Lombardi et al. [6] proposed a novel method called Empirical Model Learning (EML) that uses ML techniques to extract components and relations from optimization problems, based on data that are collected from a real system or a simulator. The effectiveness of EML approach is demonstrated in a case study of thermal-aware scheduling problem for central processing unit (CPU) chips. Verwer et al. [10] applied ML approach to learn regression models based on historical auction data and to predict potential optimized value of new auctions. The ANN is a well-known deep learning technique that is configured with a layered architecture, which usually consists of input layers that are taking the data, hidden and output layers that are generating results [[21]]. ANN has been largely applied to learn and forecast nonlinear and complex relationship such as day-ahead electricity price forecasting [[20]], renewable power generation [[23]] power dispatch strategies in wind/solar with energy storage systems [[15]]and their impact on system profitability [[22]]. Currently, the literature on the application of ML in predicting revenues from integrated renewable and energy storage systems is very limited, which implies a lot of opportunities and potential challenges related to developing tools in this area.

The aim of this paper is to use ML techniques to develop models that predict revenue for integrated generation and energy storage systems, based on inputs and outputs from a daily unite commitment, market participation optimization model; this paper uses CHEERS for this purpose. By analyzing data from solved cases using CHEERS, GAMs and ANN can learn complex relations between market price, energy generation, and technical configurations of energy storage devices, and make predictions for optimal market net revenue. This approach is intended to provide time-efficient "first step" information to help interested parties quickly estimate the net revenue for an integrated energy generation and storage system. Compared to MILP market participation optimization models that normally require hours to days of computer run time, the trained prediction models will only take minutes to get predictive results. More specifically, it is useful for decision makers who want to test economic benefits of adding battery or flywheel and quickly find out the optimal energy storage device to pair with their energy production system. With that being said, the developed approach can be integrated into an optimization tool to propose the most profitable energy storage configurations to pair with the plant, and also to estimate what some of the monetary market benefits may be. In addition, the revenue predicted by this approach can be used as a baseline for the comparison between standalone battery storage and other hybrid energy storage system (e.g., battery-ultracapacitor storage system). Lastly, though the demonstration case of this approach is a hydropower plant integrated with a storage system, it can also be applied to other renewable energy production systems such as solar and wind power production systems.

The key contributions of this study are:

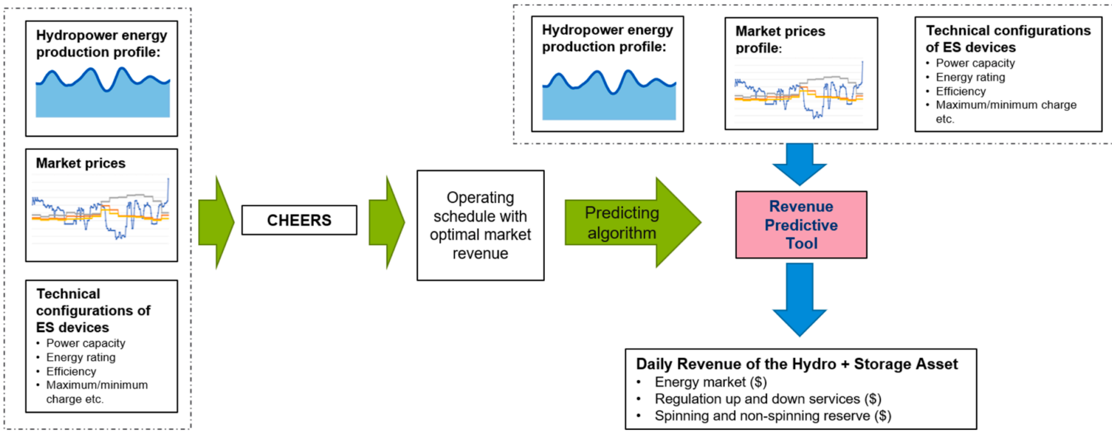

Fig. 1. Conceptual data flow in the proposed revenue prediction tool.

- A novel ML-based framework is developed to provide quick and straight-forward revenue prediction for integrated energy generation and storage system.
- A regression-based approach (GAMs) and a ML-based approach (ANN) are applied and compared to evaluate their prediction performance.
- The developed framework is implemented to provide sizing optimization for a hydropower plant integrated with a battery storage system, and to demonstrate its ability in significantly accelerating the decision-making process for potential investors.

This paper is organized as follows: Section 2 provides a detailed description of the methodologies used in this paper, including an introduction to the market participation optimization tool that provides the training data to the ML approach, the ML techniques utilized in this paper, and the approaches to evaluating and validating the performance of the regression models. Section 3 presents results from applying the developed models in various scenario and summarizing discussions, key conclusions from this study, model limitations, and potential future work directions.

2. Methodology

The specific objective of the prediction model developed here is to predict the maximum annual revenue for an integrated system with energy generation and energy storage devices. The model is trained with a large set of CHEERS runs and then the end-user implements the trained model for their own conditions based on market price profiles and hydropower generation (Fig. 1). In this paper, the wholesale power market explored is the California Independent System Operator (CAISO), and the market products considered in this study include regulation-up, regulation-down, spinning reserve, and non-spinning reserve. This section presents an introduction to the CHEERS model, the deep learning techniques utilized in this paper, and the approaches used for evaluating and validating the performance of the regression models.

2.1. CHEERS model

2.1.1. The CHEERS model

The Argonne CHEERS model is a component of the Water Use Optimization Toolset (WUOT), which itself is developed to provide dispatch guidance for hydropower operators. In the software's graphical interface, users of the model can create a node-and-link-based network representation of the system to be optimized and enter equations and constraints to describe the objectives and limitations of the system and its individual components. CHEERS converts user inputs to a MILP problem which is then solved by the commercial LINGO solver software [7].

CHEERS can be used for many different types of network and mass and/or energy flow problems that extend beyond hydropower and power system applications. In CHEERS instances used here, the system components represented include the hydropower plant, the energy storage device being evaluated, and the market (product specification and price time-series). The CHEERS model optimizes the operation of the storage devices; that is, when to charge and discharge the devices for market purchase and sale of energy and for the sale of ancillary services to ensure that storage operations maximize net revenue. In this work, we assume that the hydropower plant's dispatch has already been optimized (i.e., either because it has no flexibility or use of its flexibility has already been set prior to CHEERS). The hydropower plant is the only source of energy for the energy storage device in this model (i.e., the energy storage device is not allowed to charge from the grid).

The objective function in CHEERS maximizes the total integrated hydropower plant and storage device market net revenue, considering provision of both energy and ancillary service (regulation-up, regulation-down, spinning reserve, and non-spinning reserve) sales for each day independently, using 5 min time steps, from midnight to midnight.

Each model run requires the following main input data:

- Hydropower plant's energy production/output (5 min timeseries)
- Market price for energy and each of the four ancillary services considered (5 min timeseries)

Table 1
Plant characteristics and market prices for energy and ancillary services used in the case study.

Plant Name		Santa Ana 3 (SA)	Nimbus	French Paper Hydro (FP)	Hamilton Hydro (H)	Piney Hydro (P)
Plant characteristics	State	California	California	Michigan	Ohio	Pennsylvania
	Capacity (MW)	3.1	13.4	1.3	2.2	30.0
	Annual generation (MWh)	4,968	55	7,642	3,653	68,043
	Capacity Factor (CF)	0.11	0.52	0.96	0.58	0.36
Market prices	Source	CAISO				
	Node	GOLDHILL_1_N033				

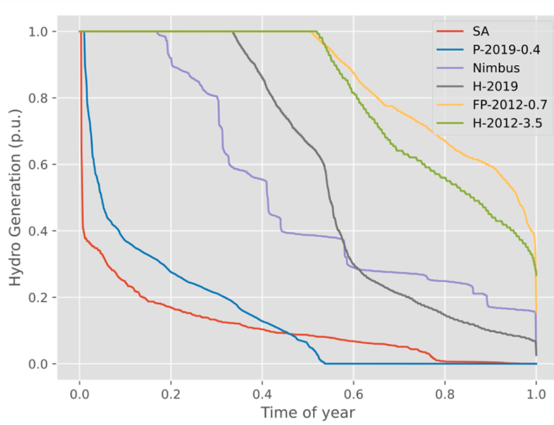

Fig. 2. Normalized power duration curves for the PJM sites.

- Storage device's operating capabilities and limitations

Each model run produces the following output as 5 min output:

- Amount of energy produced by the hydropower plant is used to charge the storage device
- Amount of energy and corresponding revenue produced by the hydropower plant directly sold to the market (energy and ancillary services)
- Amount of energy and corresponding revenue provided by the storage device (energy and ancillary services)
- Storage device's setpoint and state of charge

2.1.2. Hydropower plant characteristics and market price profiles

The case study is performed using two hydropower plants located in CAISO and three in PJM (Table 1). One selection criterion is that all five hydropower plants have publicly available 15 min discharge data from nearby United States Geological Survey (USGS) gages. The water discharge time series are used to estimate power generation profiles using the power generation equation:

$$Power\ generation = \rho g Q H e \quad (1)$$

where *power generation* is in W, ρ is the density of water (kg/m^3), g is the acceleration from gravity (m/s^2), Q is the volumetric flow rate (m^3/s), H is the head (m), and e is the overall efficiency (unitless).

We collected the real-time prices in energy and ancillary service markets for the 365 days in 2018 and 2019 from CAISO, considering the physical location of each plant.

2.2. Inputs to the CHEERS model and the revenue prediction models

2.2.1. Capacity factor (CF) categories and scaling of power generation curve

The original hydropower plant capacity factors (CFs) of the Piney Hydro, the French Paper Hydro, and the Hamilton Hydro are relatively similar (Table 1). For training the empirical revenue prediction approaches, it is important to have greater diversity in capacity factors of the training data. To achieve this, the water flow volume in some collected power generation profiles is scaled up or down. For example, the original CF of the Piney power plant in 2019 is 0.36, which is scaled down to a capacity factor of 0.14 (Fig. 2 shows the power duration curve after scaling). In this study, scaling factors used for the Piney Hydro, the French Paper Hydro, and the Hamilton Hydro are 0.4, 0.7, and 3.5, respectively.

2.2.2. Battery configurations for model training

Battery configurations used in producing the revenue prediction model training dataset are selected to satisfy two competing criteria: (1) training data should result in as much in-sample samples as possible, meaning more training combinations are better, and they should cover the range of plausible configurations a user may want to test, and (2) CHEERS runs are computationally expensive, a typical run takes 3, 4 h to complete on a high-performance workstation. Based on criteria, we first analyzed the normalized power duration curve of each power plant (Fig. 3), and then selected two normalized power capacities (0.36 and 0.11 for the scaled power curve of the Piney site), which are given by the 20th and 80th percentiles of the power duration curve. The normalized power capacities are then multiplied by the plant capacity to determine the battery capacities that should be used at that site. For each of these power capacities, storage durations of 0.5 h, 2 h, and 4 h are also used since these are common in electricity markets today [13].

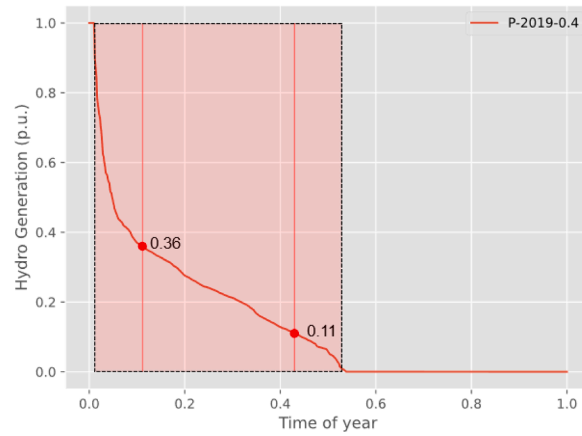

Fig. 3. Normalized power generation curve used to define the normalized battery capacity.

2.2.3. CHEERS simulations used for training

A total of 36 one-year CHEERS simulations are used to train and to test the empirical revenue prediction model based on the combination of hydropower plants (Section 2.2.1) and battery configurations (Section 2.2.2) (Table 2). For training the empirical model, each day of these 36 one-year simulations is treated as an independent training set since the CHEERS model optimized independently on a daily basis. The 36 input files are categorized into 3 CF levels: low CF (0.10–0.20), mid CF (0.30–0.60) and high CF (0.70–0.90). For the model training, 6 one-year simulations in each CF category are selected and used as the training data, while the other 6 runs are used as the test data. Specifically, training data included runs #7-#12 and #19-#30 and test data included runs #1-#6, #13-#18, and #31-#36.

2.3. The regression model approach for net revenue prediction

The three main categories of input variables for the 36 CHEERS runs are: price profiles, technology types, and technology parameters. A complete market price profile consists of energy prices (*P_E*), regulation up/down prices (*P_UP/P_DN*), spinning service (*P_S*) and non-spinning service (*P_NS*) prices. Battery configurations included variation in parameters such as power capacity (*Cap*) in MW, energy capacity (*E*) in MWh, maximum and minimum charge (*Max_chrg/Min_chrg*) in %, total round-trip efficiency (*TE*) in %, and maximum charge rate (*Max_chrg_rate*) in MW (Table 1). The outputs of the 36 CHEERS runs that are used for modeling training are the optimized market net revenue for the combined asset.

2.3.1. Net revenue prediction for the combined asset (Hydropower plant plus energy storage)

The empirical analysis uses the CHEERS inputs and outputs at a 5

Table 2
Characteristics of the input files to the CHEERS model and the revenue prediction models.

CF level	Run #	Site	Price profile	Plant capacity (MW)	CF	Percentile of the power duration curve[1]	Storage duration (hr)	Normalized battery capacity	Battery capacity (MW)	Energy rating (MWh)	Max Charge Rate (MW)
Low CF	1	SA	CAISO 2018-SA	3.1	0.11	80%	4	0.01	0.03	0.12	0.03
	2	SA	CAISO 2018-SA	3.1	0.11	20%	4	0.17	0.53	2.12	0.53
	3	SA	CAISO 2018-SA	3.1	0.11	80%	2	0.01	0.03	0.06	0.03
	4	SA	CAISO 2018-SA	3.1	0.11	20%	2	0.17	0.53	1.06	0.53
	5	SA	CAISO 2018-SA	3.1	0.11	80%	0.5	0.01	0.03	0.02	0.03
	6	SA	CAISO 2018-SA	3.1	0.11	20%	0.5	0.17	0.53	0.27	0.53
	7	P-2019-0.4	CAISO 2019-SA	30	0.14	80%	4	0.11	3.3	13.20	3.3
	8	P-2019-0.4	CAISO 2019-SA	30	0.14	20%	4	0.36	10.8	43.20	10.8
	9	P-2019-0.4	CAISO 2019-SA	30	0.14	80%	2	0.11	3.3	6.60	3.3
	10	P-2019-0.4	CAISO 2019-SA	30	0.14	20%	2	0.36	10.8	21.60	10.8
	11	P-2019-0.4	CAISO 2019-SA	30	0.14	80%	0.5	0.11	3.3	1.65	3.3
	12	P-2019-0.4	CAISO 2019-SA	30	0.14	20%	0.5	0.36	10.8	5.40	10.8
Med CF	13	Nimbus	CAISO 2019-SA	13.4	0.52	80%	4	0.24	3.22	12.88	3.22
	14	Nimbus	CAISO 2019-SA	13.4	0.52	20%	4	0.59	7.91	31.64	7.91
	15	Nimbus	CAISO 2019-SA	13.4	0.52	80%	2	0.24	3.22	6.44	3.22
	16	Nimbus	CAISO 2019-SA	13.4	0.52	20%	2	0.59	7.91	15.82	7.91
	17	Nimbus	CAISO 2019-SA	13.4	0.52	80%	0.5	0.24	3.22	1.61	3.22
	18	Nimbus	CAISO 2019-SA	13.4	0.52	20%	0.5	0.59	7.91	3.96	7.91
	19	H-2019	CAISO 2018-SA	2.184	0.58	80%	4	0.11	0.24	0.96	0.24
	20	H-2019	CAISO 2018-SA	2.184	0.58	20%	4	0.71	1.55	6.20	1.55
	21	H-2019	CAISO 2018-SA	2.184	0.58	80%	2	0.11	0.24	0.48	0.24
	22	H-2019	CAISO 2018-SA	2.184	0.58	20%	2	0.71	1.55	3.10	1.55
	23	H-2019	CAISO 2018-SA	2.184	0.58	80%	0.5	0.11	0.24	0.12	0.24
	24	H-2019	CAISO 2018-SA	2.184	0.58	20%	0.5	0.71	1.55	0.78	1.55
High CF	25	FP-2012-0.7	CAISO 2018-SA	1.42	0.86	80%	4	0.6	0.85	3.40	0.85
	26	FP-2012-0.7	CAISO 2018-SA	1.42	0.86	20%	4	0.87	1.24	4.96	1.24
	27			1.42	0.86	80%	2	0.6	0.85	1.70	0.85

(continued on next page)

Table 2 (*continued*)

	FP-2012-0.7	CAISO 2018-SA								
28	FP-2012-0.7	CAISO 2018-SA	1.42	0.86	20%	2	0.87	1.24	2.48	1.24
29	FP-2012-0.7	CAISO 2018-SA	1.42	0.86	80%	0.5	0.6	0.85	0.43	0.85
30	FP-2012-0.7	CAISO 2018-SA	1.42	0.86	20%	0.5	0.87	1.24	0.62	1.24
31	H-2012-3.5	CAISO 2019-SA	2.184	0.81	80%	4	0.44	0.96	3.84	0.96
32	H-2012-3.5	CAISO 2019-SA	2.184	0.81	20%	4	0.78	1.7	6.80	1.7
33	H-2012-3.5	CAISO 2019-SA	2.184	0.81	80%	2	0.44	0.96	1.92	0.96
34	H-2012-3.5	CAISO 2019-SA	2.184	0.81	20%	2	0.78	1.7	3.40	1.7
35	H-2012-3.5	CAISO 2019-SA	2.184	0.81	80%	0.5	0.44	0.96	0.48	0.96
36	H-2012-3.5	CAISO 2019-SA	2.184	0.81	20%	0.5	0.78	1.7	0.85	1.7

Notes:
1. This indicates the probability of plant capacity is greater than hydro power generation.
2. The minimum and maximum SOC, and round-trip efficiency of battery are 20%, 100% and 86%, respectively, for all the runs listed.

min time resolution. GAMs are used as the approach to modeling the non-linear or discrete relationships in CHEERS datasets in R [9]. The first step in setting up the model runs is choosing the predictive variables. These variables include the constituents of the electricity market prices and technology variations. The GAMs implementation for this situation is

$$Market_{net_{rev}} = \beta_0 + f_1(P_E) + f_2(P_{UP}\cdot Cap) + f_3(P_{DN}\cdot Cap) + f_4(P_S\cdot Cap) + f_5(P_{NS}\cdot Cap) + \beta_1 E + \varepsilon_i \tag{2}$$

where *Market_net_rev* is the 5 min market net revenue for the combined asset; β_0 is the intercept; f_1, f_2, f_3, f_4 and f_5 are functions fitted based on Gaussian error distribution that can pass a smooth curve through the residuals for parameters: P_E, P_{UP}, P_{DN}, P_S and P_{NS}; $\in_i$ is the error term.

In the 18 CHEERS runs used for training, the revenue from directly selling hydropower to energy market contributes around 69% to 97% to the total net revenue, and the total net revenue is highly correlated with energy price (*Pearson correlation* = 0.98). To determine the predicting variables that are suitable for the GAMs, a correlation analysis is conducted to reveal the correlation between the considered variables and the predicted variables, and the threshold value of 0.45 is used to select the predicting variable (Table 3).

2.4. The machine learning approach

2.4.1. Data preprocessing

In each time interval, not all the energy generated is available for energy storage devices; for example, if the hydropower generated is larger than the maximum charging rate of battery, only a portion of the energy can be used to charge battery. For the energy that cannot be used to charge battery, there is no need to have the machine learning model make the prediction. Therefore, we applied a data preprocessing step before model training. In this step, total hydropower generation in each time interval (hydro_total [MW]) is evaluated. If it is larger than the maximum charging rate of battery (MW), the excess portion (hydro_cal [MW]) is separated from the total generation because its corresponding revenue produced by the hydropower plant directly sold to the market can be calculated based on energy price, and the rest of energy that is potentially available to battery is categories as hydro_left (MW). If the total hydropower generation is less or equal to the maximum charging rate of battery (MW), it is assumed that hydro_left can either be used to charge battery or directly sold to the market, then the hydro_cal is equal to 0, and the hydro_left is equal to hydro_total.

2.4.2. Model input features and predictions

Based on the correlation analysis, ten input features are selected upon which to train a model to make prediction:

E, Cap, Min_chrg, TE, P_E, P_UP, P_DN, P_S, P_NS, Hydro_left;

Modeling efforts are focused on predicting 5 revenue streams:

Hydropower to energy market, storage to energy market, storage to regulation up, storage to regulation down, and storage to spinning services.

Multiple input feature configurations are evaluated starting with a base model trained on individual 5 min instances. Additionally, given that each 24 h period of instances likely contained temporal dependencies, a moving-window approach contained to each 24 h period is developed where the 5 min input features are stacked into temporal groupings of *n* hours. Because the extent of the temporal dependencies is not known, moving window sizes of 1, 2, 3, 4, 6, 8, 12, and 24 h are evaluated to discover which window size yielded the lowest Root Mean Square Error (RMSE). These specific sizes are chosen as they evenly divide into a 24 h period which is necessary for model inference.

Table 3
Correlation table for the predicting and predicted variables.

	Cap	E	P_E	P_UP	P_DN	P_SPIN	P_NSPIN	P_E_Cap	P_UP_Cap	P_DN_Cap	P_SPIN_Cap	P_NSPIN_Cap	Hydro_left	Tot_Rev_left
Cap	1													
E	0.76	1												
P_E	-0.06	-0.05	1											
P_UP	0.01	0.00	0.25	1										
P_DN	-0.04	-0.03	0.20	0.44	1									
P_SPIN	0.04	0.03	0.22	0.72	0.13	1								
P_NSPIN	0.00	-0.01	0.30	0.62	0.08	0.87	1							
P_E_Cap	0.83	0.63	0.28	0.09	-0.03	0.15	0.13	1						
P_UP_Cap	0.61	0.46	0.05	0.55	0.21	0.47	0.36	0.58	1					
P_DN_Cap	0.50	0.39	-0.03	0.29	0.55	0.17	0.08	0.37	0.63	1				
P_SPIN_Cap	0.35	0.25	0.11	0.52	0.13	0.67	0.57	0.43	0.83	0.40	1			
P_NSPIN_Cap	0.10	0.06	0.15	0.44	0.08	0.61	0.70	0.25	0.58	0.18	0.84	1		
Hydro_left	0.57	0.44	-0.01	0.10	0.06	0.11	0.03	0.53	0.46	0.42	0.29	0.10	1	
Tot_Rev_left	0.56	0.45	0.21	0.42	0.31	0.37	0.28	0.67	0.79	0.70	0.64	0.42	0.74	1

To mitigate the varying feature data scales, the training data features are standardized by calculating the z score:

$$x' = \frac{x - \mu}{\sigma^2} \tag{3}$$

where the feature mean, μ, is removed from each instance and scaled to the feature variance, σ^2 to yield x', the transformed feature value. Features of the validation and testing data are also standardized in this way but based on the respective feature's mean and variance derived from the training data.

2.4.3. Model development

An ANN configured as a densely connected multi-layer perceptron (MLP) is developed to predict revenue values. Model structure and parametrization are defined and finalized using exploratory analysis focused on minimizing total RMSE, while striving to keep the model structure as simple as possible for computational efficiency. RMSE is defined by Eq. (4):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{y}_i - y_i\right)^2} \tag{4}$$

where $\widehat{y}_i$ represents the predicted value of instance i, y_i is that actual value, and n represents the number of instances.

The resultant model architecture is shown in Fig. 4. Following the input layer, a series of hidden layers containing 64, 128, 256, 128, 64, 32, 16 nodes respectively are arranged in a sequential structure. The final output layer consisted of 5 output nodes for each revenue prediction component.

Each hidden layer is configured with a rectified linear unit (ReLU) activation function [4] shown by Eq. (5):

$$f(x) = \left\{ \begin{array}{l} 0,\ x < 0 \\ x,\ x \geq 0 \end{array} \right\} \tag{5}$$

where $f(x)$ is always positive and x, the neuron input, is not bounded in the positive direction. This activation function is commonly used as it converges faster, x does not plateau or saturate in the positive direction, and it is sparsely activated as all negative inputs are converted to zero within the network.

The models are optimized with the Adam function using a learning rate of 0.0001. Adam is a commonly used stochastic-gradient-based optimization method for training deep learning models. The batch size or number of instances processed before the model is updated, is set to 64.

2.4.4. Moving window size for the ANN approach

In the ANN approach, size of the moving window can impact the prediction accuracy. Therefore, to select the optimal moving window with the lowest RMSE, the ML model are trained using 8 different moving window sizes (1, 2, 3, 4, 6, 8, 12, and 24 h). Based on the results shown in Table 4, the ANN approach with moving window size of 8 h is selected for the ML revenue prediction tool.

2.5. Model evaluation and validation method

2.5.1. Validation

In each model training run, about two thirds of the data are randomly selected and used as the training set, the other one third is used as validation data, which is used to test model predicting performance. The validations are conducted for both the regression and the ML approach, in which the predicting accuracy is evaluated using the metrics that are described in Section 2.5.3.

2.5.2. Testing

In order to understand the prediction efficiency of both predicting approaches handling unknown data such as new energy generation profiles and battery configurations, 18 sets of CHEERS results (runs #7∼#12 and #19 ∼#30) are used as test data to perform testing for the GAMs and ML model. In the testing, the same evaluation metrics as in validation are used to evaluate the prediction performance under different validation scenarios and different prediction algorithms.

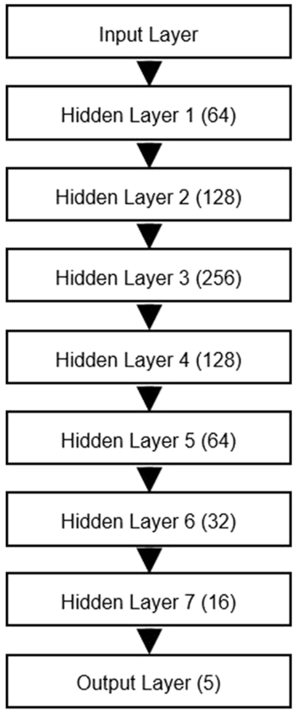

Fig. 4. Model architecture for the trained model.

2.5.3. Evaluation metrics: RMSE and prediction percent errors

In this study, the evaluation metrics used for the predicted revenue include the Root Mean Square Error (RMSE) and the percent error. The RMSE is used to evaluate the accuracy over the daily revenue prediction, and the percent error measures the accuracy for annual revenue prediction. The RMSE is calculated by Eq. (4).

Percent error, expressed as a percentage, is calculated as

$$Percent\ error = \frac{\text{Predicted total revenue} - \text{Actual total revenue}}{\text{Actual total revenue}} \times 100 \tag{6}$$

is used to evaluate predicting efficiency of each trained model.

2.6. Results postprocessing

2.6.1. Results postprocessing

For applying the trained deep learning model, a post-processing step is added to correct the predicted values in the case where the prediction tool produced negative daily revenues or unrealistically high revenues. The lower bound for predicted annual total revenue for hydropower with energy storage asset is set as the hydro energy only revenue Rev_{Hydro_only}, which is calculated as:

$$Rev_{Hydro\_only} = \sum_{d=1}^{365} \sum_{t=1}^{288} \left(P\_E_{td} \cdot E_{hydro\_total_{td}}\right) \tag{7}$$

where P_{Etd} is the energy market price ($/MW) in time interval t in day d, and $E_{hydro\_total_{td}}$ is the total hydropower generation (MW) in time interval t in day d. The reason for defining the hydropower energy's only revenue as the lower bound is that we assume the optimized total revenues for the integrated hydropower and energy storage system asset should be higher than the case with no energy storage installed. The upper bound for predicted revenue in each revenue stream is limited based on physical constraints appropriate to each revenue source (Table 5).

3. Results and discussion

3.1. Revenue prediction accuracy

3.1.1. Model validation

For the GAMs validation, the scatter plot shows that for days with larger daily revenue, the prediction model tends to underestimate revenue (Fig. 5). This may be due to the regression method that is selected. The generalized additive model is a generalized linear model with several smooth functions for each response variable, therefore, when the validation data are far away from the training data or the known range, the smooth functions may not be efficient. However, in most of the validation days, we can still conclude that it is feasible to use GAMs as an approach to provide total daily prediction for the hydropower with energy storage asset.

The learning curve and scatter plots of model validation for the ML approach indicate that the ML model efficiently learned an accurate relationship from the training data (Fig. 6), while the scatter plots of revenue from different markets indicate that the ML model overall produces accurate predictions with average percent errors of -0.99%. The learning curve shows that the model training losses for both the training and validation dataset keep decreasing over time until stabilizing at a similar level, which implies that there is no underfit or overfit issue and the trained model efficiently learns the relationship from the training data. By employing the ML approach, total daily revenue can be predicted in a more detailed manner and can be broken down into

Table 5
Upper bound for predicted revenue in each revenue stream.

Revenue stream	Upper Bound
Revenue: Hydro Energy to Grid_left ($)	$Rev_{Hydro\_left} = \sum_{d=1}^{365}\sum_{t=1}^{288}(P_{Etd} \cdot E_{hydro\_total_{td}})$
Revenue: Storage Energy to Grid ($)	$Rev_{StoE\_Max} = \sum_{d=1}^{365}\sum_{t=1}^{288}(P_{Etd} \cdot Cap)$
Revenue: Storage RegUp ($)	$Rev_{up\_Max} = \sum_{d=1}^{365}\sum_{t=1}^{288}(P_{UPtd} \cdot Cap \cdot 2)$
Revenue: Storage RegDn ($)	$Rev_{dn\_Max} = \sum_{d=1}^{365}\sum_{t=1}^{288}(P_{DNtd} \cdot Cap \cdot 2)$
Revenue: Storage Spin ($)	$Rev_{sp\_Max} = \sum_{d=1}^{365}\sum_{t=1}^{288}(P_{SPtd} \cdot Cap \cdot 2)$

Note that P_{UPtd} and P_{DNtd} are the price for the regulation up/down prices ($/MW) in time interval t in day d, P_{SPtd} is the spinning service price ($/MW) in time interval t in day d, Cap is the capacity rating of battery.

Table 4
RMSE for each predicted revenue stream in the ANN approach with different moving window sizes.

Revenue stream	Moving window size							
(h)	1	2	3	4	6	8	12	24
Revenue: Storage Energy to Grid ($)	308.07	271.27	263.68	252.83	210.20	290.57	236.77	287.20
Revenue: Storage RegUp ($)	264.16	311.10	314.68	262.93	224.23	267.31	249.72	325.79
Revenue: Storage RegDn ($)	259.93	242.72	277.19	237.07	268.84	264.53	328.34	315.40
Revenue: Storage Spin ($)	107.05	114.06	118.80	96.59	89.90	105.59	88.26	108.32
Revenue: Hydropower Energy to Grid ($)_left	135.55	134.83	122.28	118.67	110.13	130.14	136.33	150.90
Revenue: Total ($)	517.36	460.72	439.41	398.87	394.40	367.04	443.34	585.33

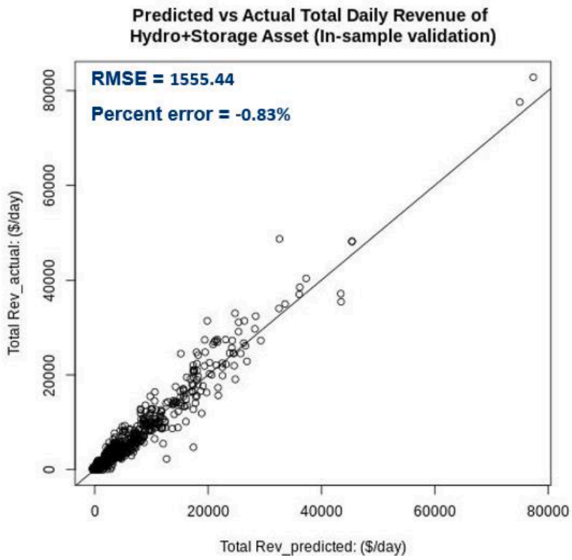

Fig. 5. Scatter plots of model validation for the GAMs approach. The plot shows the comparison between the total predicted daily revenue and the actual daily revenue, with a RMSE of 1555.44 $/day and a percent error of -0.83%.

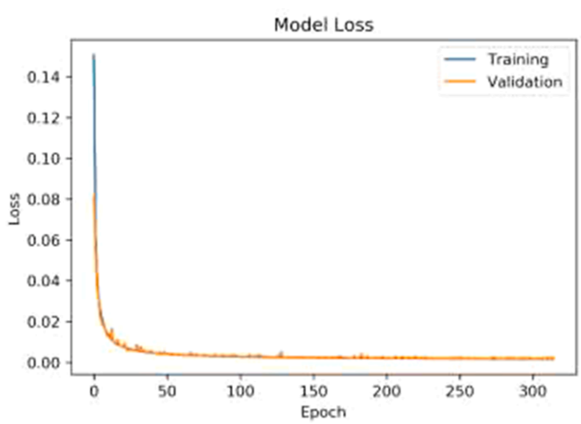

Fig. 6. Learning curve for the ML model approach: model loss during the model training and validation processes

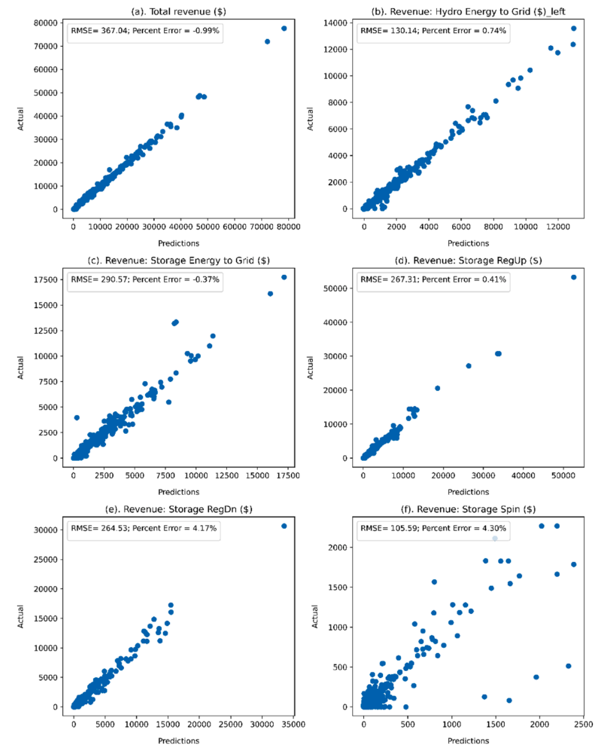

Fig. 7. Scatter plots of model validation for the ML model approach: (a-f) compare the actual and predicted values of different revenue streams, where (a) is total revenue, (b, c) are energy market (hydro energy to grid and storage energy to grid), (d) is spinning reserve service, (e) is regulation up and (f) is regulation down service.

revenue streams from different markets, such as the energy market, regulation up and regulation down services, and spinning reserve services. In addition, the revenues from the energy market are further categorized by the participating devices, i.e., whether it is directly from the hydropower plant or from the storage system. The total RMSE of the revenue prediction of the four markets are about 367.04 $/day, about 76% lower compared to the GAMs approach (1555.44 $/day). Therefore, in terms of RMSE, the ML approach has better performance. The ML approach produced an average percent error of -0.99% (Fig. 7(a)). Although the ML approach produced relatively larger RMSE and percent errors in predicting revenue from storage to spinning reserve service than in other revenue streams, since spinning reserve contributes only a small portion (about 0.10% to 2.22%) to total revenue, the larger RMSE and percent errors do not significantly impact total revenue prediction.

3.1.2. *Model testing*

The GAMs and ML models are examined in 18 model testing scenarios to test the prediction performances of the two approaches. The ML approach consistently produces lower RMSEs than the GAMs in all the scenarios for model testing (Table 6), which suggests that ML models perform better in daily revenue predictions. For example, in test runs #1, #3 and #5, the ML method produces a more than 10-fold reduction in RMSE compared to the GAMs. The percent error distributions for daily revenue prediction by using the GAMs and ML models also confirm this observation (Fig. 8). It is noticeable that the percent error distributions of ML approach are consistently narrower than that of GAMs approach, especially in runs #1 to #6, percent errors of GAMs approach widely spread in a range of -8140–4950%, compared to -65% to 687.92% of the ML approach.

The GAMs approach has about 2% to 9% lower percent errors in annual revenue prediction than the ML approach in validation runs #14,

Table 6
Prediction accuracy of the regression and the ML approach in model testing scenarios: RMSE is used to measure daily revenue predictions, and percent error is used to measure annual revenue predictions.

Metric	RMSE		Percent Error	
Model testing run (#)	GAMs	ML	GAMs	ML
1	387.4	26.8	11%	6%
2	520.7	160.3	-25%	-1%
3	387.9	27.8	12%	7%
4	512.7	168.4	-24%	-4%
5	389.3	31.2	13%	8%
6	490.5	157.4	-19%	-4%
13	2047.0	664.5	6%	-3%
14	3891.5	2577.8	-2%	-11%
15	1981.5	593.5	7%	-2%
16	3663.1	2338.6	0%	-8%
17	1896.5	445.4	12%	0%
18	3218.9	2026.5	6%	-8%
31	1058.1	297.3	12%	-2%
32	1126.9	401.6	-5%	-3%
33	1064.0	298.9	13%	-1%
34	1082.9	447.8	-3%	-2%
35	1111.8	326.4	19%	0%
36	1016.5	480.4	3%	0%

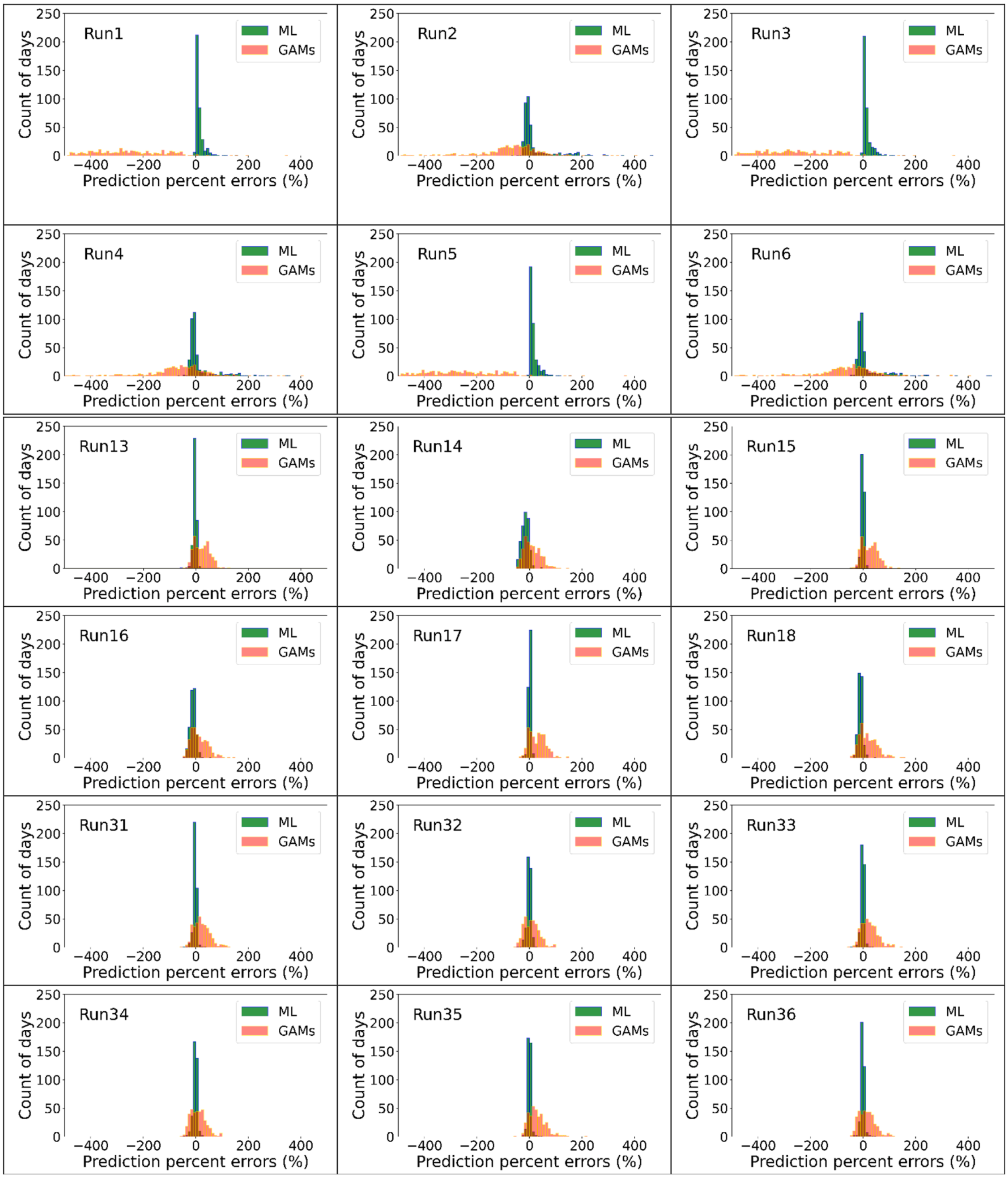

Fig. 8. Prediction errors distributions for daily total revenue prediction by using GAMs and ML models for all model testing runs (Note: this figure only shows prediction percent errors between -400% and 400%).

#16 and #18. In these runs, the GAMs approach actually produces more daily prediction errors than the ML model, as shown in Fig. 9. However, since these daily errors eventually cancel each other out, the total annual prediction errors of the GAMs approach are lower. Therefore, the lower prediction errors in these three scenarios do not mean that GAMs approach has the higher prediction efficiency.

The averaged percent error for annual total revenue prediction of the ML approach is about 4%, with the highest error of -11% in run #14 and lowest error of 0% in runs #17, #35 and #36. Data distribution of a training set can largely impact performance of the ML model. For example, runs #13 to #18 shares the same price profile and power generation curve, the only differences being the energy ratings and power capacities of the batteries that are matched, which directly lead to a difference in the amount of hydropower that is available for batteries (Total Hydro Generation (MWi)_left). In the training dataset, over 80% of the hydropower data are in the 0–2 MW range, with a small amount in the 3, 4 MW range. In run #17 (Percent error = 0%), nearly 90% of hydro power generation data are in the range of 3, 4 MW, in which there are sufficient data points in the training dataset (Fig. 10(a) and (c)). In contrast, in run #14 (Percent error = -11%), more than 40% of hydro power generation is in the range of 7, 8 MW, in which there is not enough training data to support model training; therefore, the possibility of prediction bias increases (Fig. 10(b) and 10(d)). In run #16 and #18, a similar pattern is also observed; therefore, the resulting percent errors in these scenarios are higher than other runs. On the other hand, available hydropower data in runs #13, #15, and #17 are completely in the range of training set, which leads to much more accurate revenue predictions. This result highlighted the importance of having sufficient training data that cover each data category to ensure a robust model training. In our future study, more efforts will be spent on collecting

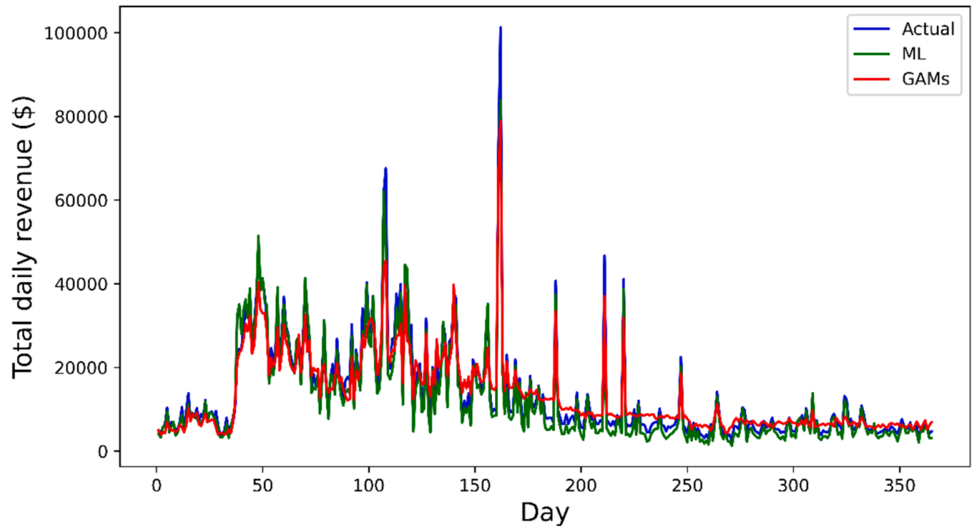

Fig. 9. Actual versus predicted daily revenues from the regression and ML approach for validation run #14. The plot shows that daily total revenue predicted by ML model is more closely aligned with the actual value, especially in days with revenue spike.

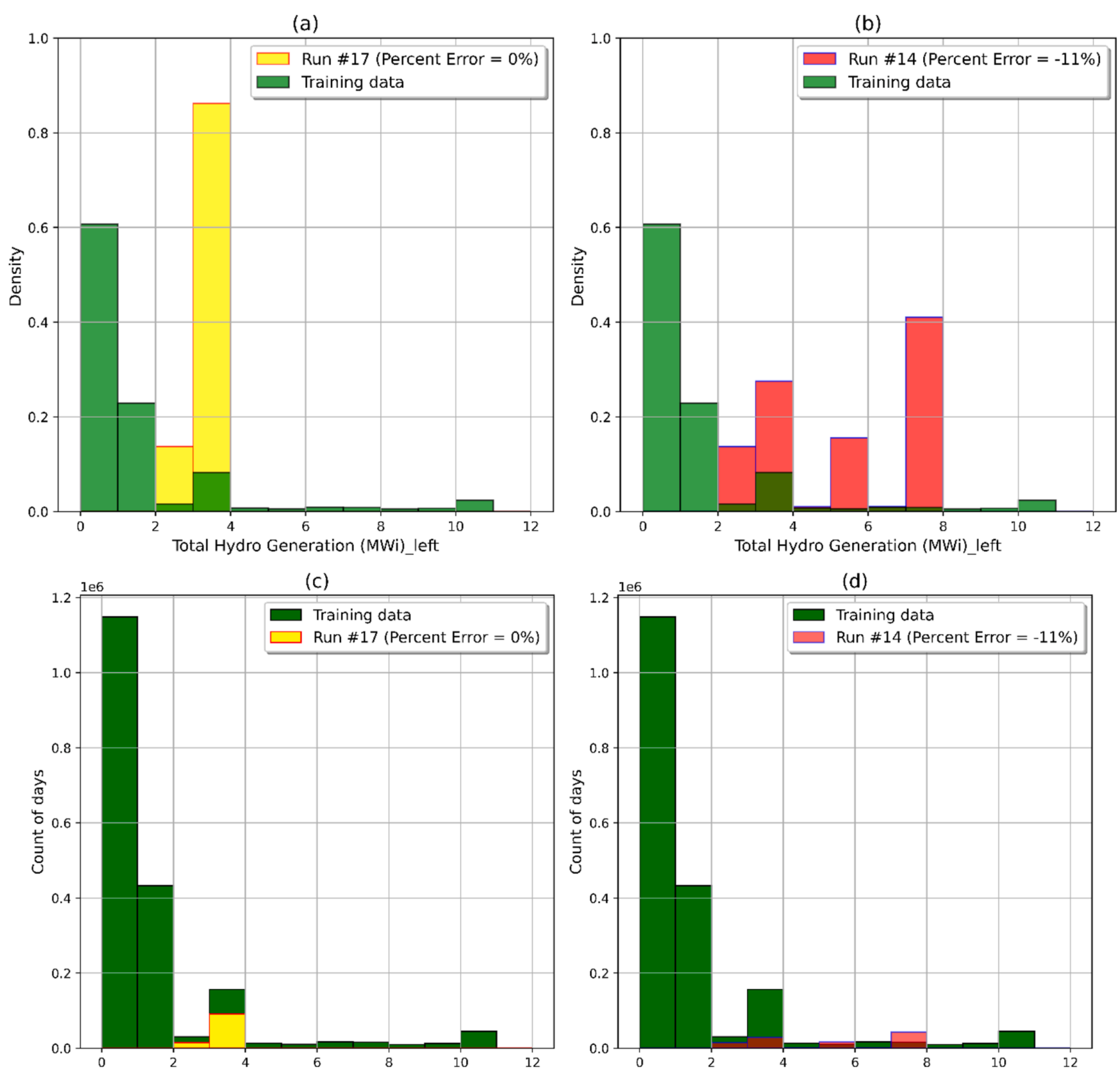

Fig. 10. Comparisons of distributions of hydropower generation between the training set and select test sets. (a), (b) show the density distributions and (c), (d) show the counting distribution.

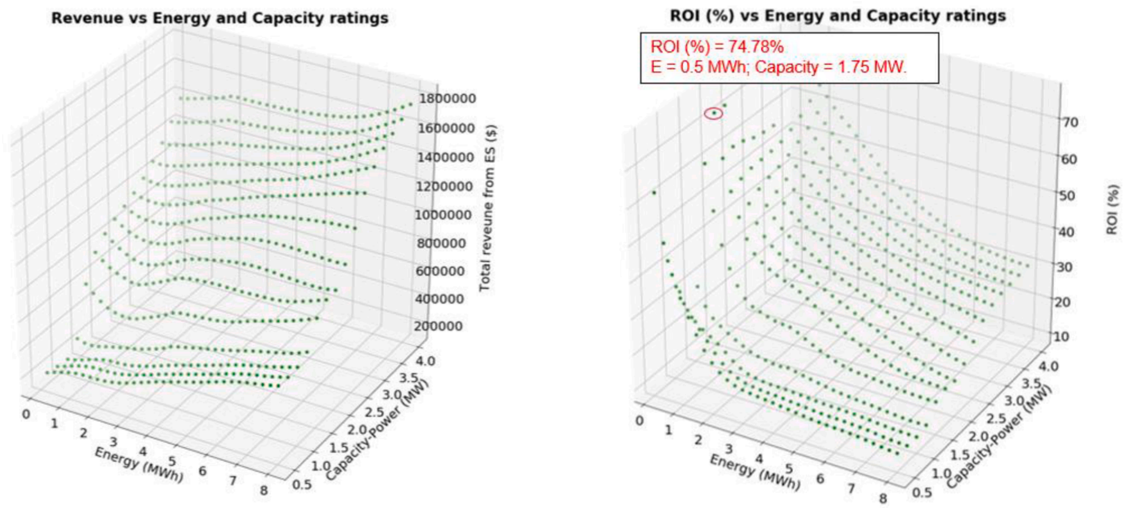

Fig. 11. Example total annual revenues (left) and 5-year ROIs (right) as a function of both energy and power ratings of the energy storage system paired with hydropower plant. There are 450 green dots in each figure and each green dot represents one battery size.

sufficient and representative training data.

3.2. Potential applications of revenue prediction

The key contribution is the ability to efficiently and accurately estimate optimal revenue in energy generation and storage systems. This is critical information for asset owners to select optimal sizing of energy storage that will benefit their power production systems. In the future, this tool will be integrated into an energy storage sizing optimization tool, which recommends an energy storage system configuration to maximize financial performance of the new energy storage asset based on hydropower characteristics, generation profiles, services to be provided, and associated fixed and operational costs. The tool will require only relatively accessible input data from the plant owners and operators, such as parameters corresponding to their plant of interest (for example nameplate capacity, ramping capabilities, and generation profiles), services the owner or operator would be interested in providing, and market parameters. Based on this information, the sizing tool will use revenue prediction and techno-economic information to determine the optimal energy storage configurations to be paired with the plant (Fig. 11). A total of 450 annual revenue and 5-year return on investment (ROI (%)) are simulated using the trained ML model for combined assets with different battery sizing (Fig. 10). The figure indicates (1) there is a non-linear relationship between battery sizing and financial performances of the combined asset; (2) batteries with smaller energy ratings generally yield at higher ROI (%); (3) the highest ROI (%) of 74.78% is identified when energy rating and power rating of the paired battery are 0.5 MWh and 1.75 MW, respectively. Processing 450 annual revenue optimization runs will take at least 1350 h (about 56 days) of computational runtime by using the CHEERS model. However, with the ML model, the process time can be largely reduced to about 4 min, which indicates the impact and key advantage of this innovative approach.

4. Conclusions

Assessing optimal revenue and financial performance of energy generation and battery systems is critical information for asset owners who may be interested in hybridizing their generation plants. Traditional models, e.g. MILP-based revenue optimization models, are generally time-consuming to setup and run and require significant data inputs to set them up correctly. Especially in the context of considering many battery sizes or configurations, the process could possibly take days or even months to simulate revenue for the combined assets. We develop an innovative revenue prediction approach that overcomes all of these challenges. This paper explores two empirical modeling approaches: a regression-based and a deep learning-based approach for predicting revenue of an integrated generation and battery asset. The model is demonstrated for a hydropower plant participating in CAISO. The results show that:

The ML approach generally provides better predicting accuracy (with an average absolute prediction error of 4%) in predicting annual and daily revenue than the GAMs, especially in days with revenue spikes.

- More training data leads to better performance for the ML approach. The results show that the ML model yields higher prediction errors in the range where there are fewer data points in the training data.
- The trained ML model is used to make revenue predictions for hydropower and battery combined asset using a total of 450 different battery sizing configurations. Compared to conventional method, the ML model largely reduces computation time by more than 99%, from about 56 days to 4 min.

These results suggest that although the performance of the trained model is sensitive to the range of predicting variables, the ML approach is sufficiently accurate to be useful in achieving the objective of this work, which is to produce a revenue prediction method that can provide first exploration insights to energy storage sizing and is easy to use by people who are non-modeling experts. Future potential directions are to integrate this revenue prediction with cost and performance information to recommend energy storage devices that maximize financial performance. In addition, to further improve the accuracy of the ML model, a hybrid approach that involves an MILP model could be developed that would inform and correct the unrealistic predictions produced by the ML model when new, sufficiently out-of-sample scenarios are provided.

CRediT authorship contribution statement

Yingqian Lin: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Binghui Li:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Thomas M. Moiser:** Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Supervision. **L. Michael Griffel:** Methodology, Software, Writing – original draft, Writing – review & editing. **Matthew R. Mahalik:** Data curation. **Jonghwan Kwon:**

Data curation. **S. M. Shafiul Alam:** Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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