Developing a module for estimating climate warming effects on hydropower pricing in California

Marion Guégan [a], Cintia B. Uvo [a], Kaveh Madani [b],*

[a] Department of Water Resources Engineering, Lund University, P.O. Box 118, SE-22100 Lund, Sweden
[b] Department of Civil, Environmental and Construction Engineering, University of Central Florida, 4000 Central Florida Blvd., Orlando, FL 32816, USA

ABSTRACT

Climate warming is expected to alter hydropower generation in California through affecting the annual stream-flow regimes and reducing snowpack. On the other hand, increased temperatures are expected to increase hydropower demand for cooling in warm periods while decreasing demand for heating in winter, subsequently altering the annual hydropower pricing patterns. The resulting variations in hydropower supply and pricing regimes necessitate changes in reservoir operations to minimize the revenue losses from climate warming. Previous studies in California have only explored the effects of hydrological changes on hydropower generation and revenues. This study builds a long-term hydropower pricing estimation tool, based on artificial neural network (ANN), to develop pricing scenarios under different climate warming scenarios. Results suggest higher average hydropower prices under climate warming scenarios than under historical climate. The developed tool is integrated with California's Energy-Based Hydropower Optimization Model (EBHOM) to facilitate simultaneous consideration of climate warming on hydropower supply, demand and pricing. EBHOM estimates an additional 5% drop in annual revenues under a dry warming scenario when climate change impacts on pricing are considered, with respect to when such effects are ignored, underlining the importance of considering changes in hydropower demand and pricing in future studies and policy making.

© 2011 Elsevier Ltd. All rights reserved.

1. Introduction

California's statewide average temperatures are expected to rise between 1.5 °C and 5 °C by 2100 (Luers et al., 2006; Cayan et al., 2008, 2009). This temperature increase is expected to decrease the state's snowpack reserve at high elevations, decrease the snowmelt peak flow, and shift the snowmelt to earlier in the year (Luers et al., 2006; Moser et al., 2009). This is a major concern for future energy generation from high-elevation hydropower plants in California. The high-elevation hydropower reservoirs in California, regulated by the Federal Energy Regulatory Commission (FERC), with high energy heads and relatively small storage capacities have been designed to take advantage of snowpack, which functions as a natural reservoir. Thus, their low storage capacity might make them vulnerable to future snowpack volume and runoff timing variations (Madani and Lund, 2010).

Besides affecting water availability for hydropower generation, higher temperatures will likely increase energy demand for cooling in warm periods and decrease the need for heating in cold periods

(Luers et al., 2006; Franco and Sanstad, 2006; Aroonruengsawat and Auffhammer, 2009). Under climate warming, higher costs from increased demand for cooling are expected to outweigh the decreases in heating costs (Franco and Sanstad, 2006). Among plausible climate scenarios, some estimate a higher temperature increase in summer than in winter (Luers et al., 2006), which might be problematic with respect to hydropower generation since the annual peak load already occurs in summer for cooling.

This study develops an Artificial Neural Network (ANN) to map a non-linear relationship between temperature, price, and electricity demand. ANNs are networks of interconnected neurons that were developed in an attempt to reproduce the powerful human brain's architecture (Hsieh and Tang, 1998). Once calibrated, this ANN model is used as a long-term price estimation tool, allowing the estimation of climate warming effects on electricity prices. Previous studies of climate change effects on hydropower in California (e.g., Medellín-Azuara et al., 2008; Madani et al., 2008; Vicuña et al., 2008; Madani and Lund, 2010; Connell-Buck et al., in press) have tried to address this issue by focusing on climate warming effects on the supply side only (exploring the effects of hydrological changes on generation and revenues), ignoring the warming effects on hydropower demand and pricing. The developed module in this study facilitates future policy making with regard to hydroelectricity in California. Allowing for simultaneous consideration of changes in

* Corresponding author. Tel.: +1 407 823 2317; fax: +1 407 823 3315.
E-mail addresses: kaveh.madani@ucf.edu (K. Madani),
mar.guegan@gmail.com (M. Guégan), cintia.uvo@tvrl.lth.se (C.B. Uvo).

energy supply and pricing, this module can be used for assessment of the adaptability of California's high-elevation hydropower system to climate warming which is essential to statewide long-term adaptation planning and of particular importance to the FERC's hydropower licensing process (Madani, 2011).

Given the importance of considering the climate change effects on hydroelectricity demand in future energy planning and policy making, the ANN model is developed as a complementary module to the existing California's Energy-Based Hydropower Optimization Model (EBHOM) (Madani and Lund, 2009) to improve its energy price representation under climate warming scenarios. EBHOM is a monthly step model. Its price representation uses revenue curves that are the integrations over the hourly price frequency distribution curves. This allows capturing the hourly variability in energy prices – on a monthly basis – of the energy market. The price representation is a function of the percent time turbines are in operation, assuming they operate in hours when the energy market offers higher prices.

California's electricity supply industry turned into a competitive deregulated market in the 1990s (CBO, 2001). The California Power Exchange (California PX) operates the day-ahead market and sets the price to which generators will sell electricity based on a bidding process. California Independent System Operator (California ISO) then operates the region's power grid and wholesale electricity market. The deregulation of the energy market created competition among electricity producers and retailers who need price forecasts to develop their bidding strategy in the electricity market (Lu et al., 2005; Amjady and Hemmati, 2006). Operations decisions are now highly dependent on market electricity price (Amjady and Keynia, 2010a). Electricity generation scheduling is based on profit maximization whereas it was based on cost minimization in the earlier regulated environment to meet the electricity demand (Zarezadeh et al., 2008).

Dealing with short-term price forecasting, Artificial Neural Networks (ANNs) have shown a good ability to forecast normal electricity prices (Zhao et al., 2007). One of the main advantage of ANNs over traditional methods such as regression, time series or regressive integrated moving average (ARIMA) is that they are more adapted to long-term patterns as they can cope with non-linear behavior of the target signal (Amjady and Hemmati, 2006). ANNs provide an appealing solution for establishing non-linear relationships between input and output variables in complex systems (ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000; Dawson and Wilby, 2001) and are capable of extracting information even with little prior physical knowledge about the systems (Zhang et al., 1998). To the best of the authors' knowledge, research on ANNs as price estimation tools has exclusively focused on short-term price forecasting, following the needs from the market. The estimation of the effects of climate warming on energy prices through ANN has not been investigated yet.

The paper first discusses how the ANN model is developed and calibrated to map a relationship between temperature, energy demand, and prices. The ANN model is then used to estimate California's long-term hydropower price patterns under different climate warming scenarios. Results from the ANN tool are presented and discussed. Finally, the ANN model's results under one of the climate warming scenarios, examined here, are fed to the EBHOM to examine the sensitivity of hydropower operations under climate change to hydropower pricing and electricity demand.

2. Method

Even though the original idea to develop ANN models was proposed in the 1940s by McCulloch and Pitts (1943), progress

was relatively slow until the 1980s when Rumelhart et al. (1986) discovered a mathematically rigorous theoretical framework by proposing the backpropagation optimization algorithm. Since then, ANNs have been successfully used for prediction and forecasting applications in hydrological problems (ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000; Kingston et al., 2005) and in short-term electricity price forecasting (e.g., Lu et al., 2005; Amjady and Hemmati, 2006; Ranjbar et al., 2006; Amjady and Keynia, 2010a).

The ANN built in this work is designed as a module of EBHOM hydropower model. EBHOM is a monthly-based model that maximizes hydropower generation revenues using monthly revenue curves that are the integrations over the hourly price frequency distribution curves as explained in Madani and Lund (2009). To meet the needs from EBHOM, the ANN model was calibrated using hourly data. Hourly output prices from the ANN are used to build revenue curves used by EBHOM.

The method used in this work to design the ANN is inspired by the protocol for implementing Rainfall-Runoff ANN models, defined by Dawson and Wilby (2001), and additional modeling suggestions from Maier and Dandy (2000). They defined a theoretical framework for ANN model design. A feed-forward ANN is chosen since it has commonly been used for prediction and forecasting applications in hydrological problems (ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000; Kingston et al., 2005) and in short-term electricity price forecasting (Ranjbar et al., 2006; Zarezadeh et al., 2008).

A typical ANN consists of a number of neurons (also called nodes) that are organized in a specific arrangement (ASCE, 2000). In a feedforward network, information flows unidirectionally from an input layer towards an output layer. Between the input and output layers there can be one or several hidden layers processing information before it reaches the output layer. A schematic diagram of a jth neuron is displayed in Fig. 1. This neuron transforms an input vector $X = (x_1, \ldots, x_i, \ldots, x_n)$ into a single output y_j. Neuron 'j' is characterized by a vector of weights represented by a vector $W_j = (w_{1j}, \ldots, w_{ij}, \ldots, w_{nj})$, a bias b_j and an activation function f. The inputs to the neuron can be causal variables, i.e., the inputs to the system if the neuron is in the input layer, or they can be outputs from neurons belonging to previous hidden layers. The activation function determines the response of the neuron as follows: $W_j = f(X \times W_j + b_j)$.

The ANN model has to be trained to obtain a model representing reality as accurately as possible. Training or calibrating an ANN model is the process of adjusting its parameters (weights) to minimize a predefined error function (Kingston et al., 2005) – the determination coefficient R^2, in this work. The global-search algorithm "Shuffle Complex Evolution" (SCE-UA) (Duan et al., 1992) is applied to train the ANN. The SCE-UA method has good convergence properties over a broad range of problems and it should have a high probability of finding the global optimum
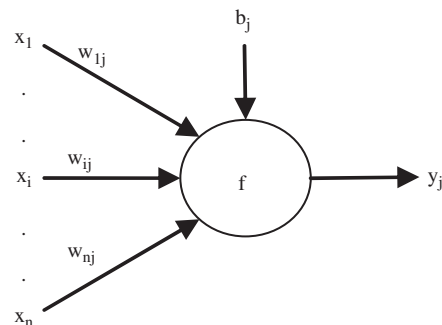

Fig. 1. Schematic representation of a neuron "j" in a feed-forward ANN.

(Duan et al., 1992). The general idea of SCE-UA algorithm is to generate a population of random points from the feasible space of parameters that will evolve towards an optimal solution, i.e., the global minimum of the error surface. The SCE-UA method uses an evolution process called the Complex Evolution Algorithm (Duan et al., 1992) to ensure that the population of points does not get trapped into unpromising regions. The reader is referred to Duan et al. (1992, 1994) for further information on SCE-UA algorithm.

During the training phase, the ANN architecture can be adjusted to minimize the error function. The optimal ANN architecture is determined through a trial-and-error procedure as commonly seen in the literature (ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000; Maier and Dandy, 2000). The procedure consists of trying out different numbers of hidden layers and hidden nodes. Increasing the size of the ANN increases the number of free parameters (weights). An ANN should contain enough parameters to improve its capacity to map a complex relationship between the inputs and outputs (Dawson and Wilby, 2001). However, increasing the size of the network over a certain threshold may produce the opposite effect if the ANN overfits the data, hindering its ability to generalize (Dawson and Wilby, 2001). Overfitting is characterized by a good performance during the training period but very poor results when a new unknown data sample is fed to the ANN for validation. The cause of this behavior is that the ANN fitted the training data so well that it fitted to the noise contained in the sample (Hsieh and Tang, 1998).

Cross-validation procedure also referred to as cross-training procedure is used in this work to decide when to stop the ANN training. This procedure is usually recommended to prevent overfitting (ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000; Maier and Dandy, 2000). It consists of dividing the data sample into three sets – usually called training, validation, and test sets – and using them independently to check when the ANN is optimized. The ANN is considered to be optimized when the training set minimizes the error function and the error increases over the validation set (ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000).The performance of ANNs is reliant on the quantity and quality of the calibration data (Kingston et al., 2005). Before calibration of the model, a preliminary statistical data analysis is performed to get an overview of existing trends, potential problems and to allow an adequate data preprocessing. Once the ANN model is trained, it can be used as a long-term price estimation tool to estimate the effects of climate warming on demand and pricing.

Five climate warming scenarios are selected here, representing a range of temperature increases and hydrological conditions (dry and wet). All climate scenarios are based on two commonly used Global Climate Model (GCM) scenarios: GFDL CM2.1 (from the NOAA Geophysical Fluids Dynamics Laboratory) and Parallel Climate Model (PCM). These GCM scenarios were combined to the low forcing B1 and high forcing A2 greenhouse gas emission scenarios. These are two of the probable sets of projection of greenhouse gas emissions for California (Cayan et al., 2008, 2009). Among plausible climate scenarios, some estimate a higher temperature increase in summer than in winter (Luers et al., 2006, Cayan et al., 2008, 2009) which would have widespread effects on water use and availability as well as on energy demand. In fact, electricity demand for cooling is projected to increase in warmer summers (Franco and Sanstad, 2006; Aroonruengsawat and Auffhammer, 2009). These combined effects of climate change on hydropower demand and supply (due to effects on water use and availability) can potentially affect California's high-elevation hydropower system with low storage capacity and

Table 1
Climate change scenarios for California (adapted from Cayan et al. (2008, 2009)).

Scenario Name	GCM	SRES	2070–2099 Temperature change (°C)[a,b]		
			Winter (DJF)	Summer (JJA)	Spring (MAM) & Autumn (SON)
GFDL-A2-Annual	GFDL	A2	+4.5	+4.5	+4.5
GFDL-A2-Seasonal	GFDL	A2	+3.4	+5.9	+4.5
PCM-A2-Annual	PCM	A2	+2.6	+2.6	+2.6
GFDL-B1-Annual	GFDL	B1	+2.7	+2.7	+2.7
PCM-B1-Annual	PCM	B1	+1.6	+1.6	+1.6

[a] Values from two regions referred to as Nocal and Socal (North and South California) were averaged to produce an average considered to be representative for entire California.
[b] Temperature change in spring and autumn was assumed to be equal to the average annual temperature change.

operation flexibility. In this work, four scenarios assume a constant increase in temperature throughout the year (e.g., scenario referred to as GFDL-A2-Annual) whereas an additional scenario (GFDL-A2-Seasonal) assumes that temperature increases more in summer than in winter. The temperature increases for all these scenarios, shown in Table 1, were adapted from the estimations by Cayan et al. (2008, 2009).

A strong assumption is made here, reasonable for facilitating a large-scale study: the statewide temperature increase considered here is the average of the temperature increases for the two regions NOCAL and SOCAL (NOCAL corresponds to Sacramento region whereas SOCAL to the area around Riverside in Southern California). This average value is considered to be representative of the highly electricity demanding areas, i.e., the highly populated areas in California which are of interest in this work. The same temperature increase estimated by Cayan et al. (2008) based on mean values for the historical period 1961–1990 was used in this work; however, the base period to which it is added is the 2005–2008 average.

3. Input data

Data for the 2005–2008 period were collected to train the ANN model as described below.

3.1. Temperature

Hourly temperature data for the period 2005–2008 were extracted from the website of University of California Statewide Integrated Pest Management Program (University of California, 2010) and were standardized. Standardizing a time series is the process of rescaling the series to get a set with a mean of zero and a standard deviation of one. First, the mean of the set is subtracted from each component of the time series and then the resulting set is divided by the standard deviation. This step is important when pre-processing the ANN model inputs to ensure all inputs receive equal attention during the ANN model training (Maier and Dandy, 2000). Data for three Pest stations were chosen and their average was considered to be representative for areas with high electricity demand in California. The three stations are located in the counties of Fresno, Colusa and San Joaquin. The average temperature of the three mentioned stations may not reliably represent the average temperature in California with high climate variability. Nevertheless, we were not able to find additional stations, providing hourly temperature data for the 2005–2008 period for which hourly price data was available. This is a limitation of this study that may be addresses in future studies.

3.2. Energy demand

Franco and Sanstad (2006) found that daily demand of electricity for the area serviced by the California ISO in 2004 is correlated to average daily temperature measured in four locations of California. They estimated daily electricity demand in MWh as a third-degree polynomial function of temperature, given in Eq. (1). They calculated a correlation coefficient of $R^2 = 0.9098$.

$$D = 3.3833T^3 - 263.75T^2 - 831.05T + 905{,}961 \qquad (1)$$

where D is the demand and T the temperature in F.

In this research work, hourly electricity demand was estimated as a function of hourly average temperatures through this function. We assumed that this was reasonable since we are interested in building a demand 'signal' that is representative of the general impact of temperature on electricity demand. Therefore, we are not trying to capture peak hourly demands through this function. Hourly electricity demand is not reliant on temperature only but on many other parameters such as the day of the week, the hour of the day, etc. In the next steps of the modeling, temperature, demand and other parameters are used as inputs to the ANN. The ANN is expected to map the non-explicit relationship between price and all these parameters based on its ability to extract information even with little prior physical knowledge about the systems (Zhang et al., 1998). The electricity demand input to our ANN model should therefore be seen as a demand signal, used to improve the performance of the ANN model, rather than an actual demand set. Among the many experiments made when designing the ANN model, a model without a demand input (signal) was tested. Results indicated that the model performed better when the demand signal was added to the set of inputs.

Finally, an input (signal) referred to as 'Base Temperature' ($Base\ Temp = |T - T_{min}|$) was created where T_{min} is the temperature corresponding to the minimum electricity demand in Eq. (1). This variable is an additional index reflecting the increase in electricity demand relative to the minimum energy demand. This was inspired from the definition of the base temperature in degree-day approaches. The demand signal and the base temperature were standardized before being fed to the ANN model.

3.3. Hydroelectricity prices

Real-time hourly energy prices for 2005–2008 were obtained from the California ISO Open Access Same-time Information System (OASIS) website (California ISO, 2010). California ISO serves more than 30 million consumers with electricity so these hourly prices are considered to be representative of California's energy market. Prices for September–December 2005 were discarded from the price dataset since those are abnormally high after perturbation of the entire US energy market by Hurricane Katrina (California ISO, 2006). Prices for January–June 2008 were also high on average due to soaring fossil fuel prices combined with dry conditions in spring (California ISO, 2009). Those prices were not discarded but an additional input to the ANN, equal to 1 for January–June 2008 (and 0 otherwise), was created to account for these specific events. Price data were standardized and then scaled between −0.9 and 0.9 to avoid squashing with a hyperbolic tangent activation function in the ANN hidden layer.

Based on the definition by Lu et al. (2005) ($P_v = \mu \pm 2\delta$, where μ is the mean value and δ is the standard deviation of the price dataset), price spikes (or price outliers) in California ISO were identified as prices exceeding $P_v = 128$ \$/MWh. They include 3.7% of the price population (or 1191 data samples) and represent 12.9% of the cumulated price intensities. Many high intensity prices are observed in 2008 but are probably not price spikes since a global increase in energy prices occurred that year. Their intensity is still 'abnormally' high so no distinction between those and other price spikes was made. Prices below the threshold P_v are referred to as normal prices hereafter.

4. ANN model setup and calibration

A multilayer feed-forward ANN model is developed and optimized using the global-search SCE-UA algorithm. The ANN architecture and inputs are shown in Fig. 2. In the following sections, the choice of ANN user-defined parameters is described, different data partitioning experiments are presented, and finally two ANN models are retained.

4.1. Sensitivity analysis, choice of ANN parameters

A single hidden layer is chosen as it should be sufficient to model any non-linear relationship, given that sufficient degrees of freedom (hidden neurons) are provided (Hornik et al., 1989). Eight hidden neurons and eight complexes for SCE-UA optimization algorithm were selected after sensitivity analysis as a compromise between architecture complexity and calibration processing speed. The range investigated during sensitivity analysis is shown in Table 2. The other algorithmic parameters in SCE-UA were initialized to the values recommended Duan et al. (1994).

Tangent hyperbolic (tansig) activation function was selected in the ANN hidden layer and combined to a linear function in the output layer as is common in short-term price electricity forecasting works (Ranjbar et al., 2006; Zarezadeh et al., 2008;
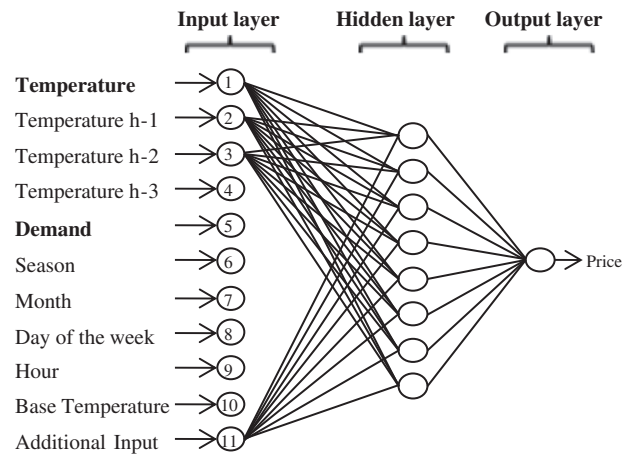
Fig. 2. Architecture of the feed-forward ANN designed and selected inputs.

Table 2
User-defined parameters of the ANN architecture and the SCE-UA optimization algorithm.

Parameter	Value adopted	Range investigated
ANN Architecture		
Number of hidden layers	1	1[a]
Number of hidden neurons	8	1–8
Activation function in the hidden layer	Tangent hyperbolic	Tangent hyperbolic & Logistic sigmoid
SCE-UA Algorithm		
Number of complexes	8	1–8

[a] A single hidden layer is supposed to be enough to map any non-linear relationship between a set of inputs and outputs (Hornik et al., 1989).

Gao et al., 2000). Sigmoid-type functions return a non-linear output response that makes them a useful tool to map non-linear processes (ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000). Logistic sigmoid function was also considered as an alternative choice, but sensitivity analysis shows that output prices from a model using tansig activation function fit best to observed prices in terms of average and maxima (Table 2).

4.2. Data partitioning experiments

Generally, in a competitive energy market, hourly electricity price series contain multiple seasonalities such as weekly and daily periodicities. Therefore, it is very hard for a single ANN to map correctly the input/output relationship of such a signal in all time periods (Amjady and Keynia, 2010b). In previous research, datasets have sometimes been partitioned along: periods of warm and cool days (Ranjbar et al., 2006), workdays and weekends (Gao et al., 2000), public holidays (Amjady and Keynia, 2010b), or stochastic components (Zhao et al., 2007). As part of the ANN calibration procedure, different data partitions were also tested in this work. They were compared to an ANN built on all data, i.e., without subdividing the dataset.

Experiments included dataset partition along seasons, months, days, and hours. Two model types were found to produce good visual agreement with observed data: (1) twelve parallel monthly-based models; and (2) two parallel models for workdays only and weekends only. The range of R^2 values obtained for those two trained ANN models are shown in Table 3, as well as for an ANN trained on all data. It can be seen from Table 3 that

partitioning the dataset results in higher R^2 values compared to when the entire dataset is fed to the ANN model. The highest R^2 value is obtained for one of the twelve monthly models.

Only one of these three models was retained for further analysis. The ANN model based on the entire dataset was discarded from further analysis since subdividing the dataset showed better correlations and should facilitate the ANN learning process. Monthly based models (hereafter referred to as ANN1) were selected since they were considered to be appropriate to capture the monthly price variability, which is of interest in this work. As mentioned earlier, monthly revenue curves (integration over the monthly price frequency distribution) are the results from the ANN models to be used as inputs to the hydropower optimization model (EBHOM). Monthly based models were trained using 9 predictors (numbered 1–5 and 8–11 in Fig. 2). The distributions of observed prices and modeled prices using ANN1 are given in Table 4 (Base case refers to the historical climate with no warming). Under Base case, ANN1 returns essentially prices in the range 25–85 $/MWh (representing 80% of data); lower and higher prices are poorly modeled and prices exceeding 360 $/MWh are not returned. This reflects the fact that ANN models learn better on the (frequent) average data than on the extreme (rare) intensities (Olsson et al., 2004).

Since outliers are not captured by the ANN1, a model trained on normal prices only was developed (using all 11 inputs shown in Fig. 2). Prices defined as price spikes (see section 0) were removed from the calibration dataset. In this case, no time-based data partition was considered and the model was trained on data from all year round. The annually-based ANN trained on normal prices improved the determination coefficient by 0.1, compared to an ANN model trained on all price intensities (Table 3). Lu et al. (2005) and Zhao et al. (2007) already highlighted that ANNs are unable to model price spikes because those are highly erratic, several orders of magnitude higher than the average price and under-represented compared to normal prices. Furthermore, price spikes are most likely not driven by the inputs selected in the present work. According to Lu et al. (2005), almost all the existing techniques for short-term price forecasting require filtering out price spike signals in order to forecast normal prices with rather high accuracy. Depending on how the energy market is projected to evolve, two options to deal with the truncated price spikes are

Table 3
Range of determination coefficient for simulations on four trained ANN models based on different data partitions.

Data partitions	Data partitions	$R^2_{\text{simulation}}$
All data – No data partition	1	0.28
Monthly-based	12	0.16–0.47
Workdays-/Weekend-based	2	0.28–0.33
Normal prices, Annually based	1	0.38

Table 4
Price distribution results from the ANN long-term price estimation tool under Base case and different climate scenarios.

Climate scenario	ANN model[a]	Prices in $/MWh				Price Percentiles in $/MWh				
		Average	Standard Deviation	Minimum	Maximum	10th	25th	50th	75th	90th
Observed data		54.87	36.54	0.00	400.0	23.88	36.88	49.13	64.14	84.28
Base Case	ANN1	54.65	22.22	0.00	358.2	31.70	40.62	50.55	64.00	81.09
	ANN2	54.85	32.32	12.96	400.0	32.22	40.44	49.07	58.60	73.93
GFDL-A2-Annual	ANN1	59.89	33.16	0.00	425.7	30.78	41.04	51.73	70.20	96.15
	ANN2	55.96	33.04	9.00	400.0	31.13	40.58	49.31	61.95	76.11
GFDL-A2-Seasonal	ANN1	61.55	35.28	0.00	425.7	31.20	41.69	52.38	71.93	99.75
	ANN2	56.67	33.07	9.00	400.0	31.64	41.15	49.87	63.24	76.98
PCM-A2-Annual	ANN1	56.94	27.51	0.00	392.8	31.11	40.64	50.91	66.91	88.49
	ANN2	55.25	32.74	9.76	400.0	31.31	40.20	49.02	60.11	74.98
GFDL-B1-Annual	ANN1	57.15	27.95	0.00	388.5	31.11	40.67	50.93	67.11	89.09
	ANN2	55.30	32.76	9.62	400.0	31.27	40.20	49.04	60.24	75.04
PCM-B1-Annual	ANN1	55.82	25.09	0.00	384.3	31.42	40.55	50.64	65.44	85.00
	ANN2	55.03	32.57	10.73	400.0	31.67	40.24	48.98	58.32	74.42

[a] ANN1: Monthly-based model trained on all price ranges; ANN2: Annually based model trained on normal prices to which the same percentage of price spikes occurred in 2005–2008 was added. Base case refers to historical climate with no warming.
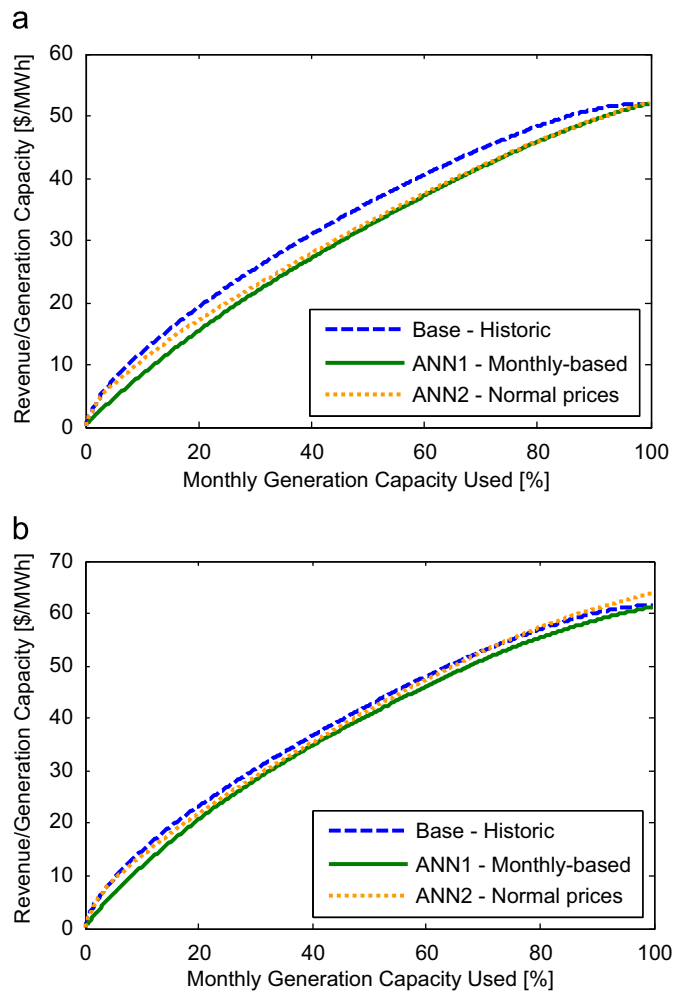
Fig. 3. Comparison of the revenue curves for ANN1 and ANN2 for January (a) and July (b) (ANN1: Monthly-based model, ANN2: Model trained on normal prices (not trained on price spikes), Base - Historic: historical prices 2005–2008).

foreseeable: assuming that price spikes will disappear from the energy market, or not. According to Lu et al. (2005), price spikes should only occur when demand exceeds supply in an ideal competitive electricity market. However, most markets are not ideally competitive, and gaming behaviors probably influence the market (Lu et al., 2005). It has also been argued that suppliers might take advantage of the vulnerability (difficulty of storing, generation capacity constraints, and transmission congestion) of the electricity market by withholding their capacity so as to shift supply–demand curves, forcing price spikes (Zhao et al., 2007). It is assumed in this work that market operation is foreseen to stay as today, so price spikes will most likely continue to occur. The same percentage of price spikes, as observed in 2005–2008 period in the California ISO market, is assumed to occur in the future energy market and unimpaired price spikes are added to the modeled price set.

Price distributions and visual agreement between observed and modeled prices were found to match best for two ANN models: twelve monthly based parallel models trained on all price ranges (ANN1) and an annually based model trained on normal prices (ANN2). Price distributions obtained from the trained ANN1 and ANN2 for the Base case are given in Table 4. Fig. 3 shows results from calibration in terms of monthly revenue curves (integration over the price frequency distribution) for the months of January (winter season) and July (summer) for the

ANN1 and ANN2 models. Both calibrated models return prices with very similar distributions to the observed values.

5. ANN results under climate warming forcings

Table 4 indicates the results from the simulations for different climate warming scenarios. Estimated average prices under all climate warming scenarios exceed Base case's average price (55 $/MWh). ANN1 predicts higher 50th, 75th and, 90th price percentile increases than ANN2 for all scenarios (i.e., ANN1 estimates higher price increases than ANN2).

Fig. 4 shows the monthly revenue curves (developed based on the method suggested by Madani and Lund (2009)) for January and July obtained from ANN1 model run under different climate warming scenarios. Corresponding results for ANN2 are not presented here because patterns are similar to those obtained from ANN1, except that the magnitude of changes relative to Base case is less. For both ANN models, all climate warming scenarios lead to increases in revenue in summer months and revenue drops in winter. This behavior corresponds to what was expected, increased need for cooling in warm months and decreased need for heating in cold months. In spring and autumn, patterns vary between months and ANN models. This is especially noticeable in April and October, which are transitioning months between warm and cold periods of the year. When comparing results from different climate scenarios, high forcing scenarios lead to larger changes in revenue curves than low forcing scenarios.
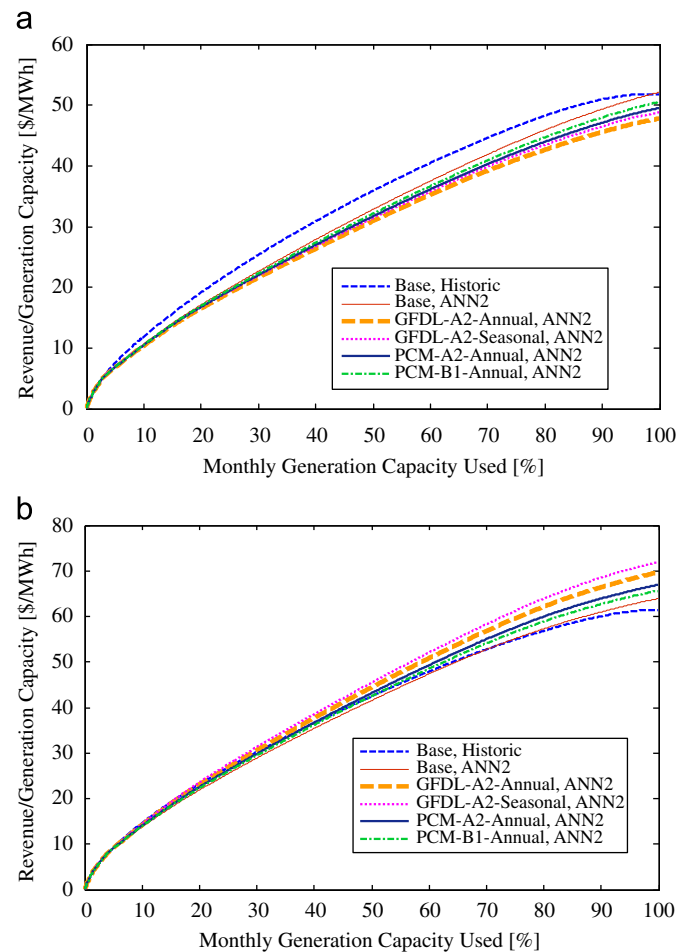

Fig. 4. Monthly Revenue Curves obtained from ANN1 model under different climate warming scenarios for January (a) and July (b) (ANN2: ANN model trained on normal prices; Base-Historic: historical prices 2005–2008).
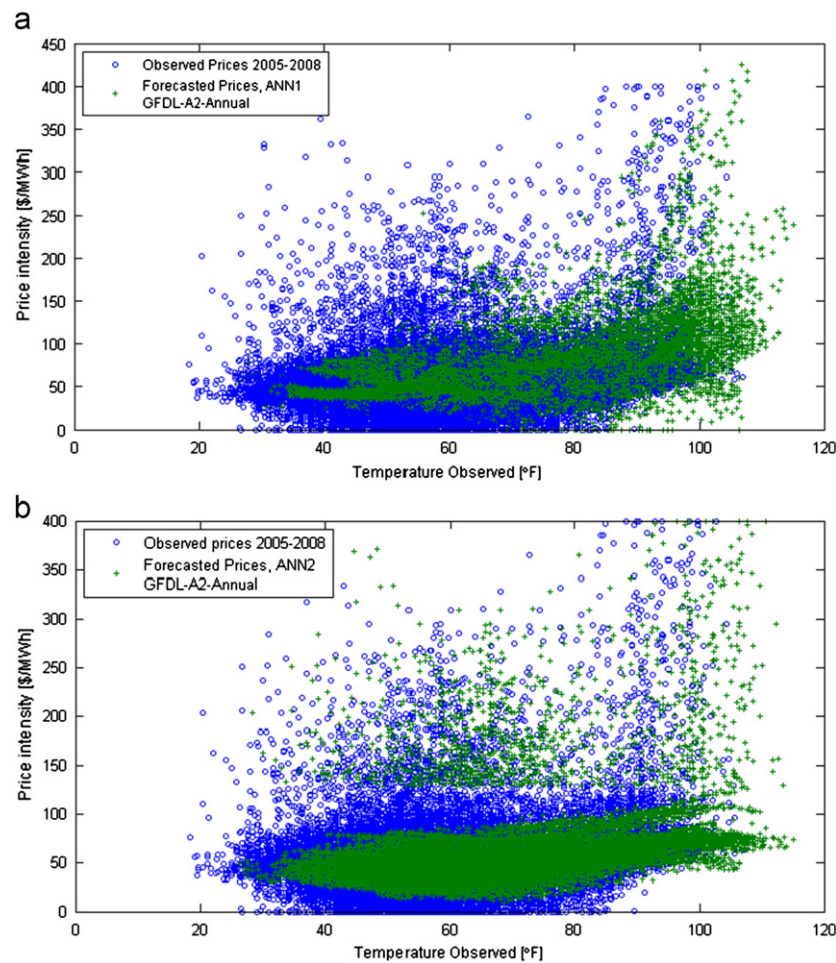
Fig. 5. Estimated ANN prices and historical prices (2005–2008) for GFDL-A2-Annual climate warming scenario for ANN1 (a) and ANN2 (b). (ANN1: Monthly-based ANN; ANN2: ANN model trained for normal prices and unimpaired price spikes).

Fig. 5 shows the modeled price intensities plotted against temperature for both ANN models under the high forcing scenario GFDL-A2-Annual. Relative to historical prices, prices increase as temperature raises. This was also highlighted in Fig. 4.

Generally, ANN1 predicts higher price increases than ANN2. One of the possible reasons is that each monthly-based model in ANN1 has only been trained on the range of temperature occurring in that specific month. Therefore, it is blind to the price-temperature relationship mapped in other months. When temperatures are perturbed to simulate climate warming scenarios, the resulting highest temperatures in each month will always be out of bounds of the training temperature dataset. The inability of ANNs to extrapolate (Maier and Dandy, 2000) might lead to a misrepresentation of prices by ANN1. Another possible reason for the higher price increase predicted by ANN1 is that price spikes have not been removed from the monthly datasets. During training, ANN1 adjusted its parameters trying to represent those high prices. Some price spikes derive from natural circumstances (e.g., warm period, peak hour) and ANN1 might be able to map them. However, price spikes also derive from extraordinary circumstances in the energy market (discussed in Section 4.2) and might bias the price representation by ANN1. Finally, ANN2 might also underestimate prices. Being trained only on normal prices, ANN2 will most likely not return output prices higher than the price spike threshold. This discussion led us to decide that ANN2 is better suited to be a long-term price estimation tool for climate warming simulations.

6. Integration with EBHOM

EBHOM is a non-linear hydropower revenue optimization model which finds optimal hydropower operations for 137 high-elevation hydropower plants throughout California during the 1985–1998 period. More details about EBHOM are provided in Madani and Lund (2009, 2010).

The original purpose for the development of an ANN price estimation tool in the present research was to integrate it with the California's Energy-Based Hydropower Model (EBHOM) as a complementary module. EBHOM's present price representation uses historical pricing (2005–2008) and ignores the effects of climate warming on energy demand and pricing. However, considering the effects of climate change on hydroelectricity demand is essential to energy planning and policy making. This developed price estimation module in this study is to be used when EBHOM is applied as a planning tool to assess the adaptability of California's high-elevation hydropower system to climate warming.

To investigate the sensitivity of hydropower operations and revenues to the possible climate warming effects on hydropower demand and pricing, we ran EBHOM for a dry warming scenario (GFDL-A2-Annual). This scenario is expected to be one of the plausible worst case scenarios with regard to the adaptability of California's high-elevation hydropower system. ANN2 was used to estimate future price representation considering warming effects on demand (scenario referred to as Dry ANN2 hereafter). Results examine energy generation, storage and revenue patterns,

as well as benefits from expanding energy generation and storage capacities. Results are compared to those obtained by Madani and Lund (2010) under Base case (historical) climate and the same dry scenario (referred to as Dry scenario hereafter), when historical pricing is considered, ignoring the effects of climate warming on demand and pricing. Table 5 indicates how California's high-elevation hydropower generation, spill, and annual revenue change with Dry and Dry ANN2 scenarios in comparison with the Base case scenario. Energy generation, energy spills, and revenues decrease under dry scenarios relative to the Base case as a result of reduction in total annual runoff. Generally, the drop in revenue is less than the drop in generation under dry climate warming, as the operators tend to minimize the revenue losses by generating when hydropower prices are higher (Madani and Lund, 2010). Under dry climate warming, generation decreases by 20%. Such a reduction results in 19% decrease in revenues under the Dry ANN2 and 14% decrease in revenues under the Dry scenario. Therefore, it is reasonable to suggest that California's high-elevation hydropower system may be more vulnerable to climatic changes than what expected under previous studies (Vicuña et al., 2008; Madani and Lund, 2010).

Fig. 6 shows how the average monthly energy generation during the 1985–1998 period changes with dry climate warming. Results are summed from all 137 units modeled. Under the Base case, generation peaks between April and August. On average, Dry scenario leads to less generation than under the Base case except in January and February. In July, the peak storage under the Base case exceeds Dry scenario's peak by more than 600 GWh on average. When climate warming effects on hydropower demand and pricing are considered (Dry ANN2), generation peaks in July and outweighs the peak under Dry scenario by nearly 1000 GWh (the peak reaches 2500 GWh). In contrast in winter, average generation decreases when changes in demand are considered.

These results clearly indicate how the increasing demand for cooling in summer and decreasing demand for heating in winter can affect the operations.

Fig. 7 shows how average end-of-month energy storage in all reservoirs combined changes with different climate scenarios when reservoirs are operated for energy revenues only. Reservoirs start refilling one month earlier under both drier scenarios (December) compared to the Base case (January). Under dry scenarios, the system must take maximal advantage of the water available from the shifted snowmelt, to be released when prices are on-peak, i.e., in summer. The timing of the patterns is similar to the monthly runoff distributions. Between January and June, the system stores more water in its reservoirs when future changes in demand are considered (Dry ANN2) than when they are ignored (Dry). Less energy is needed in cold months so more water is available to be stored for high-electricity demanding months. The peak storage occurs in May under both dry scenarios whereas it is in June under Base case. When changes in demand are considered, the peak storage exceeds Dry scenario's peak by more than 300 GWh. On average, the system's total storage capacity is never met. However, this does not imply that there is no energy spill in the system as storage may reach the maximum capacity in some reservoirs (Madani et al., 2008).

Table 5
EBHOM's results (average of results over 1985–1998 period) for dry climate warming scenarios under historical pricing and estimated prices using ANN2 model (ANN2: ANN model calibrated on normal prices).

	Base	Dry	Dry ANN2
Generation (1,000 GWh/year)	22.3	17.9	17.9
Generation change with respect to the base case (%)		*−19.8*	*−19.8*
Spill (GWh/year)	130	96	96
Spill change with respect to the base case (%)		*−26*	*−26*
Revenue (million $/year)	1,726	1,482	1,400
Revenue change with respect to the base case (%)		*−14.1*	*−18.9*

Fig. 7. Average total end-of-month energy storage (1985–1998) for historical climate and dry warming scenarios under historical pricing and estimated prices using ANN2 (ANN2: ANN model calibrated on normal prices).
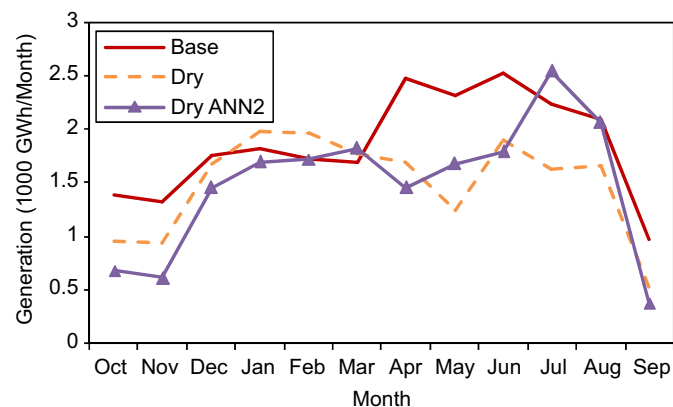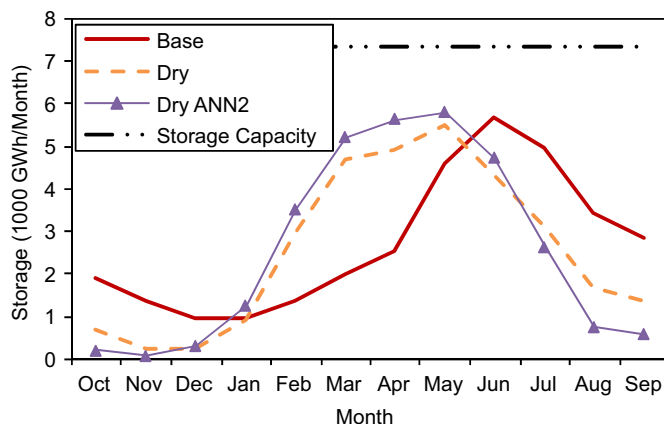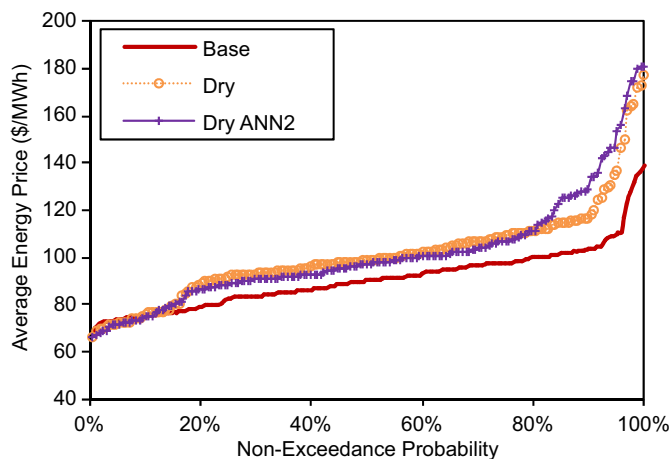

Fig. 6. Average Monthly Generation (1985–1998) for Base case scenario and dry warming scenarios (under historical pricing and estimated prices using ANN2 model (ANN2: ANN model calibrated on normal prices)).

Fig. 8. Frequency of monthly energy price (1985–1998) for historical climate and dry warming scenarios under historical pricing and estimated prices using ANN2 model (all months, all years, all units) (ANN2: ANN model calibrated on normal prices).

Fig. 8 shows dry climate warming effects on monthly average price received for generated energy in the period 1985–1998. Prices received under both dry scenarios exceed the Base case prices 85% of the time, with monthly generation being less than the Base case 100% of time. This is what was expected given the non-linear relationship between electricity prices and generation. Average prices received here reach about 175 $/MWh under drier scenarios and 135 $/MWh under Base case. Energy prices received under Dry ANN2 exceed those under Dry scenario in 20% of months and are lower the 80% rest of the year. On average, annual revenues under Base case exceed those under Dry scenario by $240 million, and those under Dry ANN2 by $325 million (Table 5). Less revenue is received under Dry ANN2 because prices received were lower than under Dry conditions 80% of time. Although monthly average prices received for generated energy were higher under drier scenarios than Base case, those do not compensate for the loss in energy generation.

Fig. 9 indicates, on average, how energy storage capacity expansion changes hydropower generation revenues for different dry climate scenarios over the 14 years study period. This figure indicates the average shadow price of energy storage capacity (the increase in annual revenue per 1 MWh energy storage capacity expansion) for all 137 reservoirs. For instance, increase in annual revenue per 1 MWh energy storage capacity expansion is less than $29, $48, and $45 for the 137 studied plants under the Base, Dry, and Dry ANN2 scenarios, respectively. Storage capacity expansion reduces spills and allows the system to capture more snowmelt water to be released when energy is the most valuable. Average annual revenues can be increased by expanding storage capacity in all plants (except for four plants under Base case and seven under both dry scenarios), although such expansion might not be justified due to expansion costs.

Fig. 10 indicates the average shadow price of energy generation (turbine) capacity (increase in annual revenue per 1 MWh of annual energy generation capacity expansion) for all 137 plants under different climate scenarios. All scenarios benefit from an increase in generation capacity, reducing spills and allowing more energy to be generated when prices are high. Increase in annual revenue per 1 MWh energy storage capacity expansion is around $22, $18, and $15 for the 137 studied plants under the Base, Dry, and Dry ANN2 scenarios. Considering climate warming effects on demand attenuates the benefits from expanding energy generation. Even though generation capacity expansion produces benefits, expansion costs might be prohibitive.

Under both dry warming scenarios, expanding energy storage capacity is typically more beneficial than expanding generation
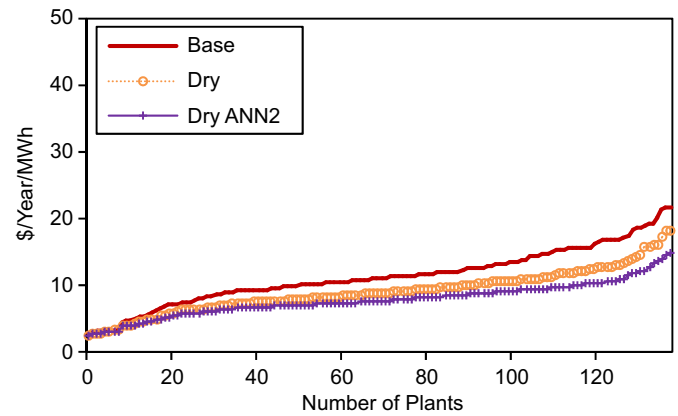

Fig. 10. Average Shadow Price of Energy Generation Capacity of 137 hydropower units in California in the 1985-1998 period for historical climate and dry warming scenarios under historical pricing (Dry) and estimated prices using ANN2 model (Dry ANN2) (ANN2: ANN model calibrated on normal prices).

capacity if the expansion costs are the same. Energy storage capacity shadow price are on average 1.4 and 1.8 times higher than the energy generation shadow price for all power plants under Dry scenario and Dry ANN2 respectively. Expanding energy storage capacity allows storing water in off-peak months and releasing it through turbines when prices are higher. This ratio is 1.0 under Base case.

Under dry scenarios, the system benefits less from energy generation expansion on average than under Base case since water supply availability is the limiting factor. There is less inflow, so the existing generation capacity is often sufficient to avoid spills. On the contrary, for 69 plants (50%) and 75 plants (55%) the benefit from expanding energy storage capacity under Dry and Dry ANN2 scenarios respectively is greater than under Base case. For a single plant, the difference between benefits gained from 1 MWh of storage capacity expansion under Base and drier scenarios can be as high as $28.

7. Conclusions

Two ANN models were developed to estimate the effects of future climate warming on energy demand and pricing. The first model is composed of 12 parallel ANN models, one for each month, and is trained on all price intensities (ANN1). The second model (ANN2) is an ANN model trained on a dataset from which price spikes were excluded (prices exceeding 128 $/MWh). Price spikes in the future energy market were assumed to occur in the same frequency as presently, since California's deregulated energy market is not ideally competitive and is not foreseen to become so. In an ideal energy market, price spikes should only occur when demand exceeds supply, but gaming behaviors (Lu et al., 2005) and market manipulations (Zhao et al., 2007) are forcing price spikes. California ISO hourly price spikes were identified as prices exceeding 128 $/MWh. The ANN price estimation models assume current socio-economic conditions and current operation of the electric grid. For instance, the interaction between increased temperature and the trend towards greater development in the state's interior, requiring greater cooling demand (Franco and Sanstad, 2006) is ignored. However, there are so many uncertainties regarding the future energy market and future socio-economic-technologic conditions that these were assumed to remain as in present time.

The ANN long-term price estimation tool developed here estimates higher price increases under high forcing scenarios
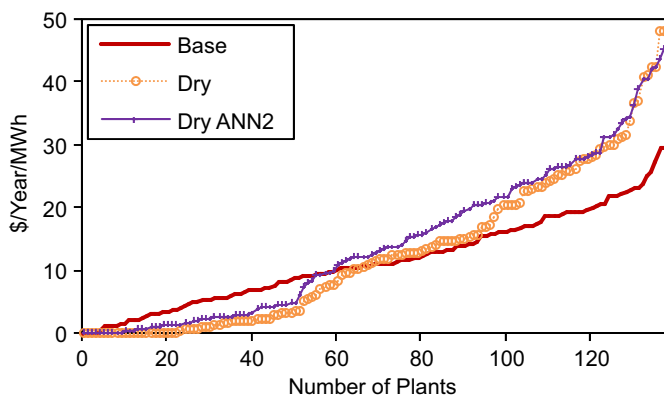

Fig. 9. Average Shadow Price of Energy Storage Capacity of 137 hydropower units in California in the 1985–1998 period for historical climate and dry warming scenarios under historical pricing (Dry) and estimated prices using ANN2 model (Dry ANN2) (ANN2: ANN model calibrated on normal prices).

and lower price increases under low forcing scenarios. Revenue curves (integration over the price frequency distribution) show that both ANN models estimate increases in revenue in warm months and decreases in colder months. This corresponds to increased need for cooling in warm months and decreased need for heating in colder months.

Generally, ANN1 predicts higher price increases than ANN2. One of the reasons is the time-scales difference of the models: twelve models trained on each month's temperature and price datasets, and one single model trained on all year round data. The monthly models are blind to the price-temperature relationship mapped in other months. When perturbing the input temperature dataset to the ANN model to simulate climate warming scenarios, it might lead to a misrepresentation of prices by ANN1 because ANNs are unable to extrapolate. The highest temperatures in each month will always be out of bounds of the training temperature sample. The ANN1 model might also estimate higher price increase than ANN2 because it was trained on a price dataset including price spikes. Some price spikes derive from natural circumstances (e.g., warm period, peak hour) and an ANN might be able to map them. However, price spikes also derive from extraordinary circumstances in the energy market and probably bias the price representation by ANN1. For these reasons, ANN2 was considered to be more reliable than ANN1 in estimating prices under climate warming simulations.

ANN2 was designed as a complementary module of EBHOM, the California's hydropower optimization model. To underline the utility of the developed module and investigate the importance of consideration of climate warming effects on hydropower demand and pricing in addition to consideration of climate warming effects on hydropower supply in planning and policy making, EBHOM was run using ANN2 for a dry warming scenario. Results suggest that California's hydropower system might be more vulnerable to climatic changes when changes in demand are considered than expected under previous studies (Vicuña et al., 2008; Madani and Lund, 2010). Such an observation has an important policy implication, suggesting that consideration of climate change impacts on energy demand and pricing should be integral to future energy planning and decision-making. In is noteworthy that while this study was focused on California's hydropower system, other regions of the U.S. and the world, with similar electricity market structures, can benefit from the developed method in their hydropower planning studies.

EBHOM estimated an increase in energy prices received under dry conditions relative to baseline. This increase in prices would however not compensate for the generation loss and annual revenues are expected to decrease compared to baseline. Under dry climate warming, generation decreases by 20%. Such a reduction results in 19% decrease in revenues when changes in demand are considered (under the Dry ANN2 scenario) and 14% decrease in revenues when changes in demand are ignored (Dry scenario). When changes in demand are considered under dry climate warming, generation is foreseen to decrease in winter with less generation required. This allows the system to store more water during the snowmelt period to be released later on when prices peak. In this case, an optimized operation of the hydropower system suggests that the system is still able to compensate (revenues decrease by 19%) for some of the loss in generation (-20%) compared to baseline. Results showed that expanding energy storage capacity should be beneficial for the system to increase its revenues under dry conditions. With generation decreasing in winter when changes in demand are considered, expanding energy storage capacity allows storing water in this period and is estimated to be even more beneficial than under current energy demand. However, such expansions might not be justified due to expansion costs.

This study required some simplifying assumptions to design the ANN models. Nonetheless, it gives insights and suggests how energy prices might be affected by a range of climate warming scenarios. It also gives insights on some degree of adaptability from California's high-elevation hydropower system to dry climate warming. Refined ANN models could be developed, for instance by including additional inputs driving energy price spikes and also by defining another estimation of the demand-temperature relationship. Price elasticity of demand was neglected in this work, but could be included in further works, even though uncertainties in the future energy market operation and in future socioeconomic situation are expected to outweigh its impact on energy pricing.

Acknowledgments

References

Amjady, N., Hemmati, M., 2006. Energy price forecasting – problems and proposals for such predictions. IEEE Power & Energy Magazine 4 (2), 20–29.

Amjady, N., Keynia, F., 2010a. Electricity market price spike analysis by a hybrid data model and feature selection technique. Electric Power Systems Research 80 (3), 318–327.

Amjady, N., Keynia, F., 2010b. Application of a new hybrid neuro-evolutionary system for day-ahead price forecasting of electricity markets. Applied Soft Computing 10 (3), 784–792.

Aroonruengsawat, A., Auffhammer, M., 2009. Impacts of climate change on residential electricity consumption: evidence from billing data. California Climate Change Center, publication #CEC-500-2009-018-D, March 2009. Available at: ⟨http://www.energy.ca.gov/2009publications/CEC-500-2009-018/CEC-500-2009-018-D.PDF⟩.

ASCE Task Committee on Artificial Neural Networks in Hydrology, 2000. Artificial neural networks in hydrology. I: preliminary concepts. Journal of Hydrologic Engineering, ASCE 5 (2), 115–123.

California ISO, 2006. 2005 Annual Report on Market Issues and Performance. Department of Market Monitoring. California ISO, California. ⟨http://www.caiso.com/17d5/17d59ec745320.pdf⟩ (available at: accessed 24 March 2010).

California ISO, 2009. 2008 Annual Report on Market Issues and Performance. Department of Market Monitoring. California ISO, California. ⟨http://www.caiso.com/2390/239087966e450.pdf⟩ (available at: accessed 24 March 2010).

California ISO, 2010. Hourly Average Energy Prices. Open Access Same-Time Information System (OASIS), California ISO (Available at, Accessed 16 March 2010)⟨http://oasis.caiso.com/⟩.

Cayan, D.R., Maurer, E.P., Dettinger, M.D., Tyree, M., Hayhoe, K., 2008. Climate change scenarios for the California region. Climatic Change 87 (1), 21–42.

Cayan, D., Tyree, M., Dettinger, M., Hidalgo, H., Das, T., Maurer, E., Bromirski, P., Graham, N., Flick, R., 2009: Climate Change Scenarios and Sea Level Rise Estimates for the California 2009 Climate Change Scenarios Assessment. California Climate Change Center, publication #CEC-500-2009-014-F, 64 p. Available at: ⟨http://www.hugohidalgoleon.com/files/papers/CEC-500-2009-014-D.PDF⟩.

Connell-Buck, C.R., Medellin-Azuara, J., Lund, J.R., Madani, K., in press. Adapting California's water system to warm vs. dry climates. Climatic Change. doi:10.1007/s10584-011-0302-7.

CBO, 2001. Causes and Lessons of the California Electricity Crisis. ⟨http://www.cbo.gov/ftpdocs/30xx/doc3062/CaliforniaEnergy.pdf⟩ (available at: accessed 25 March 2010).

Dawson, C.W., Wilby, R.L., 2001. Hydrological modelling using artificial neural networks. Progress in Physical Geography 25 (1), 80–108.

Duan, Q., Sorooshian, S., Gupta, V., 1992. Effective and efficient global optimization for conceptual rainfall–runoff models. Water Resources Research 28 (4), 1015–1031.

Duan, Q., Sorooshian, S., Gupta, V., 1994. Optimal use of the SCE-UA global optimization method for calibrating watershed models. Journal of Hydrology 158 (3), 265–284.

Franco, G., Sanstad, A.H., 2006. Climate change and electricity demand in California. California Climate Change Center, publication #CEC-500-2005-201-SF, February 2006. Available at: ⟨http://www.energy.ca.gov/2005publications/CEC-500-2005-201/CEC-500-2005-201-SF.PDF⟩.

Gao, F., Guan, X., Cao, X.-R., Papalexopoulos, A., 2000. Forecasting power market clearing price and quantity using a neural network method. IEEE Power Engineering Society Summer Meeting, 2000.

Hornik, K., Stinchcombe, M., White, H., 1989. Multilayer feedforward networks are universal approximators. Neural Networks 2 (5), 359–366.

Hsieh, W.W., Tang, B., 1998. Applying neural network models to prediction and data analysis in meteorology and oceanography. Bulletin of American Meteorology Society 79 (9), 1855–1870.

Kingston, G.B., Maier, H.R., Lambert, M.F., 2005. Calibration and validation of neural networks to ensure physically plausible hydrological modeling. Journal of Hydrology 314, 158–176.

Lu, X., Dong, Z.Y., Li, X., 2005. Electricity market price spike forecast with data mining techniques. Electric Power Systems Research 73 (1), 19–29.

Luers, A.L., Cayan, D.R., Franco, G., Hanemann, M., Croes, B., 2006. Our Changing Climate – Assessing the Risks to California. California Climate Change Center, publication #CEC-500-2006-077. Available at: ⟨http://www.energy.ca.gov/2006publications/CEC-500-2006-077/CEC-500-2006-077.PDF⟩.

Madani, K., 2011. Hydropower licensing and climate change: insights from cooperative game theory. Advances in Water Resources 34 (2), 174–183. doi:10.1016/j.advwatres.2010.10.003.

Madani, K., Lund, J.R., 2009. Modeling California's high-elevation hydropower systems in energy units. Water Resources Research 45, W09413. doi:10.1029/2008WR007206.

Madani, K., Lund, J.R., 2010. Estimated impacts of climate warming on California's high-elevation hydropower. Climatic Change 102, 521–538. doi:10.1007/s10584-009-9750-8.

Madani, K., Vicuna, S. Lund, J.R., Dracup, J.A., Dale L.L., 2008. Different approaches to study the adaptability of high-elevation hydropower systems to climate change: the case of SMUD's Upper American River Project, In: Proceedings of the 2008 World Environmental and Water Resources Congress, Honolulu, Hawaii, R.W. Babcock and R. Walton (eds.), pp. 1–10, American Society of Civil Engineers, Reston, VA, doi:10.1061/40976(316)372.

Maier, H.R., Dandy, G.C., 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environmental Modelling and Software 15, 101–124.

McCulloch, W.S., Pitts, W.H., 1943. A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biophysics 5, 115–133.

Medellín-Azuara, J., Harou, J.J., Olivares, M.A., Madani, K., Lund, J.R., Howitt, R.E., Tanaka, S.K., Jenkins, M.W., Zhu, T., 2008. Adaptability and adaptations of California's water supply system to dry climate warming. Climatic Change 87 (1), 75–90. doi:10.1007/s10584-007-9355-z.

Moser, S., Franco, G., Pittiglio, S., Chou, W., Cayan, D., 2009. The future is now: an update on climate change science impacts and response options for California. California Climate Change Center, publication #CEC-500-2008-071, May 2009. Available at: ⟨http://www.energy.ca.gov/2008publications/CEC-500-2008-071/CEC-500-2008-071.PDF⟩.

Olsson, J., Uvo, C.B., Jinno, K., Kawamura, A., Nishiyama, K., Koreeda, N., Nakashima, T., Morita, O., 2004. Neural networks for rainfall forecasting by atmospheric downscaling. Journal of Hydrologic Engineering 9 (1), 1–12.

Ranjbar, M., Soleymani, S., Sadati, N., Ranjbar, A.M., 2006. Electricity price forecasting using Artificial Neural Network. In: IEEE, 2006 International Conference on Power Electronic, Drives and Energy Systems. doi:10.1109/PEDES.2006.344294.

Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986. Learning internal representations by error propagation. In: Rumelhart, D.E., McClelland, J.L., Group, P.R. (Eds.), Parallel Distributed Processing, vol. 1. MIT Press, Cambridge, MA, pp. 318–362.

University of California, 2010. Weather data and products Statewide Integrated Pest Management Program. Agriculture and Natural Resources, University of California (Available at: Accessed 15 March 2010⟨http://www.ipm.ucdavis.edu/WEATHER/wxretrieve.html⟩.

Vicuña, S., Leonardson, R., Hanemann, M.W., Dale, L.L., Dracup, J.A., 2008. Climate change impacts on high elevation hydropower generation in California's Sierra Nevada: a case study in the upper American river. Climatic Change 87 (1), 123–137.

Zarezadeh, M., Naghavi, A., Ghaderi, S.F., 2008. Electricity price forecasting in Iranian electricity market applying Artificial Neural Networks. IEEE Electrical Power and Energy Conference, 2008. doi:10.1109/EPC.2008.4763300.

Zhang, G., Patuwo, B.E., Hu, M.Y., 1998. Forecasting with artificial neural networks: the state of art. International Journal of Forecasting 14 (1), 35–62.

Zhao, J.H., Dong, Z.Y., Li, X., 2007. Electricity market price spike forecasting and decision making. IET Generation, Transmission & Distribution 1 (4), 647–654.