



Development of an Artificial Neural Network Model for Predicting Surface Water Level: Case of Modder River Catchment Area

Jandre Janse van Vuuren, Muthoni Masinde^(✉), and Nicolaas Luwes

Unit for Research in Informatics for Droughts in Africa,
Central University of Technology, Bloemfontein, Free State, South Africa
JandreJansevanVuuren@outlook.com,
muthonimasinde@yahoo.com

Abstract. Water is vital for life; however, water is a scarce natural resource that is under serious threat of depletion. South Africa and indeed the Free State is a water-scarce region, and facing growing challenges of delivering fresh and adequate water to the people. In order to effectively manage surface water, monitoring and predictions tools are required to inform decision makers on a real-time basis. Artificial Neural Networks (ANNs) have proven that they can be used to develop such prediction models and tools. This research makes use of experimentation, prototyping and case study to develop, identify and evaluate the ANN with best surface water level prediction capabilities. What ANN's techniques and algorithms are the most suitable for predicting surface water levels given parameters such as water levels, precipitation, air temperature, wind speed, wind direction? How accurately will the ANNs developed predict surface water levels of the Modder River catchment area?

Keywords: Artificial Neural Networks · Modder River · Free State Surface water · Prediction and monitoring

1 Introduction

Water is vital for life; every living entity needs water in order to prosper. On the other hand, water is a scarce natural resource that is under serious threat of depletion from events such as climate change, population and economic growth and poor management of its use around the world (Schewea and Heinke 2014). South Africa and indeed the Free State is a water-scarce region; the constant droughts, very low annual rainfall, poor infrastructure support (rusty water pipes and leaks) and unpredictable water usage patterns by large-scale farmers and other irrigation activities in the province only makes things worse (Ishmael and Msiza 2007). There is evidence that the current challenges of delivering fresh and adequate water to people of the Free State will only get worse as the effects of climate change, population and economic growth become a reality (Blerk 2012).

The government, relevant stakeholders and parties have put measures and strategies in place; they include water restrictions to inform the masses on the sustainable water usage patterns. There is however, an urgent need to develop accurate models for predicting future water levels (Hedden and Cilliers 2014). One way to effectively

manage surface water is a monitoring and prediction tool that is able to accurately inform decision makers on real-time basis, of the amount of water available for a period of time: short-term, medium-term and long-term. Surface water is found in lakes, rivers, dams and streams, which is drawn into the public water supply. Despite their various shortcomings, Artificial Neural Network's (ANN) have proven that they can be used to develop such prediction models (Govindaraju and Rao 2013). ANN has evolved as a branch of artificial intelligence and has been regarded as an efficient tool for the learning of any nonlinear input-output systems (Chiang et al. 2010).

2 Related Literature

2.1 Water Management in Free State

Water management is the control and movement of water resources to minimize damage to life and property while maximizing the benefits of water (Agriculture n.d.).

The Free State is the third largest province in South Africa covering approximately 129 825 km² and is located in the centre of the country. Bloemfontein is the capital of the province which comprises five district municipalities and nineteen local municipalities (Reform 2013).

The Orange River and the Vaal River together with their tributaries, are the main sources of surface water in the Free State province. The Orange River Basin stretches over six other provinces of the country's nine provinces. The Orange River System drains approximately 47% of South Africa's total surface area and approximately 22% of the country's mean annual rainfall run-off (Reform 2013).

2.1.1 Study Area: Modder River

The whole Modder River is a large basin with a total of 1.73 million hectares. It is divided into three sub-basins, named as the Upper Modder, Middle Modder and the Lower Modder. It is located within the Orange water management area (WMA) to the east of the city of Bloemfontein (central South Africa) (Woyessa and Pretorius 2005).

The Upper Orange WMA lies to the centre of South Africa and extends over the southern Free State and parts of the Eastern and Northern Cape provinces. The WMA also borders on Lesotho to the east, where the Orange River originates as the Senqu River. Draining in the Highlands of Lesotho, the Senqu River contributes close to 60% of the surface water associated with the Upper Orange WMA, at the point where it enters South Africa to become the Orange River (Tetsoane and Woyessa 2008).

2.2 Current Surface Water Level Prediction Processes

Water availability of surface water resources is determined by a combination of measurement and modelling. The long-term availability of the surface water resources is determined using rainfall-runoff models. The models that have been used in South Africa include WRSM2000, ACRU, SWAT, VTI and HSPF. The monthly time step WRSM2000 model is widely used in DWAF water resource studies for large catchments. ACRU and SWAT are essentially daily time-step models, while VTI and HSPF

are short-time-step models. The latter four models have as yet only found niche or “special question” applications in the determination of water availability for water resource studies. WSM2000 and HSPF are conceptual models of the hydrological cycle while ACRU, VTI and SWAT have a more physical basis (Coleman and van Rooyen 2007).

2.3 Artificial Intelligence

Artificial Intelligence (AI) refers to the computing paradigm that aims to develop solutions that mimic human perception, learning and reasoning to solve complex problems (Masinde et al. 2012). Although AI is usually thought of as part of computer science, AI overlaps with disciplines as diverse as philosophy, linguistics, psychology, electrical engineering, mechanical engineering and neuroscience (Shoham 2014).

2.3.1 Neural Networks

Neural Network (or Artificial Neural Network) are computational networks which attempt to simulate the decision process in networks of nerve cells (neurons) of the biological central nervous system. The neural network, by its simulating of a biological neural network, is in fact a novel computer architecture and a novel algorithm architecture relative to conventional computers. It allows the use of very simple computational operations (addition, multiplications, and fundamental logic elements) to solve complex, mathematically ill-defined problems, nonlinear problems or stochastic problems (Graupe 2013).

2.4 Artificial Neural Networks

ANN's are widely applied in a broad range of fields such as image processing, signal processing, medical studies, financial predictions, power systems, pattern recognition and more. Their success has also inspired applications to water resources and environmental systems, because ANN models have the ability to recursively learn from the data, they can result in significant savings in the time required for model development and are particularly useful for applications involving complicated, nonlinear processes that are not easily modelled by traditional means (Govindaraju and Rao 2013). The ANN model can be broadly divided into the following three types (Chhachhiya and Sharma 2013):

Feed-forward network – In this network output from one layer of neurons feeds forward into the next layer of neurons. There are never any backward connections and connections never skip a layer (Chhachhiya and Sharma 2013). Can make use of supervised or unsupervised learning (Karayiannis 2013).

Recurrent network – This type of network has at least one feedback loop and is mainly used for associative memory and optimization calculation (Chhachhiya and Sharma 2013).

Self-organization network – This network is based on unsupervised learning. In this network, the target output is not known to the network. Mainly used for cluster analysis (Chhachhiya and Sharma 2013).

3 Research Questions

- What ANN's techniques and algorithms are the most suitable for predicting surface water levels given parameters such as water levels, precipitation, air temperature, wind speed, wind direction, atmospheric pressure and evaporation?
- How accurately will the ANNs developed using the algorithms in question 1 above, predict surface water levels of the Modder River catchment area?

4 Research Objectives

The main objective of this research project is to investigate and develop an effective ANN model that is able to predict surface water levels for short-term medium-term and long-term lead-times. The model will be based on data from the Modder River catchment area of Free State.

This main objective will be achieved through the following sub-objectives:

- To develop a custom ANN model that is capable of predicting surface water levels given a set of pre-defined, pre-processed parameters such as water level, precipitation, air temperature and humidity.
- To evaluate and implement interfaces that will use the ANN model above to provide a real-time surface water level prediction system prototype.
- Evaluate the working of the system prototype for a specific period of time.

5 Methodology

Quantitative data that included temperatures, humidity, wind speed, wind direction, rainfall must be requested and received from the South African Weather Services (SAWS) that is in relationship around Case study of the Modder River catchment area. Water level data has been received from the Department of Water Affairs online website. All of this data is pre-processed using a custom developed application to ensure the data is in a generalized form and stored in a database for use. The feed forward back-propagation ANN framework is developed using Visual Studio C#. Using the pre-processed data from the database, experimenting with different data sets in the ANN is in order. Using the weather data as inputs and the water level data as output for the ANN during training, the data set that produces the least amount of error measurements, will be used as the main data set to train the ANN and develop a real-time prototype, where the entities that produced the training data, can connect through some interface to the ANN to provide real-time data.

6 Preliminary Results and Discussion

The graph below is an example of the raw data before being processed. The rain fall is in mm, the temperature in Celsius degrees, the wind speed in km/h and wind direction is between 0 and 360°.

B	C	D	E	F	G	H	I	J
StasName	Latitude	Longitude	DateT	Rain	Temperature	WindSpeed	WindDir	Humidity
QUEENSTOWN	-31.92	26.88	17-Nov-1998 18:00	3.4	11.1	5.6	110	91
QUEENSTOWN	-31.92	26.88	17-Nov-1998 19:00	0.2	11.3	4.8	120	91

This raw data is then pre-processed into a better format for data management and stored in the database, for example: the rain might be 3.4 mm in the raw data, but the pre-processed value might be 4 mm. The pre-processed data is then formatted again to have generalized values and have a smaller number of nodes to work with, for example: Identifying the minimum and maximum value of each input parameter, the level of nodes is developed for the value, for example: using the value of 30 mm rainfall, 0–20 mm rainfall might have minimum impact, there for the range of 0–20 mm rainfall is assigned only 1 input node, but 21 mm–25 mm might have a bigger impact, and therefore every 5 mm after the 0–20 mm range is given 1 input node each. Another generalization example is the temperature, where it can be -5 or -10 °C, which can be placed in the generalization range of cold, therefore giving it 1 input node for the range of any value beneath 0 to range 10.

The generalized data is then retrieved from the database, and put through the developed ANN in C#. The output of the ANN will consist of range 0 to 110, there for having 110 output nodes, this can also be generalized at a later stage to reduce the number of nodes. Each output node represents 1% of the water level, so if the final output is 70 nodes as true, then the surface water level is predicted to be 70%.

References

- U.S. Agriculture: Natural Resources Conservation Service—Water Management (n.d.). <http://www.nrcs.usda.gov/wps/portal/nrcs/main/national/water/manage/>. Accessed 8 Aug 2016
- Blerk, J.V.: Water for equitable growth and development, Chap. 2. In: Natural Water Resource Strategy (2012)
- Chhachhiya, D., Sharma, A.: Recapitulation on transformations in neural network back propagation algorithm. *Int. J. Inf. Comput. Technol.* **3**, 323–328 (2013)
- Graupe, D.: Principles of Artificial Neural Networks. World Scientific, Singapore (2013)
- Ishmael, S., Msiza, F.V.: Artificial neural networks and support vector machines for water (2007)
- Scheweia, J., Heinke, J.: Multimodel assessment of water scarcity under climate change. *PNAS* **111**, 3245–3250 (2014)
- Masinde, E.M.: Bridge between African Indigenous knowledge and modern science on drought prediction. *ITIKI* (2012)
- Karayannis, N., Venetsanopoulos, A.N.: Artificial Neural Networks: Learning Algorithms, Performance Evaluation, and Applications. Springer, New York (2013)

- Govindaraju, R.S., Rao, A.R.: Artificial Neural Networks in Hydrology. Springer, Heidelberg (2013)
- Reform, N.D.: Free State Province Provincial Spatial Development Framework (PSDF), 2 (2013)
- Tetsoane, S.T., Woyessa, Y.: Impact of rainwater harvesting on the hydrology of Modder River Basin. Water Institute of SA (2008)
- Shoham, Y.: Artificial Intelligence Techniques in Prolog. Morgan Kaufmann, Burlington (2014)
- Hedden, S., Cilliers, J.: The emerging water crisis in South Africa. African Futures Paper (2014)
- Coleman, T.J., van Rooyen, P.: Framework for future water resource analysis in South Africa (2007)
- Woyessa, Y.E., Pretorius, E.: Implications of rainwater harvesting in a river basin management: evidence from the Modder River basin, South Africa. *Prog. Water Resour.* **12** (2005)
- Chiang, Y.-M., Chang, L.-C., Chang, F.-J.: Dynamic neural networks for real-time water level predictions of sewerage systems-covering gauged and ungauged sites. *Hydrol. Earth Syst. Sci.* **14**, 1309–1319 (2010)