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Medium-term storage volume prediction for optimum reservoir management: a hybrid data-driven approach

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Abstract

A hybrid regressive and probabilistic model was developed that is able to forecast, six weeks ahead, the storage volume of Little Nerang dam. This is a small elevated Australian drinking water reservoir, gravity-fed to a nearby water treatment plant while a lower second main water supply source (Hinze dam) requires considerable pumping. The model applies a Monte Carlo approach combined with nonlinear threshold autoregressive models using the seasonal streamflow forecasts from the Bureau of Meteorology as input and it was validated over different historical conditions. Treatment operators can use the model for quantifying depletion rates and spill likelihood for the forthcoming six weeks, based on the seasonal climatic conditions and different intake scenarios. Greater utilization of the Little Nerang reservoir source means a reduced supply requirement from the Hinze dam source that needs considerable energy costs for pumping, leading to a lower cost water supply solution for the region.

Keywords

Probabilistic forecasting; drinking water treatment; nonlinear regression; water level prediction; data-driven modelling

1. Introduction

Accurately predicting water level variations in lakes and reservoirs in response to hydroclimatological changes is crucial for efficient water demand – related decision-making (Güldal and Tongal, 2010) and eventually developing wise and sustainable water usage policies (Buyukyildiz et al., 2014). Understanding and forecasting water level fluctuations (WLFs) is also critical for a variety of water resource management operations such as flood control, local water supply management, shoreline maintenance, ecosystem sustainability, recreation, and economic development (Altunkaynak, 2014). In this research study, we have focused on the importance of predicting the water level of a drinking water reservoir to optimize the operations of the water treatment plant (WTP) receiving raw water from it. The study objective was to provide WTP operators with a support tool to inform decisions on the volume of reservoir raw water that could be withdrawn, considering both spill minimization and depletion risk scenarios. When WTP operators have two raw water source options available to withdraw from, an increased use of the source not requiring pumping has significant implications on the energy costs of the water supply of the city. Based on the electricity billing frequency and other contextual factors, a medium-term (i.e. 1-2 months) forecasting horizon was targeted for such prediction model. Although several studies exist that forecast WLF as detailed in the “Background” section, usually they aim at predicting either (1) in the very short term through very accurate, but computationally demanding models, or (2) in the longer term with more vague, statistical models mainly based on historical seasonal behaviors. For the context of forecast model development (i.e. targeted forecast horizon, data limitations and uncertainty) pertaining to this research study, an effective compromise between accuracy and computational time was required. As a result, we proposed a probabilistic model, founded on a Monte Carlo approach coupled with nonlinear regression analysis, whose outputs are based not only on historical lake behavior and planned outflows, but also on future long-term inflow predictions provided by the Australian Bureau of Meteorology (BoM). Such an integrative approach, detailed later in the paper, allows not only for exploiting existing data and other third-party prediction models to enhance accuracy in a computationally effective manner, but also for improved handling of uncertainty through probabilistic outputs and simulation of several different scenarios.

The paper is structured as follows: in Section 2 we provide background information regarding the importance of predicting WLFs as well as previous WLFs prediction models; we then

identify challenges and limitations of existing models, and propose a modelling approach that best suits our case study. In Section 3, the research methodology is described in detail, starting with a description of the research domain, data collection and analysis procedure, and finally model development and validation. In Section 4, we describe the results obtained, and in Section 5 we conclude this paper by summarizing the findings and the relevance of this study.

2. Background

2.1. The importance of water level fluctuations

The role that WLFs play, either within and between years, in influencing water quality is not quite well understood, in spite of a rise in water level regulation (White et al. 2008). However, White et al. (2008) found that WLFs between years showed relevant concordance with water quality parameters, as has been proposed by other authors. It was demonstrated by Webster et al. (1996, 2000) that Wisconsin lakes of different landscape positions reacted distinctively to increases in magnesium and calcium concentrations after a drought that lasted 2 years. It has been noticed that water quality in aquatic ecosystems is decreasing, during low-water periods: for instance Arfi (2003) showed that a Mali reservoir shifted from an oligotrophic to a eutrophic state during low water levels. Similarly, Kangur et al. (2003) found that water level greatly affects the nutrient concentrations of an Estonian lake, and in turn the stability of its ecosystem. Nõges et al. (2003) confirmed this finding, determining that the amount of phytoplankton in another Estonian lake was proportional to the water level. Also, WLFs can directly affect the hydrology and ecology within the lake and the surrounding watersheds (Leira and Cantonati, 2008), with high levels affecting the lakeside plant and animal communities and possibly resulting in shoreline erosion (Meadows et al., 1997).

Moreover, depending on specific physical aspects of a body of water, the entire trophic structure of the ecosystem may be harmed by human-induced WLF, spoiling not only water quality but also endangering fish resource exploitation. Nevertheless, as Coops and Hosper (2002) and Roelke et al. (2003) have observed for, respectively, restoration of shallow lakes and phytoplankton control, WLF represents a means to improve water quality and may be utilized as a management tool for freshwater ecosystems. In the case of a dam, which is used as source of water for a water treatment plant, good-quality raw water would reduce the

amount of chemicals dosage needed, eventually enhancing the water treatment plant efficiency.

2.2. Forecasting storage volumes

Forecasting future storage volumes can be challenging, as changes in lake water level are considerably complex outcomes of many hydrological factors such as rain falling on the lake surface or lake watershed, evaporation from the lake surface, direct and indirect runoffs from neighbour basins, humidity, air and water temperature, wind speed and groundwater change (Buyukyildiz et al., 2014), as well as hysteresis effects between storage volume and runoff (Wu et al., 2011). As a consequence, to build a reliable water level prediction model, it is crucial to determine the correlations between the change in lake water level and those hydro-meteorological variables (Kisi et al., 2012). However, a number of models have been developed, which could forecast lake water levels one day (e.g. Kisi et al., 2012; Afq et al., 2013), month (e.g. Altunkaynak, 2007; Buyukyildiz et al., 2014), or year (e.g. Privalsky, 1992) in the future with different modelling approaches.

If all the required hydrological and hydro-meteorological data are available, the change in lake water level can be generally determined by water balance methods, which in essence estimate the difference between inflow to, and outflow from, the body of water. For instance, Crapper et al. (1997) made use of an existing soil moisture prediction model to estimate surface runoff flowing into an Australian lake, and along with rainfall and evaporation data, they could estimate monthly lake water level variations. However, evaporation was the only outflow considered and thus it was assumed that the model overestimates the real lake level. Potentially, this problem could have been solved by comparing observed and predicted levels and correlating the values (e.g. regression analysis).

Classical mathematical and statistical approaches have been also widely applied for lake water level forecasting (Goodarzi et al., 2014). A lot of research in relation to this topic has been performed in the Great Lakes region. Although some more recent studies have used deterministic models (e.g. Lofgren et al. (2002) deploying a hydrological modelling approach using the input of a global circulation model to assess climate change impacts), most of these studies applied conventional parametric time series modeling techniques. Examples are given by DeCooke and Merejian (1967), with multiple linear regression up to 6 months ahead;

Cohn and Robinson (1976), based on historical cycles identified through spectral analysis; or Irvine and Eberthardt (1992) up to six months ahead using seasonal ARIMA. In addition, a seasonal autoregressive model (SAR) was developed by Privalsky (1992) for predicting the Lake Erie water level up to 12 months ahead based on over 60 years of historical mean monthly water level data. Despite not being able to take into account nonlinear behaviors, SAR is believed to be fast and easy to use in this context (Khan and Coulibaly, 2006). However, it could be argued that they offer a “naïve” forecast, largely based on historical seasonal behaviors, which might work well for large lakes, prone to proportionally much lower rates of level fluctuations over a period of 1-2 months, compared to a small reservoir such as the one of this study.

More recently, artificial intelligence techniques have been applied to develop increasingly accurate water level forecasting tools. Khan and Coulibaly (2006) investigated the potential of support vector machine application for long-term prediction of the water level in Lake Eire. Vaziri (1997) used a hybrid artificial neural network (ANN) and ARIMA model to predict water levels of the Caspian Sea; he observed that on average the ANN model underestimates the levels by 3 cm while the ARIMA model overestimates by the same amount. To develop the ANN he took 12 nodes in the input layer, representing the Caspian Sea water levels of the previous 12 months. Altunkaynak (2007) stated that, in the attempt to predict Lake Van water level one month ahead, neural networks could successfully model the complex relationship between rainfall and water levels; he also concluded that both ANN and ARMAX models can be effectively applied for short term predictions of the relevant time series data. Kakahaji et al. (2013), after developing different linear (i.e. ARX and Box-Jenkins approaches) and artificial intelligence (Multi-Layer Perceptron ANN and Local Linear Neuro-Fuzzy) models for water level prediction based on the water budget approach, concluded that intelligent methods are superior to traditional models. ANN alternatively have been also used to predict meteorological variables which could be input to a water level prediction model, such as solar radiation (Qazi et al., 2015). Neural Networks were also used by Güldal and Tongal (2010) as one of the models to predict the water level in Lake Egirdir, in Turkey. In Buyukyildiz et al. (2014), five different artificial intelligence methods were used to estimate monthly water level changes in the Turkish Lake Beysehir, with support vector regression being the best performing model. In other studies (Altunkaynak, 2014) ANN's have been combined with other techniques (such as wavelet transform and fuzzy logic) to predict up to 12 months ahead the WLF in Lake Michigan-Huron based on a large

dataset (i.e. over 150 years) of historical water level values. However such models, based on the lake's historical behavior only, are not deemed reliable by the authors, as it can be stated that "stationarity is dead" (Milly et al., 2008) and recent global climate changes have completely reformed the behavior of traditional lake level fluctuations (Kakahaji et al., 2013), leading to different inflow conditions and flood risk (e.g. Kang et al., 2007). In addition, previous studies by the author (Bertone et al., 2015) showed that ANN results can often have a higher variance than regression models, and this can be detrimental if the model is sequentially applied a number of times (e.g. week-ahead prediction model applied n times to get a n weeks-ahead prediction) as the error variance would be amplified.

2.3. Dealing with uncertainty

Additionally, as observed by Maier and Dandy (2000) and Kingston et al. (2005), another of the main limitations of ANN in this context is that they typically provide a crisp prediction, without quantifying the uncertainty associated with the predicted value. Considering water resource management optimization approaches, the majority of past studies either did not account for uncertainty, or only in an implicit way (Maier et al., 2014). Generally speaking, the lack of any quantification of the uncertainty associated with the predicted value may constitute a factor that limits the deployment of the forecasting model in practical applications such as management of water resources or flood protection (Alvisi and Franchini, 2011). A forecasting model that disregards the uncertainty associated with the prediction may cause the user of the model, or decision maker, to have excessive confidence in the forecasted value; in case the latter will be incorrect, this may lead to even worse consequences than if no forecasting model had been available (Montanari and Grossi, 2008).

However, although a forecasting model cannot eliminate the uncertainty associated with a future event, it can reduce it (Krzysztofowicz, 2001) or at least visually identify its sources. Bayesian Networks are an example of model accounting for uncertainty that has been recently applied for optimised reservoir management (Bertone et al., 2016b). Already two decades ago, Lee et al. (1997) demonstrated how risk assessment using probabilistic monthly water level forecasts could have contributed to a better historical decision-making for the Great Lakes region. As shown by Shrestha and Solomatine (2006), there is a number of different approaches to take into account the uncertainty associated with a model's output, including fuzzy number theory (e.g. Alvisi and Franchini, 2011) for water level forecasting in

combination with ANN or the Monte Carlo method (e.g. Hassan et al., 2009, Goodarzi et al., 2014). Monte Carlo simulation (Metropolis and Ulam, 1949) is a technique that can be deployed to generate values for uncertain variables in mathematical models and it can be used to combine stochastic data and stochastic models; it can be effectively used to quantify and analyse data uncertainties (Wu et al., 2014). Monte Carlo simulations are also commonly used to combine probability distributions and examine the relationships between model components and outcome variables described by deterministic equations (Nash and Hannah, 2011). Their deployment substantially increased because of the interest in the assessment of parameter uncertainty in hydrologic models and advances in computing technology (Hassan et al., 2009). Accurate measurement of the hydro-meteorological variables associated with water level predictions often comes with a great amount of ambiguity (Buyukyildiz et al., 2014); accordingly, a probabilistic approach is recommended whenever the data are incomplete or highly uncertain.

2.4. The context of Little Nerang Dam

Little Nerang dam (LND) is connected gravimetrically to the Mudgeeraba drinking water treatment plant (WTP) which can also pump raw water from a second reservoir; current practice dictates that this latter raw water source is most heavily utilized, as operators prefer to keep Little Nerang as a backup source of water in case of pumping system failures, despite the extra electricity costs related to pumping. However, a recently developed treatment cost prediction model (Bertone et al., 2016a) demonstrated that this operational protocol is extremely costly for the water utility. An increased use of the gravity fed Little Nerang source would be highly recommended, provided that the risk of excessive depletion is reasonably low. The development of a storage level prediction model would induce an operational change which would make the WTP operators rely more on this water source that has no associated pumping costs. The recent introduction of a different decision support tool (Bertone et al., 2015) in a nearby WTP demonstrated that WTP operators are willing to embrace such tools, as long as they are user-friendly, sufficiently accurate, and all relevant end-users are actively engaged during the development process. Such a storage level prediction model will have to account for predicted inflows and both natural and controlled outflows. This is necessary in order to optimize the withdrawal rate to the Mudgeeraba WTP. Also, the model will have to provide a prediction over the medium term (i.e. between 1 or 2 months): this is because the current electricity billing is set up in a way that, if water is pumped from the other reservoir even for only one day in a month, a number of fixed charges

will be triggered, drastically limiting the potential economic benefits of an increased use of LND. Consequently, the WTP operators will want to use the developed model towards the end of a given month, in order to make an informed decision for the whole upcoming month.

2.5. Modelling challenges and proposed approach

Given the forecast horizon required (1 to 2 months), developing such model appears to be challenging based on existing literature. Most of the previously developed models either predict in the very short term (e.g. deterministic models for flood management: hours to day) or long term (e.g. statistical seasonal models). Deterministic models are not suitable over such medium term due to the long computational time and the amount of input data required, while statistical seasonal models would not provide enough detailed outputs for this sort of reservoir management optimization task. In addition, a probabilistic approach, based on the literature, is recommended for such prediction modelling issue to account for uncertainties.

For this study location (a small drinking water reservoir) the available empirical data are incomplete and some of the required variables (e.g. spill amounts) were generated through hydrodynamic models simulations, thus adding further uncertainty to the system to be modelled. However, to reduce the uncertainty when forecasting a number of weeks ahead, Seasonal Streamflow Forecasts (SSF) are freely available for rivers in nearby catchments from the Australian Bureau of Meteorology (BoM) website. The SSF service is based on both a statistical (Wang and Robertson, 2011) and a dynamic (Wang et al., 2011) approach relying on antecedent catchment conditions and forecasts of future meteorological conditions. The typical output for a given river is the probability of having a below-median, near-median and above-median flow over the next three months.

Given the uncertainty behind many of the required parameters, and the probabilistic nature of one of the main inputs (i.e. inflow forecast), a probabilistic methodology based on a Monte Carlo – type approach, combined with a nonlinear threshold autoregressive model, was proposed in this research study in order to forecast, up to six weeks ahead, the storage volume of a small subtropical drinking water reservoir (i.e. Little Nerang dam, Australia) given different scenarios of raw water supply amounts. Based on historical data analysis, we developed a model to predict one week ahead the storage volume, given known inflows and outflows. Different models were tested. In order to subsequently forecast a number of weeks

into the future, we used the SSF predictions to generate quasi-random weekly inflow values; this enabled the sequential (n times) application of the week-ahead prediction model and a n weeks-ahead storage volume prediction. A high number (100,000) of simulations are run through this Monte Carlo approach, in order to account for uncertainty related to the SSF prediction and our week-ahead model errors. An implicit stochastic approach such as Monte Carlo was preferred to explicit approaches, as they are typically computationally lighter (Maier et al., 2014). The main issue identified by Maier et al. (2014) with implicit approaches is the difficulty to merge multiple runs together in a robust way; however, the fact that the sampling method is not random but quasi-random (i.e. the generated inflow values are based on SSF) helps dealing with this issue, reducing the uncertainty and increasing robustness. The final output is a probability distribution, rather than a fixed value, identifying the most likely final volume of the reservoir. Such outputs are embedded in a user-friendly decision support tool, easily interpretable by the user, enabling the WTP operators to take a more informed decision for an increased usage of the LND source over the next billing month.

3. Methods

3.1. Research domain

Little Nerang Dam (153.28°E, 28.14°S) is a concrete gravity dam which was completed in 1961 and was the first source of potable water for the Gold Coast region, South-East Queensland (Australia). It has a maximum capacity of 6,705 ML (8,400 ML when the drum gates were operative), a surface area of 0.5 km² and a catchment area of 35.2 km². The LND's only intake tower is made of reinforced concrete; it houses five screened 450 mm diameter inlet pipes at 5-7 m intervals. An 850 mm diameter gravity raw water main that is 7.845 km long transports the raw water to the Mudgeeraba WTP (DERM, 2010).

The Mudgeeraba WTP is the second largest drinking water treatment facility in the Gold Coast region, Queensland (Australia), after the Molendinar WTP; in its current state, it can treat a maximum of 110 ML/day of raw water (Rogers et al., 2008). In addition to drawing water through a gravity pipeline from LND, the Mudgeeraba WTP can also draw water from the upper intake of Hinze dam (HUI), which is the main reservoir for the Gold Coast region (maximum capacity: 310,730 ML). The locations of LND, HUI and the Mudgeeraba WTP are shown in Figure 1. The HUI tower is located 4.5 km upstream of the main embankment of Hinze Dam, on the Little Nerang Creek arm of the impoundment; it consists of a 58 m

high dry well reinforced concrete tower, housing nine 900 mm diameter inlet pipes at about 5 m intervals. Three electric pumps transfer up to 87.4 ML/day of water to the header tank, where the water then flows by gravity to the Mudgeeraba WTP, at a rate of up to 74 ML/day (DERM, 2010).

Figure 1: Locations of LND, HUI and Mudgeeraba WTP (see green dot) (from Bertone et al., 2016a)

On a daily basis, operators at the Mudgeeraba WTP make a decision on where to draw raw water from (among the 5 LND gates and the 9 HUI gates). Presently there is no formal procedure on which source to draw water from that considers water quantity (i.e. current and forecasted availability), quality (i.e. at different offtake gates) and operational costs (i.e. pumping for HUI). Currently, operators have a preference for drawing the majority of raw water from HUI, and leaving a relatively large buffer of supply availability in the gravity-fed LND source. This is since LND can serve as a reliable backup source of raw water when there are power outages. However, at its full capacity, LND can provide raw water to the WTP for up to three months assuming no rain (Hamilton, 2015), while power failures can be fixed in a matter of days at most. Additionally, in recent studies, Bertone et al. (2016a) developed a treatment cost prediction model, and demonstrated that HUI raw water quality would rarely be of a sufficiently higher quality, when compared to LND, to make its selection

cost-effective, as any reduction in chemical dosages and associated costs would be outweighed by additional pumping costs. In fact, Bertone et al. (2016a) predicted that the current conservative source selection process, when compared to an optimal process, had resulted in Seqwater spending up to \$250,000 in additional electricity charges over a four year period (2010-14). Moreover, during this period the LND volume always exceeded 5,400 ML (i.e. 80% of its capacity), and the dam often spilled during wet weather events, leading to a waste of a relatively cheap source of drinking water. Consequently, the benefits of an increased use of the LND source by the WTP operators, which is backed by an evidence-based source selection decision support tool, are evident. This paper is predominately focused on one critical module of this overarching decision support tool for WTP operators, namely developing the likely medium term storage level forecast.

3.2. Methodology overview

An overview of the research method followed for the development of the long-term storage level forecasting tool is described below.

1. *Data collection*: historical data were collected from a number of different sources and include any parameter that can be relevant for storage volume prediction.
2. *Data pre-processing and analysis*: data were pre-processed to account for missing data, outliers, different frequencies and time periods. Relationships between variables were then subsequently assessed both visually and through linear and nonlinear regression approaches.
3. *One-week ahead regression model development*: based on the correlations identified through data analysis, a number of linear and nonlinear regression models were developed to predict one week ahead the storage volume variation.
4. *Monte Carlo approach for long term prediction*: in order to predict n weeks ahead using the week-ahead model of Step 3, a number of simulations are run to develop a probabilistic prediction model accounting for uncertainty in model prediction and for the probabilistic nature of SSF.
5. *Final model validation*: the accuracy of the model was quantified numerically and qualitatively (e.g. based on operations' preferences and multiple objectives). Different

models were checked and compared (including different values for n , i.e. number of week-ahead prediction)

6. *Model deployment*: a graphical user interface (GUI) was developed in order to facilitate the deployment of the model by the WTP operators.

3.3. Data collection and analysis

Historical data relevant for building the herein water storage level prediction model was collected from different sources. In order to apply a water balance approach, inflows and outflows information were also required. The available time-series data utilised in the study covered different time periods and frequencies. Daily rainfall data for a period of 90 years (1926-2015) were available from the BoM; however, this variable was eventually not used in developing the model, as it is based directly on inflow data (and its seasonal forecasts). River flow data starting from 1890 were collected from Seqwater, with a monthly frequency. In order to have higher frequency data, the daily Little Nerang river flows (which would represent the inflow to LND only after the actual dam construction in 1961) from 1890 to 2011, simulated with a hydrologic model, were collected from the Department of Science, Information Technology and Innovation (DSITI) of the Queensland Government. A good match between recorded monthly, and simulated monthly totals of daily data, was noticed. Recorded and simulated spill amounts were also collected from Seqwater for 35 flood events affecting LND from 1967 to 2015. Seqwater also provided other critical data such as: (1) historical LND volumes (daily from 1970, but with a considerable amount of missing data; on an average, 4 out of 7 days per week of data were available); (2) environmental flow releases (daily, operational decision based on the amount of inflow, i.e. whenever the inflow is more than 6 ML/day, then 3 ML/day are released); and (3) outflow to the Mudgeeraba WTP (daily from 1999). Rates of evaporation were not available, but it was assumed that this variable could reasonably be estimated using other available and well correlated meteorological parameters such as solar radiation and wind speed/direction. The BoM SSF are not available for the river flowing into LND (i.e. Little Nerang river), hence a weighted average of SSF for nearby locations was performed to feed the model. The adopted method was considered to be acceptable as the SSF are the result of long-term large scale climatic conditions and no important difference in the forecasted outputs can be noticed in nearby catchments of the same region.

Once all the relevant available data were collected, data analysis was performed in order to identify the optimal period and frequency of the data given this particular modelling exercise. Results suggested working with the data from 1999 to 2014, i.e. when accuracy is higher and less outliers/missing data are present. Also, because of the objective of this study (i.e. medium-term prediction), it was assumed that a daily data frequency, besides being more unreliable due to missing data, would be out of scope for this application, and unfeasible from a computational time perspective.

Figure 2 represents the time series of rainfall, main river inflow, and gross volume variation (i.e., before detracting all the outflows such as spills, environmental flow, and withdrawn raw water by the Mudgeeraba WTP). It can be seen how, expectedly, on a general basis heavy rainfall events (usually occurring in summer) are followed by high inflow and an increase in gross storage volume. However, this is not always the case, with inflow events not always proportional to the rainfall amount (due to e.g. different soil moisture in the catchment), and with some high inflows not corresponding to remarkable increases in storage volume (e.g. due to missing or miscalculated spill amounts, or different evaporation rates). This justifies the need for a model to be built in order to better predict storage volume variations.

Figure 2 – Time series of rain, inflow and gross volume variation (weekly aggregates), LND, 2000 – 2011.

3.4. Regression model development

Applying a water balance approach for modelling LND volume implies that its storage volume variation is determined as:

$$\Delta_{LNDVol} = Inflows - Outflows \quad (1)$$

However, due to the available inflows/outflows data being partially incomplete, simulated, or missing (e.g. evaporation), the Δ_{LNDVol} obtained by applying Equation (1) with the available data will not correspond to the actual measured LND volume variation (as also explained in the previous section with reference to Figure 2). Consequently, a model must be built in order to correlate real and calculated volume variations.

In order to do so, a number of regression models were developed; due to the nonlinear behavior of hydrologic systems, nonlinear regression models were expected to yield higher accuracy than linear ones. Microsoft Excel was used for this part of the research work. Black-box approaches such as ANN were not applied for this particular part of the prediction tool, as we wanted to clearly identify variables/factors involved in the water balance, and because nonlinear regression models recently developed by the authors for similarly complex environmental systems yielded more accurate predictions than ANN (Bertone et al., 2015).

Eventually, the best performing model resulted to be a threshold autoregressive nonlinear model, with an exponential/logarithmic and a quadratic component, based on the two equations below:

$$\begin{cases} LNDVol_{fin} = LNDVol_{in} + e^{(0.4494 \cdot \ln(Infl) + 2.4128)} - Sp - enfl - WTPint & Infl \leq 2,000 \\ LNDVol_{fin} = LNDVol_{in} + 6 \cdot 10^{-5} \cdot Infl^2 - 0.1113 \cdot Infl + 185.69 - Sp - enfl - WTPint & Infl > 2,000 \end{cases} \quad (2)$$

Where:

$LNDVol_{fin}$ = Final volume [ML] of LND (at the end of the week)

$LNDVol_{in}$ = Initial volume [ML] of LND (at the start of the week)

Sp = Spill amount from the top of the dam wall [ML/week]

$enfl$ = Environmental flow [ML/week]

$Infl$ = Inflow from Little Nerang Creek [ML/week]

WTP_{int} = Raw water from LND drawn to the Mudgeeraba WTP [ML/week]

Rainfall was also considered during model development as an extra potential input (i.e. increasing storage volume by direct contribution from the lake surface) but did not improve accuracy and therefore was omitted. Combining the two different nonlinear techniques enabled the development of equations that best characterized LND volumes at the end of each week. Figure 3 for instance, shows the model performance over a number of weeks (dates were not specified since the 1999-2014 time series data was refined to exclude weeks having missing or incomplete information). Specifically, the chart represents the performance of the model in predicting the volume variation based on the above equations, but before considering outflows (e.g. spills, environmental flows, intake to the WTP), as those will be known amounts, depending on operational decisions once the model is deployed. It can be seen how, based on the “High inflow” (HI) regression part of the model, the major peaks (i.e. corresponding to flood events and leading to major spilling events) are relatively well predicted. However, as Figure 4 shows, during periods of low flows such model, due to the nature of its equation, cannot sufficiently explain such smaller variations. For these smaller inflows the former HF equation typically yielded an almost constant output of about 200 ML. As a result, another regression model was deemed more suitable for predicting LND volumes during low inflow periods; Figure 4 confirms the higher accuracy of the “Low inflow” (LI) regression model component for dry periods. On the other hand, LI prediction during very high inflow events was inaccurate: this implies that the two models needed to be combined and a boundary condition set for each model. A number of simulations were run with different threshold values; the procedure enabled to identify the optimal threshold above which the application of the HI regression model was more beneficial to be 2,000 ML. Other available predictor variables were examined (i.e. evaporation-related variables such as solar radiation or wind) to determine whether they could explain the remaining variance but were not supported as significant predictors. The final regression model (Eq. 2) yielded an adjusted R^2 value of 0.78 and a root mean squared error (RMSE) of 621 ML. Although the RMSE seems to be relatively high, the high adjusted R^2 provides evidence that, despite in terms of absolute values the model might not be extremely reliable, the amounts of underestimations and overestimations are relatively similar, implying that over the long term most of the errors cancel each other. For traditional predictions this behavior would still be not acceptable, but

in this case, as we will sequentially apply the model n times (to predict n weeks ahead), adjusted R^2 represents a more valid performance indicator.

Figure 3 – Model prediction of gross LND volume variation

Figure 4 – Prediction of gross LND volume variation for low flow/high flow models; interval variations < 500ML

3.5. Long term probabilistic prediction tool set up

In order to predict n weeks ahead, the regression model was tested and applied n times sequentially. After the full model was developed, the optimal n was calculated to be 6. This means that predicting six weeks ahead provided a temporal horizon long enough to be very

useful for operational purposes, but also not too long to obtain an unacceptable cumulative error. Section 3.6 provides additional information regarding the model validation.

In order to develop such long-term probabilistic model, firstly, as the SSF provide probabilities of having the river flow below, near or above median values for the next three months, these median values were calculated for the Little Nerang Creek (i.e. main inflow to LND) and are presented in Table 1.

Table 1 – Little Nerang Creek weekly inflows general statistics (STD=standard deviation)

Month from	Month to	Mean [ML]	STD [ML]	Median [ML]
January	March	1,480.542	2,578.899	466.264
February	April	1,092.664	1,743.074	422.4035
March	May	772.1705	1,259.544	311.8475
April	June	614.3736	1,196.148	204.1382
May	July	529.0719	1,068.768	147.9115
June	August	426.382	918.4003	108.223
July	September	389.9232	836.8914	89.2202
August	October	362.1461	1,032.436	83.25
September	November	413.3358	1,049.363	85.4831
October	December	655.5919	1,533.724	125.215
November	January	1,149.925	2,492.9	195.161
December	February	1,512.805	2,773.358	297.984

Also, different probability distributions were fitted to the probability density function (PDF) of the inflow data (e.g. exponential, generalized Pareto, generalized extreme value, etc.); it was found out that an exponential distribution with $\lambda=0.001274$ could approximate well the inflow's PDF. After this step, it was possible to calculate the associated cumulative distribution function (CDF) and then the quantile function (i.e. inverse CDF). The idea underpinning these calculations is that, by randomly selecting a number x between 0 and 1, and applying the following quantile function:

$$Inflow(x) = -\frac{-\ln(1-x)}{0.001271} \quad (3)$$

it is possible to generate the equivalent random inflow value; however, the inflow value will not be totally random, but it will be linked to the features of the inflow's PDF. Table 2, as a further clarification, better explains this concept: it can be seen how, for any random number x between 0 and 0.7, the inflow value will be below 1,000 ML. However, a further slight increase in x to 0.9 would lead to an equivalent inflow of almost 2,000 ML. This is due to the exponential nature of the inflow frequency distribution, with most of the days having rather low inflows (i.e. 70% of times below 1,000 ML) and few times (e.g. flood conditions) extremely high. By knowing that the median value corresponds to a generated number x of 0.5, three intervals were selected:

- Below median inflow: $0 < x \leq 0.35$
- Near median inflow: $0.35 < x \leq 0.65$
- Above median inflow: $0.65 < x < 1$

Table 2 – Weekly inflow values generated from different random numbers between 0 and 1.

Number (x)	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99	0.999
Inflow [ML]	0	82	175	280	401	544	719	945	1,263	1,807	3,614	5,421

As a consequence of the previous calculations, it is now possible to use the SSF information as model input. A Monte Carlo approach is used: 100,000 simulations are run, and for each simulation, 6 random numbers between 0 and 1 (one for each weekly inflow required as input) are generated. These numbers however are not totally random either, but they are selected with a frequency proportional to the probabilities stated by the SSF. That is, for each 100 random number generations, if the probability of below median inflow is, for instance, 63%, then 63 times the random number generated will be below, or equal to, 0.35 (according to the previously defined intervals). This quasi-random number generation is a critical step for a reliable prediction and management of uncertainty.

A similar approach was applied to the distribution of the prediction error; as the error is not totally random, but it was found to be well approximated by a logistic distribution ($\mu = -50.75$; $s = 581.74$), the authors decided to add a model error prediction to the forecasted volume; although it is quasi-randomly generated, it is believed that in this way the results could be more reflective of the uncertainty of the system (a higher variance in the simulations results is

expected) and of the actual accuracy of the regression model. This step is optional and the user can decide whether to apply the model error prediction or not.

The step-by-step procedure of the full hybrid regressive/probabilistic model is as follows:

1. Specify initial conditions such as environmental flow and planned daily raw water intake to the WTP;
2. Generate quasi-random number based on the SSF given by the BoM (after weighted interpolation from nearby catchments);
3. Estimate the quasi-random weekly inflow value through quantile function;
4. Apply the threshold nonlinear autoregressive model to calculate the “gross” amount of water flowing into LND during the following week (i.e. before removing outflows);
5. Optional: add quasi-random error predicted through quantile logistic function from generated random number;
6. Remove the outflows stated in Step 1: if the predicted volume is above the maximum LND capacity, assume $\text{LND Volume} = \text{LND maximum capacity}$ and consider the excess inflow as spill;
7. The week-ahead volume has been estimated; go back to Step 2 until week 6 is reached;
8. Repeat Steps 2-7 until 100,000 simulations are run;
9. Model outputs: (1) distribution of the 100,000 final LND volumes; (2) probability of high/medium/low volume; and (3) probability of high/low/no spill.

The end-users (i.e. WTP operators/decision-makers) can run the forecasting tool multiple times with different scenarios of planned water intake to the WTP, until they reach an average intake volume value which makes them comfortable in terms of expected future residual volume in LND and spill risks.

3.6. Model validation and deployment

The week-ahead regression model was validated using traditional statistical performance indices as described above. In order to evaluate the probabilistic outputs based on the different modelling objectives (i.e. minimizing depletion and spill risks and predicting the

likely volume), we had to apply a number of alternative validation scenarios using the historical data set. Firstly, we qualitatively examined model performance through visual assessments of the model outputs by WTP operators. Secondly, we numerically compared different model variants based on the average probability of predicting spill risk and likely volume in the correct interval. Depletion risk accuracy could not directly be evaluated as the dam has never been empty historically, but this performance metric could be indirectly assessed by examining the accuracy in predicting the likely volume in dry scenarios.

The model was compiled into a user-friendly and interactive graphical interface (GUI) developed through a Matlab Compiler (Figure 5). The user (i.e., WTP operators and decision-makers) can manually run the GUI for a number of scenarios by entering different proposed daily withdrawal amounts and, based on the current storage volume and the SSF collected from the BoM website, the output charts will provide depletion/spill risks as well as the most likely predicted volume at the end of the six-week period. Based on the level of uncertainty/accuracy of the SSF and week-ahead model prediction, the probability distribution will be more concentrated around a specific value. This representation of the likely volume of the reservoir after 6 weeks provides a visualization that is useful for operators as it also informs them about prediction uncertainty which is an important criterion for water related decision tools (Maier et al., 2014).

Figure 5 – GUI main screen

4. Results

The structure of the conceptualized forecasting tool was then developed using MatlabR2012a; on a Windows computer with a processor Intel® Core™ i5-2400 CPU@3.10GHz and 4GB of installed memory (RAM), the model took 248 seconds to run 100,000 simulations (for comparison, it took only 5 seconds to run 10,000). The model was also deployed on a Windows laptop with a processor Intel® Core™ i7-5600U CPU@2.60GHz using MatlabR2015a, and it took 362 seconds to run the 100,000 simulations. Whichever simulation time is considered, both are well within acceptable limits for end-users dealing with these kinds of long-term operational decision-making tasks.

Figure 6 illustrates a sample of the typical model outputs, for two different hypothesized scenarios of raw water intake and given predefined SSF. In this case, the error prediction was accounted for in the model outputs. It can be seen how the final frequency distribution (histogram on the left panel) of the final LND volume follows a bell shape typical of a Gaussian distribution; the high value of the last bin on the right-hand side of the figure is due to the summation of that bin frequency with the frequencies of values predicted to be above the maximum capacity (i.e. in reality leading to dam spills and the volume to go back to the maximum capacity, i.e. the last bin). The bell shape is partially due to the addition of the error prediction (the logistic distribution of the error has a similar bell shape): in case the predictive error is not added, then the distributions are much narrower, with almost all the values concentrated in 2-3 bins (i.e. 400/600 ML range). Despite being synonymous with higher accuracy, it might not be reflective of the actual uncertainty behind the process and lead the WTP decision-makers to be overconfident on the model's prediction of a specific value. As stressed earlier in the paper, and highlighted by Montanari and Grossi (2008), if the end-users confidently rely on a specific forecasted value that eventually proved itself to be incorrect, this would have a worse effect than not having a prediction whatsoever. As a consequence, it is believed that having the error prediction added to the model would lead to a frequency distribution of the output that is safer to adopt.

The other two graphical outputs wanted to provide a more integrated, easy to read representation of the results of the simulations, and also to reproduce the graphical output of the SSF in the BoM website. The pie chart in the center displays the probability of having, in six-week time, a volume in LND which is low, medium, or high. The thresholds were

identified as being: 4,800ML between low and medium; and 6,700ML between medium and high. These can be easily adjusted by the decision-makers based on necessity and operational issues. For instance, it has been recently assessed (Hamilton, 2015) that the LND gravity main should be able to deliver 50ML/day (for the historical period used for this study, no more than 55/60ML has been treated in the same day at the Mudgeeraba WTP) with a safe head loss and no vortexing effects only down to two meters above Level 3 draw off (i.e. approximately down to a volume of 1,500ML). Based on that, operationally the lowest 1,500ML of storage are not usable (i.e. only lower daily flows can be fed to the WTP). However approximately 3 months of demand at 50 ML/day can be satisfied when starting from crest level, assuming little or no inflow, before reaching this critical threshold (Hamilton, 2015).

The third chart is a similar pie chart representing the probability of having, over the upcoming 6 weeks, no spill, medium spill, or high spill amounts. Similarly, the selected thresholds, which can be modified, were: 10ML between no and medium spills; and 1,000ML between medium and high spills. The numbers are calculated by summation of the predicted spill amounts over the 6 weeks of each simulation; then the 100,000 predicted spill amounts are classified based on the predefined thresholds. This is deemed to be important and valuable information provided by the model: even though the main concern for the WTP operators is to avoid high risks of depletion, it is also important to avoid high risks of spill: this would be most likely considered an economic loss of raw water with no associated pumping costs.

Thanks to the two pie charts, the WTP operators and decision-makers can run the model a handful of times with different preselected intake amounts, in order to find the optimal value that minimises both the risk of depletion, and the risk of LND spilling. Figure 6 provides an example of this optimization process.

Figure 6 - LND volume prediction model outputs: predicted volume probability (left), probability of low/medium/high volume (centre), probability of no/medium/high spill (right).

Top panel: high usage (55ML/day) scenario. Bottom panel: medium usage (30ML/day) scenario. Common fixed inputs: (1) Initial month: January; (2) Predicted inflow: 65% low; (3) Initial volume: 5,800ML; (4) Environmental flow: 3ML/day. Medium usage seems the safer option as it substantially reduces the risk of low volume, and it also keeps the risk of spill to only 9%.

In order to test the model, this was run on a range of different historical conditions and scenarios, listed in Table 3. Those are quite different both in terms of initial conditions (e.g. initial dam volume, season) and in terms of weather events (e.g. future inflow) and operational behaviors (e.g. WTP intake, environmental flow). As for this validation the future

inflows were known from historical data, the quasi-random number generation process based on SSF was removed; instead, a fixed number was calculated in order to extract, from the exponential distribution fitted to the inflow frequency distribution, exactly the expected inflow value. Essentially, the inverse of Equation (3) was applied. As a consequence, all the simulations yielded the same total inflow values over 6 weeks, but each simulation divided the total amount in different weekly combinations. The model was run with, or without, the error prediction to compare performances.

Table 3 – Features of the five different tested scenarios

Scenario #	1	2	3	4	5
Initial Month	March	October	July	December	January
Average future 6-week intake [ML]	413	94	53	6,368	43
Historical average future 6-week intake [ML]	772	655	390	1,513	1,481
Random number generated	0.41	0.13	0.13	0.99	0.03
WTP Intake [ML/week]	91	44	137	360	84
Environmental flow [ML/week]	21	19	13	21	17
Total Spill [ML]	0	0	0	1939	0
Initial LND Volume [ML]	6,881	6,283	6,485	6,868	5,088
Final LND Volume [ML]	6,847	6,757	5,940	6,825	4,689
LND Volume change [ML]	-34	474	-545	-43	-399

Figure 7 illustrates the outputs by running the model with the conditions established in the five scenarios of Table 3, against the real variations in volume recorded for those historical events. The numbers reported represent the most likely final volume (i.e. the volume corresponding to the top of the bell curve) predicted by the model. Results are shown for the model run both with and without error prediction inclusion. For Scenario 1, with LND full and normal inflow conditions, both the models correctly predicted the final LND volume to be still high, with very little variation and limited spill. In Scenario 2, both models underestimated the final volume, with the “no-error model” being close to the real final volume. This was, however, a particular and interesting scenario, as it was very dry and

accordingly it was atypical to obtain such an increase in volume. In Scenario 3, initial conditions were quite similar, but a larger WTP intake meant a considerable loss in storage volume at the end of the period; in this case, the “no-error model” supplied a near-perfect forecast, while the “error model” overestimated the volume loss. Scenario 4 instead provides an example of a very wet period. Both models correctly predicted the dam to be at full supply capacity, and they also correctly predicted a considerable risk of high (i.e. > 1,000ML) spill (45.25% for the “error model”; 99.7% for the “no-error model”). Finally, Scenario 5 came with a lower initial volume and a subsequent further loss due to an extremely dry 6-week period. The loss was slightly underestimated by the “no-error model” and slightly overestimated by the “error model”.

Figure 7 – Model prediction for the 5 tested scenarios

Overall, both models produced results with acceptable accuracy when used to replicate historical events conditions, consistently predicting the expected behavior (i.e. expected loss or gain) and also quite often obtaining very close numerical predictions. Generally, the “no-error model” seems to yield a more accurate prediction, while adding the error prediction typically leads to an underestimation of the final LND volume. This is due to the logistic distribution of the error having a negative mean: more often than not adding the error prediction implies adding a negative quantity to the predicted volume variation. However, overestimating the risk of LND depletion might be a safer measure, because despite the high level of uncertainty underlying the system, it is easy for the user to be overconfident with the exact numerical prediction of the model and consequently take reckless decisions (Maier et al., 2014). It is believed that using the model with incorporated error prediction might be

operationally beneficial and more representative of the uncertainty underlying the modelled system.

A numerical quantification of the performance of the models is provided in Table 4. For sake of comparison, we also assessed a model based on the LI part only of the system in Equation (2), against the performance of the final threshold autoregressive model combining the two equations of the system. We assessed the average proportion of the resulting distribution falling into the correct interval of volume and spill amount (i.e. the proportion of simulations predicting the volume and total spill amount in the correct interval). We have also assessed the performance of the same model over different time horizons (4, 5, 6, 7 and 8 weeks ahead predictions) but based on the operational purpose of this tool (i.e. a prediction of less than six weeks would be much less useful for the management of the reservoir) and accuracy (there was a considerable drop in performance from 7 weeks onwards), it was decided to keep a prediction horizon of 6 weeks.

Table 4: Models' performance

Accuracy parameter	Model 1	Model 2	Model 3	Model 4
Correct volume interval prediction	55%	80%	59%	81%
Correct spill interval prediction	69%	60%	75%	89%

Model 1 = LI, with error

Model 2 = LI, without error

Model 3 = Combined, with error

Model 4 = Combined, without error

Firstly, it can be noticed how the combined models (Models 3 and 4) have consistently higher performance than the LI model, especially for spill amount prediction. This is a sensible conclusion, as the LI model applies only the first equation in (2), while the combined model applies two separate equations for week-ahead prediction, improving the accuracy during wet weather events (meaning better spill amount predictions). Secondly, for both models, not including the error prediction usually leads to higher performances. This is mainly due to the aforementioned underestimation of the results when including error prediction: since two of the scenarios considered present a final volume just above the interval threshold, this implies that a slight underestimation led to the distribution of the results to shift towards the wrong interval. However, based on previous considerations, despite the apparent higher accuracy the

operators might opt for the use of Model 3, as it would typically predict a higher risk of depletion leading to a more conservative storage volume management.

5. Conclusions

A hybrid nonlinear regressive and probabilistic model was built in order to forecast, six weeks in advance, the storage volume of a small, subtropical drinking water reservoir in South-East Queensland, Australia (namely, Little Nerang dam). The forecast horizon was selected as a compromise between accuracy loss and operators' needs. The model applies a Monte Carlo – based approach, where a number of simulations are run, and each simulation generates six weekly “quasi-random” inflows, with values linked to the probabilities provided by the BoM seasonal streamflow forecasts. Based on the inflow values, a nonlinear threshold autoregressive model forecasts the expected storage volume variations, as well as the amount of water spilling from the dam wall (if any). Optionally, a “quasi-random” prediction of the model error can be added, in order to account for the actual uncertainty behind the model and the full modelled system in general. A user-friendly graphical interface was also developed in order to facilitate the model deployment among WTP decision-makers and operators.

The model was tested over different scenarios of historical data, under totally different initial and weather conditions; the results show how the model could reliably forecast the final volume in any conditions; adding the error prediction, despite underestimating the final volume, is deemed beneficial and operationally a safer option for the end users. Future work will consider if the prediction is considerably affected by the relative accuracy of the BoM seasonal streamflow forecasts. The correlation between water quality parameters and WLF was not analyzed here but certainly deserves a closer examination in future studies, as it may result in financial benefits for Seqwater, the custodian of the Mudgeeraba WTP, through a more careful WLF management that would lead to water quality improvement (Naselli-Flores and Barone 2005).

To the authors' knowledge, the developed model is unique and novel compared to existing ones in terms of: (1) The medium-term forecast horizon selected (6 weeks), as well as the relatively small maximum storage volume of the reservoir considered; (2) The integration of a traditional regression-based statistical approach, with a probabilistic Monte Carlo-based method to account for uncertainty; and (3) The combined use of information based on

historical, past reservoir behavior, and of future predicted long-term inflows freely available from the BoM. The proposed methodology can be applied to other relevant sites with similar historical data and long-term inflow forecast availability.

The developed model will be very beneficial for the WTP operators and decision-makers, and more broadly for the water utility (i.e. Seqwater). As a treatment cost prediction model based on raw water quality is already available (Bertone et al., 2016a) and it demonstrated how an increased use of LND and decrease use of the energy-intensive HUI would considerably reduce the total treatment costs, it is now possible to devise the best raw water intake strategy over the medium-term timeframe in order to minimize both depletion and spill risk for LND, and in turn the energy costs. This would eventually lead to substantial monetary benefits for Seqwater, as well as more proactive treatment operations. Moreover, provided enough data is available, such model can be developed for similar reservoirs around Australia and the Asia-Pacific region, for a better prediction and control of depletion and spill risks leading to an improved management of such water resources.

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