# Artificial neural networks: applications in the drinking water sector

G. O'Reilly, C. C. Bezuidenhout and J. J. Bezuidenhout

## ABSTRACT

Artificial neural networks (ANNs) could be used in effective drinking water quality management. This review provides an overview about the history of ANNs and their applications and shortcomings in the drinking water sector. From the papers reviewed, it was found that ANNs might be useful modelling tools due to their successful application in areas such as pipes/infrastructure, membrane filtration, coagulation dosage, disinfection residuals, water quality, etc. The most popular ANNs applied were feed-forward networks, especially Multi-layer Perceptrons (MLPs). It was also noted that over the past decade (2006–2016), ANNs have been increasingly applied in the drinking water sector. This, however, is not the case for South Africa where the application of ANNs in distribution systems is little to non-existent. Future research should be directed towards the application of ANNs in South African distribution systems and to develop these models into decision-making tools that water purification facilities could implement.

**Key words** | artificial neural networks, artificial neural networks in water, forecasting tool, prediction tool, water management, water quality modelling

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## INTRODUCTION

Supplying adequate and safe drinking water to communities is currently one of the most important challenges that water purification facilities in developing and developed countries face (Badejo *et al.* 2015; Gray & Vawda 2016). To ensure treatment processes are efficient, knowledge of certain contaminants in the water is very important to ensure they are correctly removed (Meng *et al.* 2015). Most of the water treatment plants use purification technologies developed decades ago (Trussel 2005). Traditional water purification methods include flocculation, sedimentation, sand filtration and chlorination (Rigobello *et al.* 2013). Even though these purification methods may be effective, deterioration of source water quality may require advanced treatment methods to ensure that the water is effectively purified (van der Hoek *et al.* 2014; Ang *et al.* 2015; Meng *et al.* 2015). Advanced treatment methods usually include membrane filtration, reverse osmosis (RO), ozonation, activated carbon and advanced oxidation (van der Hoek *et al.* 2014; Meng *et al.* 2015). However, advanced treatment technologies are costly (Houtman 2010), which means poor quality raw water is thus more expensive to treat (Adgar *et al.* 2000; Ang *et al.* 2015).

To ensure safe drinking water is produced, the implementation of an effective water quality management program is important, but should not only be compliance driven. For compliance to water quality standards, such as those prescribed by the World Health Organization (WHO), United States Environmental Protection Agency (EPA) and the South African National Standards (SANS 241:2015), the levels of specific parameters are determined. Analysing a large number of variables in aquatic systems can be complex which makes the monitoring of water quality

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challenging (Ranković *et al.* 2010; Antanasijevic *et al.* 2013; Chen & Liu 2014), particularly for small water supply authorities. Typical monthly monitoring of water quality parameters may also lead to missing values in the data set (Tabari & Talaee 2015). In areas where pollution episodes regularly occur, preventative methods, such as automatic monitoring, is an option (Iglesias *et al.* 2014). However, automatic monitoring could also be costly and time consuming, particularly when the pollution events are sporadic (Iglesias *et al.* 2014). Thus, qualitative and quantitative decisions based on real data are a challenge for environmental engineers monitoring water quality (Lermontov *et al.* 2009; Tabari & Talaee 2015). Water quality modelling is thus a valuable tool to ensure optimum water quality management (Antanasijevic *et al.* 2013; Vieira *et al.* 2013).

ANNs are modelling approaches that could be used in predicting the impacts of deteriorating water quality on drinking water purification processes. This could then be used to identify critical parameters as well as steps in the purification processes to be monitored or to be addressed. Whenever there are drastic changes in the water quality, water purification facilities usually rely on past experience or extra bench-scale testing to resolve the problems (Veerapaneni *et al.* 2010). However, ANNs can be a useful tool for managing certain aspects of the water treatment operation (Veerapaneni *et al.* 2010). This is due to the fact that ANNs have the ability to produce predictions in systems where information on particular interrelationships is inadequate (Veerapaneni *et al.* 2010). Hidden relationships in historical data can be revealed by using ANNs, which assists in the forecasting of water quality (Najah *et al.* 2013).

These approaches (ANNs) are not new to the water sector where they have been applied as modelling and forecasting tools (Wu *et al.* 2014). They have found applications in water engineering, environmental sciences and ecological sciences since the 1990s (Palani *et al.* 2008; Najah *et al.* 2013). Advantages that ANNs bring to water quality modelling include: (i) model building does not require a physics-based algorithm and this makes the modelling approach faster and more flexible; (ii) non-linear relationships can be handled properly and without any effort (Tabari & Talaee 2015); and (iii) user experiences and knowledge can be incorporated in construction of a model (Zhang & Stanley 1997). The aim of this review is to give an overview on the principles of ANNs, the application of ANNs in the water sector, the current scenario with regard to drinking water and future prospects.

## SEARCH APPROACH

Research for this review article was done using six databases: Google Scholar, Science Direct, EbscoHost, Emerald Insight Journals, SAePublications and Web of Science. Searches were sorted according to relevance and only articles relevant to drinking water and distribution systems were used.

## PRINCIPLES OF ANNS

Artificial neural networks are computational techniques that mimic some operational features of the human brain (Haykin 2009; Vicente *et al.* 2012). ANNs are not programmed like conventional computer programs, but they have mechanisms which can learn certain data or patterns (Sarkar & Pandey 2015). Data in ANNs are connected to each other by weights parallel to synapses (Seth 2015). Training of the ANN is done by adjusting these connections through a learning algorithm (Seth 2015). ANN modelling usually consists of the following steps: data collection, data analysis and training of the neural network (Antanasijevic *et al.* 2013). ANNs can identify intricate nonlinear relationships between input and output data sets (Antanasijevic *et al.* 2013; Najah *et al.* 2013). There are various types of artificial neural network available, but the most commonly used are: Multi-layer Perceptrons (MLPs), Radial Basis Function (RBF), General Regression Neural Network (GRNN), Cascade Forward Networks (CFN) and Kohonen's self-organizing maps (SOM) (Farmaki *et al.* 2013; Wu *et al.* 2014).

MLPs are the most commonly used feed-forward neural networks (Piotrowski *et al.* 2015; Tabari & Talaee 2015). The architecture of a typical feed-forward network (Figure 1) contains an input layer, a hidden layer and an output layer (Piotrowski *et al.* 2015; Salami Shahid & Ehteshami 2016). The neurons in one layer are connected to the next layer, but the neurons of the same layer are not connected to

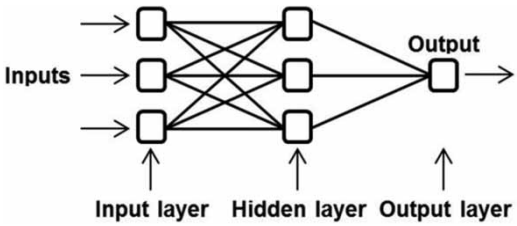


**Figure 1** | Architecture of a feed-forward network (adapted from Najah *et al.* 2013).

each other (Najah *et al.* 2013). The back-propagation training algorithm is used most commonly with MLPs (Vicente *et al.* 2012). During training of the model, actual and target output values are compared. By using the back-propagation algorithm, errors resulting from the comparison are propagated backwards through the network, adjusting the weight values and the errors are minimized (Abdulkadir *et al.* 2012). A feed-forward network trained with the back-propagation algorithm can be referred to as a Back Propagation Neural Network (BPNN) (AL-Allaf 2012). Since the introduction of the feed-forward ANN, research into the application of ANNs has thrived (Maier & Dandy 2000).

The Radial Basis Function is similar to the MLP neural network consisting of three layers: an input layer, a hidden layer (known as the kernel) and an output layer (Hannan *et al.* 2010). Just like MLPs, each layer is connected to the next layer, but with the RBF, the neurons in the hidden and output layer are interconnected to each other by weights (Sharma *et al.* 2003; Farmaki *et al.* 2010). The GRNN is a variation of the RBF network (May *et al.* 2008; Hannan *et al.* 2010). Unlike networks using the back-propagation algorithm, GRNN does not need a repetitive training procedure (Hannan *et al.* 2010). It estimates random functions between input and output neurons directly from the training data (Hannan *et al.* 2010).

Cascade Forward Networks (Figure 2) are similar to feed-forward networks, but each layer is connected to the

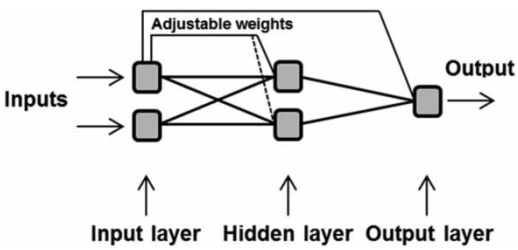


**Figure 2** | Architecture of a Cascade Forward Network (adapted from Al-Allaf 2012).

successive layers by means of a weight connection (Goyal & Goyal 2011; Al-Allaf 2012). In other words, not only is layer 1 connected to layer 2 and layer 2 connected to layer 3, but layer 1 is also connected to layer 3 by means of a weight connection (Goyal & Goyal 2011; Al-Allaf 2012). The back-propagation algorithm can also be used to update the weights of the layers (Chayjan 2010; Goyal & Goyal 2011). The Kohonen self-organizing map (Figure 3) consists of only an input layer and a Kohonen layer (Bowden *et al.* 2005; Farmaki *et al.* 2013). Each input element is connected to all the other neurons of the Kohonen layer (Farmaki *et al.* 2013). These networks have the unsupervised ability to learn and organise data without being given associated output values for the input data, hence the term 'self-organizing' (Mukherjee 1997; Farmaki *et al.* 2013).

A neuro-fuzzy network is a combination of artificial neural networks and fuzzy logic (Rani & Moreira 2010). Fuzzy logic is a representation of knowledge (obtained from data analysis or expert knowledge) that is based on reasoning that is approximate rather than predicated logic (Christodoulou & Deligianni 2010). For example, a set of objects or a scenario can be characterized by being true or false. If 'true or false' are given values of '1 and 0', fuzzy logic allows grades of characterization assigned to each object ranging between the values of 0 and 1, basically referred to as 'degrees of truth' (Zadeh 1965; Christodoulou

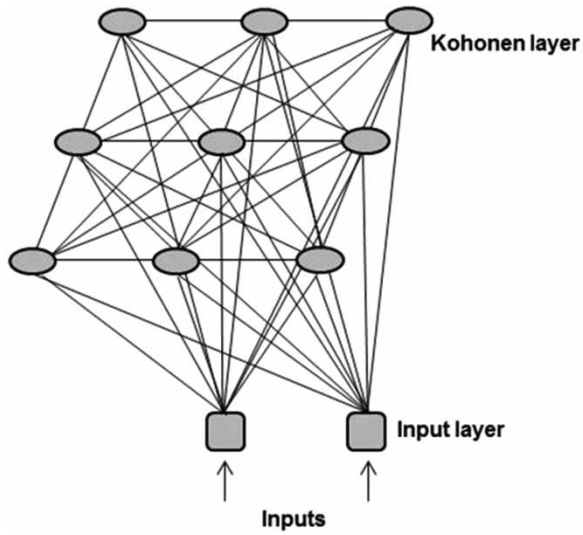


**Figure 3** | Architecture of Kohonen's self-organizing map (adapted from Bowden *et al.* 2005).

& Deligianni 2010). One of the most popular neuro-fuzzy methods is the Adaptive Network-based Fuzzy Inference System (ANFIS) (Rani & Moreira 2010).

## APPLICATION OF ANNS IN THE DRINKING WATER SECTOR

Since the late 1980s into the 1990s, ANNs have been applied in drinking water distribution system management to predict pipe pressure/leakage (Bargiela & Hainsworth 1989; Vairavamoorthy & Lumbers 1998), scheduling of booster disinfection (Boccelli *et al.* 1998) and coagulation/flocculation (Zhang & Stanley 1999). During the early 21st century ANNs became more popular and were applied to various applications such as membrane filtration (Cabassud *et al.* 2002), predicting disinfection residuals (Gibbs *et al.* 2003; Legube *et al.* 2004), chemical dosing (Valentin & Denœux 2001) and disinfection by-products (DBPs) (Milot *et al.* 2002).

However, during the period from 2006–2017, the application of ANNs in the drinking water sector has increased about four times compared to the previous decade. Researchers applied ANNs in fields such as the prediction of water quality parameters, municipal water production/consumption, contamination events and operational costs. Some of the studies from 2006–2017 are summarized in Table 1.

## PIPES/INFRASTRUCTURE

As seen in Table 1, the most popular area of interest was the prediction of pipes and infrastructure problems at water purification facilities. Several authors used ANNs to predict pipe leakages (Table 1). Pressure in a water distribution network may play a role in aggravating leakage (Makaya & Hensel 2015). This parameter (pressure) can be measured by sensors, but sensors cannot be placed at every node which means leaks are not always detected (Ridolfi *et al.* 2014). Measurements and data analysis of sensor monitoring as well as other leakage detection methods may be time and cost consuming (Wachla *et al.* 2015). Therefore, ANNs could be used to predict pipe pressure, which may reduce water leakage. Mounce & Machell (2006); Nazif *et al.* (2010); Ridolfi *et al.* (2014) and Makaya & Hensel (2015) used MLP neural networks to detect leakages, whereas Ho *et al.* (2010) used RBF and Wachla *et al.* (2015) used ANFIS (Table 1). Results of these studies indicated that ANNs were successfully used to detect pipe leakages.

The study by Nazif *et al.* (2010) concluded that implementing the ANN model to optimize tank water levels can reduce leakage annually by 30%. Ridolfi *et al.* (2014) used ANNs to simulate water pressure at every node in the distribution system. The model is useful to determine which pressure monitoring sensors can be omitted from the distribution system without any loss of information. A study by Ho *et al.* (2010) included earthquake data as a major input parameter to predict pipe breakage events and pipeline leakage problems (Table 1). LuoDong Township in Taiwan is frequently affected by earthquakes and was therefore chosen as the study site. It was noted that the inclusion of earthquake data yielded a higher prediction performance. The study concluded that the implementation of the model will not only address leakage problems, but also the labour requirement and costs involved in pipe replacement could be reduced.

Pipe failure may lead to financial loss due to repairs and maintenance being carried out (Jafar *et al.* 2010). Traditional statistical methods have been used to determine pipe failures, but the main disadvantage of these methods are that they do not usually take all the parameters that may have an influence on pipe failure into account (Tabesh *et al.* 2009). To overcome this challenge, Tabesh *et al.* (2009); Christodoulou & Deligianni (2010); Jafar *et al.* (2010) and Al-Barqawi & Zayed (2008) used ANNs to predict pipe failures (Table 1). Tabesh *et al.* (2009) used MLP and ANFIS neural networks, whereas Christodoulou & Deligianni (2010) used a neuro-fuzzy network and Jafar *et al.* (2010) and Al-Barqawi & Zayed (2008) used BPNNs. In all these studies, ANNs were successfully applied to predict pipe failures, which may reduce financial losses. Tabesh *et al.* (2009) also concluded that even though both the MLP and ANFIS models were able to predict pipe failures successfully, the MLP model slightly outperformed the ANFIS model. Christodoulou & Deligianni (2010) not only used pipe parameters as input variables, but also included traffic parameters as well (Table 1). This was due to the study

**Table 1** | Summary of applications of ANNs in the drinking water sector (2006–2017)

| | Authors | ANN/Model type | Predict/Model | Input variables | Study area |
|---|---|---|---|---|---|
| Pipes/infrastructure | Mounce & Machell (2006) | MLP | Detection of burst pipes | Flow, pressure | United Kingdom |
| | Martínez *et al.* (2007) | Feed-forward | Operational control settings | Pump and valve settings, storage tank water level & demands of district metering areas | Spain |
| | Rao & Alvarruiz (2007) | Feed-forward | Operational control settings | Pump settings, valve settings, demands for the various district-metering areas, storage tank water levels | – |
| | Rao & Salomons (2007) | Feed-forward | Operational control settings | Pumping power, pressures, flows, costs, penalties | – |
| | Salomons *et al.* (2007) | Feed-forward | Operational control settings | Pumping status, valve settings, storage levels & demands of district metering areas | Israel |
| | Al-Barqawi & Zayed (2008) | BPNN | Performance of municipal water mains | Pipe length, size, age, type of material, depth, slope & type of sewer | Canada |
| | Tabesh *et al.* (2009) | MLP & ANFIS | Pipe failure and mechanical reliability | Pipe length, diameter, age, installation depth & hydraulic pressure | Iran |
| | Christodoulou & Deligianni (2010) | Neuro-fuzzy | Performance of pipes and failure analysis | Pipe parameters: previous breaks, length, materials & diameter<br>Traffic parameters: traffic load, pipe's proximity to a highway, underground railway & roadway or block intersection | New York City (USA) & Limassol (Cyprus) |
| | Ho *et al.* (2010) | RBF | Pipeline replacement and leakage | Pipe diameter, material & seismic factor (earthquakes) | China |
| | Jafar *et al.* (2010) | BPNN | Model the failure of the pipes | Historical failure, hydraulic pressure, characteristics, location of pipes & soil type | France |
| | Nazif *et al.* (2010) | MLP | Pipe pressure | Elevation of nodes, storage tank levels & demand at each node | Iran |
| | Farokhzad *et al.* (2012) | MLP | Faults in centrifugal water pump | Mean, standard deviation, sample variance, kurtosis, skewness, root mean square, crest factor, slippage & fourth, fifth and sixth central moment | Iran |
| | Ridolfi *et al.* (2014) | Three layered feed-forward (MLP) | Pressure distribution | Water pressure | Italy |
| | Makaya & Hensel (2015) | MLP | Flow dynamics to detect leakage | Flow logging data | Zimbabwe |
| | Wachla *et al.* (2015) | ANFIS | Leakage detection | Water flow rates | Poland |
| | Kamiński Kamiński & Mizerski (2017) | MLP | Tool for renovation decisions in water supply | Pipe diameter, material, age, failure rate, forces affecting the pipeline | Poland |
| Coagulation/ flocculation dosage | Wu & Lo (2010) | MLP | PAC | Turbidity, temperature, colour, pH & coagulant dosage | Taiwan |
| | Gholikandi *et al.* (2011) | BPNN | PAC | Influent turbidity, poly aluminium chloride (PAC) dosage & coagulant types | Iran |

(*continued*)

**Table 1** | continued

| | Authors | ANN/Model type | Predict/Model | Input variables | Study area |
|---|---|---|---|---|---|
| | Heddam *et al.* (2011) | RBF, GRNN | Aluminium sulphate | Turbidity, EC, pH, temperature, DO & ultraviolet absorption | Algeria |
| | Dharman *et al.* (2012) | Feed-forward | PAC | Plant flow, raw water alkalinity, TOC, pH, total hardness, turbidity, iron, fluorides, hardness (calcium), temperature, polymer $FeCl_2$, flow at lock 10, pH adjustment, disinfectant (pre ammonia) & coagulant polymers | Kentucky, USA |
| | Heddam *et al.* (2012) | ANFIS | Aluminium sulphate | Turbidity, EC, pH, DO, temperature & ultraviolet absorption | Algeria |
| | Naidoo & van der Walt (2013) | Feed-forward | Polymeric coagulant | Turbidity, pH, alkalinity & colour | South Africa |
| | León-Luque *et al.* (2016) | Not mentioned in article | Aluminium sulphate | Turbidity, pH, EC, temperature, alkalinity & colour | Colombia |
| Filtration efficacy | Chen & Kim (2006) | RBF, BPNN | Membrane filtration: predict permeate flux decline | Particle size, solution pH, transmembrane pressure, elapsed time & ionic strength | Hawaii |
| | Curcio *et al.* (2006) | Feed-forward | Membrane filtration: model permeate flux decay | Operating time, sampling time & inlet flow rate | Italy |
| | Griffiths & Andrews (2011) | MLP | Granular media filtration: predict post-filtration particle counts and settled water turbidity | Temperature, pH, filter flow rate, filter head loss, filter run time, settled water turbidity & pre-chlorination dosage | Canada |
| | Kabsch-Korbutowicz & Kutylowska (2011) | MLP | Membrane filtration: predict turbidity retention coefficient during ultrafiltration | Feed water turbidity, turbidity in the tank, pH, temperature in the tank, transmembrane pressure & permeate flux | Germany |
| | Tashaouie *et al.* (2012) | MLP | Performance of pressure filters | Turbidity, filtration rate & pressure | Iran |
| | Madaeni *et al.* (2015) | MLP | Performance of RO plant | Time, conductivity, transmembrane pressure & flow rate | Iran |
| | Corbatón-Báguena *et al.* (2016) | Feed-forward | Membrane filtration: permeate flux decline | Transmembrane pressure, cross-flow velocity, operating time, flux normalization & fouling indicator | Spain |
| Municipal water demand | Adamowski (2008) | MLP | Daily water demand | Water demand, temperature, rainfall data | Canada |
| | Firat *et al.* (2009) | GRNN, RBF, Feed-forward | Monthly water use | Average monthly water bill, population, number of households, gross national product, temperature, rainfall, humidity & inflation rate | Turkey |
| | Yurdusev & Firat (2009) | ANFIS | Monthly water use | Average monthly water bill, population, number of households, gross national product, temperature, rainfall, humidity & inflation rate | Turkey |
| | Adamowski & Karapataki (2010) | MLP | Weekly water demand | Water demand, temperature, rainfall data | Cyprus |

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|---|---|---|---|---|---|
| | Firat *et al.* (2010) | GRNN, CCNN, Feed-forward | Monthly water consumption time series | Historical water consumption data | Turkey |
| | Ajbar & Ali (2015) | MLP | Monthly & annual water demand | City population, housing density, personal income, maximum monthly temperature & number of monthly visitors | Saudi Arabia |
| Disinfection residuals | Bowden *et al.* (2006) | GRNN | Residual chlorine | Flow, turbidity, pH, temperature & chlorine | Australia |
| | Gibbs *et al.* (2006) | MLP, GRNN & SOM | Residual chlorine | Water temperature, flow, chlorine concentration, dissolved organic carbon (DOC), ultraviolet absorbance ($UV_{254}$) & time of measurement | Australia |
| | May *et al.* (2008) | GRNN | Residual chlorine | Distribution plant 1: Chlorine at different nodes, tank level, pump flow rate & pipe flow rate<br>Distribution plant 2: Free chlorine, pH, turbidity, tank level, outlet flow & temperature | Australia |
| | Soyupak *et al.* (2011) | MLP | Residual chlorine | pH, EC, turbidity, water flow rates, temperature & free residual chlorine | Turkey |
| | Wu *et al.* (2011) | GRNN | Residual chlorine and free ammonia levels | Chlorine & free ammonia | Australia |
| | Cordoba *et al.* (2014) | MLP | Residual chlorine | Temperature, pH, turbidity, flow, initial chlorine & free chlorine | Czech Republic |
| Water quality | Mustonen *et al.* (2008) | SOM | Water quality changes | Particle measurement & EC | Finland |
| | Vicente *et al.* (2012) | MLP | Nitrate, manganese, sodium and potassium | pH & conductivity | Portugal |
| | Juntunen *et al.* (2013) | SOM | Various physico-chemical parameters | Well water level & flow, lake flow, lake surface level, total inflow, solvent water, lime feed, $KMnO_4$ dose, Al dose, $CO_2$ feed, temperature & flow<br>Raw water: turbidity, pH, alkalinity, EC, COD, iron, manganese & aluminium<br>Treated water: pH, alkalinity, EC, free chlorine, COD, aluminium, iron, manganese & calcium | Finland |
| | Rak (2013) | MLP | Turbidity | Raw water turbidity, water flow, water retention level, daily rainfall & reservoir temperature | Poland |
| | Gaya *et al.* (2017) | Feed-forward | Turbidity | Influent parameters: Free $CO_2$, calcium, suspended solids, hardness, chloride, conductivity, TDS, pH, turbidity | Nigeria |
| DBPs | Kulkarni & Chellam (2010) | BPNN | THM, haloacetic acids (HAA), total organic halides (TOX) | $UV_{254}$, contact time, temperature, pH, TOC, bromium & chlorine dose | USA |
| | Ye *et al.* (2011) | BPNN | THM, HAA | Residence time, water temperature, pH, $UV_{254}$, TOC, bromium concentration & residual free chlorine | China |

(*continued*)

**Table 1** | continued

| | Authors | ANN/Model type | Predict/Model | Input variables | Study area |
|---|---|---|---|---|---|
| | Singh & Gupta (2012) | Feed-forward, RBF | THM | pH, temperature, contact time, Br concentration & dissolved organic carbon normalized chlorine dose ($Cl_2$/DOC) | India |
| Organic matter removal | Bieroza *et al.* (2011) | SOM, BPNN | – | Organic matter fluorescence data | United Kingdom |
| | Bieroza *et al.* (2012) | SOM, BPNN | – | Organic matter fluorescence data | United Kingdom |
| Contamination event | Perelman *et al.* (2012) | BPNN | – | EC, pH, temperature, turbidity, total chlorine & TOC | USA (CANARY database) |
| | Arad *et al.* (2013) | BPNN | – | EC, pH, temperature, turbidity, total chlorine & TOC | Israel/USA (CANARY database) |
| Organic & inorganic pollutants | Cauchi *et al.* (2011) | Feed-forward | Anthracene, naphthalene, phenanthrene, cadmium, lead & copper | Anthracene, phenanthrene, naphthalene, cadmium, lead & copper | United Kingdom |
| Residual aluminium | Tomperi *et al.* (2013) | MLP | – | Raw water temperature, colour, pH, potassium permanganate ($KMnO_4$) & Poly-Aluminium Chloride/Potassium permanganate ratio (PAC/$KMnO_4$) | Finland |
| Cost of treatment plant | Marzouk & Elkadi (2016) | MLP | Construction cost | Soil type, clarifier type & land property | Egypt |
| Performance efficiency of treatment plant | Saha *et al.* (2017) | Not mentioned in article | Most important parameter of a water treatment plant | Amount of intake water, time of treatment, discharge rate, amount of output water, efficiency of clariflocculator, filter bed, chlorination unit & channel efficiency | India |

ANFIS: Adaptive Network-based Fuzzy Inference System; BPNN: Back Propagation Neural Network; CCNN: Cascade Correlation Neural Network; DBP: Disinfection By-Product; GRNN: General Regression Neural Network; MLP: Multi-layer Perceptron; RBF: Radial Basis Function; RO: Reverse Osmosis; SOM: Self-organizing Map; THM: Trihalomethane.

areas being subjected to heavy traffic. The use of the neuro-fuzzy network made it possible for the authors to establish a repair-or-replace rule and to determine to which areas priority should be given. Inspection of existing water mains is costly and time-consuming. Therefore, Al-Barqawi & Zayed (2008) developed their model into a user friendly, web-based condition rating tool which will benefit municipal engineers, consultants and contractors.

Martínez *et al.* (2007) and Salomons *et al.* (2007) used ANNs to optimize operational control settings (Table 1). These two studies formed part of a Potable Water Distribution Management (POWADIMA) research project. Previous studies by Rao & Alvarruiz (2007) and Rao & Salomons (2007) indicated that it was possible to form a near-optimal control process for a small, hypothetical water distribution network by using ANNs (Table 1). The next step was to apply the methodology from that study to a real network. Hence, the first of the two case studies was performed by Salomons *et al.* (2007) and included data from the Haifa-A distribution network located on Mount Carmel in Israel (Table 1). The second case study was performed by Martínez *et al.* (2007) and included the Valencia water distribution network in Spain (Table 1). Haifa-A is smaller than the Valencia distribution network and due to its geographic convenience and relationship with the Municipal Department of Water, Sewage and Drainage, it was chosen to be the first of the two case studies. Results of both studies indicated that ANNs were useful tools to optimize operational control settings, which could reduce annual operating costs by around 25% for Haifa-A and 17% for Valencia.

Centrifugal pumps play a significant role in the production process and early detection of faults may help to prevent system shutdowns, human fatalities and material damage (Farokhzad *et al.* 2012). Vibration signals are often used in fault diagnosis systems of rotating machinery. However, human expertise to convert vibration data into maintenance information is sometimes unavailable (Farokhzad *et al.* 2012). Therefore, Farokhzad *et al.* (2012) applied a MLP network to predict faults in centrifugal water pumps by using vibration condition monitoring. The study concluded that the ANN was able to predict faults, based on vibration differences, with 100% accuracy.

Kamiński *et al.* (2017) used a feed-forward MLP network as a decision making tool for renovation needs of a water supply system in Poland. Failure of distribution pipes contributes to half of all failures in a water supply system (Kamiński *et al.* 2017). Therefore, to avoid breakdowns, the pipes need to be kept in good condition. The study indicated that, should expert human advice be absent, artificial neural networks could be successfully implemented to aid in the formation of renovation plans. This will ensure that the water purification plant is maintained and can operate efficiently.

## COAGULATION/FLOCCULATION DOSAGE

The application of ANNs in the area of coagulation management during water purification has increased. The required coagulation dosage is usually determined by using traditional jar tests. However, jar tests can be time consuming and water samples have to be taken regularly, relying on manual intervention. If the quality of the raw water changes, operators have to perform a new jar test (Lamrini *et al.* 2005). In earlier studies, aluminium sulphate was the main coagulant for which the dosage was predicted, but over the past decade, poly aluminium chloride (PAC) has also proven to be popular (Table 1). Feed-forward networks remained the ANN of choice in these studies, but other ANNs were also explored. Heddam *et al.* (2011) compared RBF and GRNN for predicting aluminium sulphate dosing at a drinking water treatment plant in Boudouaou, Algeria. Results indicated that the GRNN consistently outperformed the RBF network. The study concluded that GRNN is an effective tool for modelling coagulant dosage and can be a timesaving option when compared to the usual jar tests.

ANNs have the advantage of being efficient in adapting and learning, but have the negative aspect of the 'black box'. Fuzzy logic, on the other hand, is not efficient in learning, but has the advantage of approximate reasoning (Heddam *et al.* 2012). ANFIS combines the advantages of these two methods making it a very efficient modelling tool. For this reason, Heddam *et al.* (2012) performed a study where aluminium sulphate was predicted, but they used ANFIS as the modelling tool. The same water treatment plant and input variables were used as in the 2011 study (Heddam *et al.* 2011) (Table 1). It was found that ANFIS was able to

predict the coagulant dosage successfully and the authors suggested that ANFIS might also be used instead of jar tests due to its quick responsive tools, low cost and applicability in a real-time process.

Wu & Lo (2010) and Dharman *et al.* (2012) used feed-forward networks to predict optimal PAC dosage, whereas Gholikandi *et al.* (2011) used a BPNN (Table 1). Results of the studies indicated that the various ANNs were able to predict PAC dosage levels accurately. Wu & Lo (2010) also concluded that the prediction model is useful when information on influent water quality is not provided. Dharman *et al.* (2012) noted that the ANN model outperformed the multiple linear regression (MLR) model and provides a quicker response to changing influent data. Therefore, time-consuming jar tests should be used only to crosscheck the validity of ANN predictions during periodic re-training of the model.

## FILTRATION EFFICACY

During the early 21st century, ANNs were used to predict the efficacy of membrane filtration in water purification facilities. Over the past decade, studies in this area continued, but the performance of granular media filtration and pressure filters have also been included (Table 1). Feed-forward networks proved to be the most popular ANN to predict membrane fouling (Table 1). Membrane fouling may lead to increased energy, operational and maintenance costs (Gao *et al.* 2011). Therefore, Curcio *et al.* (2006) and Corbatón-Báguena *et al.* (2016) used feed-forward networks to predict permeate flux decay which proved to be successful. Chen & Kim (2006), however, applied RBF and BPNN models. In their study, a comparison was made between these two ANNs and between the ANNs and a multiple regression method. Results indicated that the RBF neural network outperformed the BPNN and multiple regression models and was able to predict permeate flux with a limited number of training points.

In the studies by Griffiths & Andrews (2011) and Tashaouie *et al.* (2012), both used MLP to determine the performance of granular media filtration and pressure filtration, respectively (Table 1). Even though the type of filters used varied, results of both studies indicated that ANNs were able to successfully predict the efficacy of the filters. The ANN models established by Griffiths & Andrews (2011), were implemented into an online optimization application and installed at the Elgin Area water purification facility in Canada to monitor and optimize filtration conditions. In the study by Kabsch-Korbutowicz & Kutylowska (2011) a MLP was used to determine the turbidity retention coefficient after an integrated coagulation/ultrafiltration process (Table 1). Results indicated that the ANN was able to predict the turbidity retention coefficient successfully and that transmembrane pressure played a major role in the prediction model. The authors suggested that the created model can be used for forecasting quality parameters of permeate in hybrid processes, but the conditions of the membrane processes and input variables should be similar.

The operating conditions of RO are very important to ensure efficient performance of other processes such as membrane filtration (Madaeni *et al.* 2015). Madaeni & *et al.* (2015) used a MLP network to determine the performance of a RO plant by predicting process performance degradation (Table 1). The study concluded that the ANN was able to accurately predict long-term performance degradation, which is useful for RO process control. Determining the efficacy of filtration is important, because membrane fouling or ineffective filtration may lead to deterioration in the produced water quality (Chen & Kim 2006; Griffiths & Andrews 2011).

## MUNICIPAL WATER DEMAND

One of the areas where the application of ANNs has increased is the prediction of municipal water demand. Globally, source water has become stressed due to factors such as climate change, population growth and increased water consumption (Adamowski & Karapataki 2010). For planning and management of water resources, it is important to know what the future needs for drinking water may be (Ajbar & Ali 2015). Various authors have used ANNs to predict short- and long-term water demands (Table 1). Adamowski (2008) used a MLP network to predict daily water demand in the Ottawa West Center pressure zone in Canada. Summer water demand levels in this region indicated an increase from 67.8 ML/day in 1993 to

109.3 ML/day in 2002, which was an indication of the variability in the water demand. For this reason, and the fact that research into daily water prediction was limited, the authors were motivated to use an ANN to develop a prediction model. Results indicated that the ANN was able to predict daily water demand and outperformed the MLR model. The study also concluded that the daily water demand correlated better with rainfall occurrence rather than rainfall levels. The latter statement was later challenged by Adamowski & Karapataki (2010). Their challenge was based on a study by Bougadis *et al.* (2005) which arrived at a different conclusion. Adamowski & Karapataki (2010) compared different MLP networks with a MLR model to predict weekly water demand for two regions in Cyprus (Table 1). Results of the study concurred with those of Adamowski (2008).

Firat and colleagues applied various ANN models for the prediction of monthly water demand during 2009 and 2010 for the metropolitan area of Izmir, Turkey (Table 1). In the study by Firat *et al.* (2009), GRNN, RBF and feed-forward neural networks were compared. This study was followed by a study by Yurdusev & Firat (2009) where similar input variables were used, but the ANFIS network was applied (Table 1). The studies concluded that the GRNN and ANFIS model with three input variables (monthly water bill, population, monthly average temperature) gave the best results for forecasting monthly water consumption. From these studies, Firat *et al.* (2010) identified the need to compare a GRNN, a Cascade Correlation Neural Network (CCNN) and feed-forward neural networks for modelling monthly water consumption time series (Table 1). Various combinations of historical monthly water consumption values were used as input data. Results indicated that the CCNN outperformed the other models and was able to successfully forecast monthly water consumption time series.

More recently, Ajbar & Ali (2015) predicted monthly and annual water demand for Mecca city, Saudi Arabia (Table 1). Saudi Arabia is an arid country, which depends on costly desalination plants to satisfy water demands. With a large number of tourists visiting Mecca city every year and a lack of effective water management policies, the authors saw the importance to predict the future water demand. The MLP model was able to predict monthly and annual water demands successfully. This may be a useful tool for optimal operation of urban water systems. However, the authors stated that municipal data might be influenced by unforeseen leaks, changing policies and social habits.

## DISINFECTION RESIDUALS

Applications of ANNs to determine residual chlorine levels have also increased during the past decade, especially in Australia (Table 1). In many Australian studies, the GRNN was the preferred ANN. Bowden *et al.* (2006) used a GRNN to forecast chlorine residuals in the Myponga distribution system in South Australia. Results indicated that the GRNN model was able to forecast chlorine levels very accurately for up to 72 hours in advance. Their study also concluded that the GRNN outperforms the MLR model. Based on these results, May *et al.* (2008) and Wu *et al.* (2011) used GRNNs in their studies as well (Table 1). Even though the main focus of the study by May *et al.* (2008) was the improvement of the methodology in developing ANN models, the authors also found the GRNN to be successful in predicting residual chlorine levels.

In the study of Gibbs *et al.* (2006), a comparison between a MLP, a GRNN and a SOM was made for the prediction of residual chlorine levels in the Hope Valley distribution system, South Australia. Results of this study, however, found the MLP model to consistently outperform the other models. Soyupak *et al.* (2011) and Cordoba *et al.* (2014) also used MLPs in their studies (Table 1) and found that they was able to predict residual chlorine levels successfully, but Cordoba *et al.* (2014) concluded that the model from their study can only be used to predict chlorine decay for that specific study area.

Some distribution systems use chloramines as a disinfectant, which may cause free ammonia levels in the water. Nitrifying bacteria can use the free ammonia as a nutrient source which may cause nitrate levels in the water to increase and have various health effects in humans (Wu *et al.* 2011). Therefore, Wu *et al.* (2011) used a GRNN not only to predict residual chlorine levels, but free ammonia levels as well (Table 1). Results indicated that the GRNN was able to predict chlorine levels, but due to noisy and inaccurate ammonia data, the model performed poorly for the prediction of free ammonia. The authors suggested accurate

free ammonia analysers are required to obtain accurate data for the development of a successful ANN model.

## WATER QUALITY

Over the past decade, interest in the prediction of water quality parameters has increased. Online sensors are able to measure various water quality parameters continuously. However, this means large amounts of data with different time measurements are accumulated which makes pinpointing abrupt changes in water quality challenging (Mustonen *et al.* 2008). Therefore, Mustonen *et al.* (2008) used a SOM to evaluate water quality changes of online data due to biofilm detaching in a pilot drinking water distribution system (Table 1). Results indicated the SOM was able to separate sudden changes in the data from normal data. The authors suggested their research could be used to develop alert systems or prediction models for controlling water quality.

Data obtained during a water treatment process may be complex due to the non-linear relationships of all the variables (Juntunen *et al.* 2013). Hence, Juntunen *et al.* (2013) also used a SOM to model water quality in a treatment process (Table 1). The study concluded that the SOM was able to comprehensively indicate important characteristics of large data sets. This can be useful to determine the most essential states of water treatment systems, to predict the performance of the process and to use it as a graphical monitoring tool (Juntunen *et al.* 2013). In the study by Vicente *et al.* (2012), the authors used a MLP network to predict nitrate, manganese, sodium and potassium (measured less frequently) using only pH and conductivity (measured more frequently) as input variables (Table 1). Results indicated that the MLP model successfully predicted the four parameters with conductivity being the most important input variable.

Turbidity is one of the basic parameters for assessing water quality. During rainfall seasons or spring thawing, water levels may rise and increase turbidity levels. The prediction of turbidity allows operators to optimize treatment methods in advance. Rak (2013) and Gaya *et al.* (2017) used neural networks to predict turbidity in a treatment plant (Table 1). Rak (2013) used a MLP to predict turbidity during the treatment process. Results of the study indicated that the ANN was able to predict turbidity levels successfully. The study also concluded that the model could be useful to predict other parameters, such as pH and colour. Gaya *et al.* (2017) used a Hammerstein-Weiner model and a neural network to predict turbidity in a water treatment plant. The study concluded that the feed-forward neural network outperformed the Hammerstein-Weiner model. The neural network was able to predict turbidity accurately and had a Mean Absolute Percent Error (MAPE) of 12.82%, whereas the Hammerstein-Weiner model had a MAPE of −45.17%. Even though both these studies predicted turbidity, different input parameters were used (Table 1).

## DISINFECTION BY-PRODUCTS

DBPs may form during the disinfection process and may pose a health risk to consumers. In the studies by Kulkarni & Chellam (2010) and Ye *et al.* (2011), BPNNs were used to predict various DBPs (Table 1). These studies had similar input variables and results for both studies indicated that ANNs were able to predict DBPs successfully. In the study of Singh & Gupta (2012), however, two different ANNs were compared with support vector machine (SVM) and gene expression programming (GEP) models to predict THMs (Table 1). Even though all the models were able to predict THMs, the study concluded that the SVM slightly outperformed the ANN and GEP models. It was also found that pH followed by contact time had the highest effect on THM formation. Nevertheless, ANNs were useful tools to predict DBP levels and may assist drinking water facilities during design and operation decisions to meet the required DBP standards (Kulkarni & Chellam 2010).

## ORGANIC MATTER REMOVAL

Even though research into the removal of DBPs has been carried out, another contributing factor to the formation of DBPs is organic matter. This is due to chlorine reacting with organic matter present in the water which could lead to the formation of THMs (Bieroza *et al.* 2012). Usually organic matter is removed during treatment processes such

as coagulation, flocculation, clarification, filtration and granular activated carbon processes. However, these processes may sometimes only reduce the level of organic matter. Methods for quantification of organic matter are laborious (Bieroza *et al.* 2011). Therefore, Bieroza *et al.* (2011; 2012) used ANNs to predict the levels of organic matter removal by using fluorescence data (Table 1).

The study during 2011 provided the first insight for using different data mining techniques, where advanced multiway analysis (parallel factor analysis (PARAFAC), principal component analysis (PCA) and partial least squares (PLS)) and ANN approaches (BPNN and SOM) were compared (Bieroza *et al.* 2011). Results indicated little difference between advanced and conventional peak-picking methods. In a follow up study during 2012, the authors used the same data, but added the stepwise regression (SR) calibration algorithm (Bieroza *et al.* 2012). Results were similar than the previous study, indicating that PLS and BPNN models are both useful to predict organic matter removal. However, the study also indicated that, unlike the peak-picking methods, the SOM model enables advanced interpretation of fluorescence data.

## CONTAMINATION EVENTS

ANNs have also been applied for the prediction of contamination events. Perelman *et al.* (2012) applied a BPNN network to predict possible contaminants in a water distribution system, based on online data (Table 1). An event detection algorithm using Bayesian analysis was established to detect abnormal behaviour of water quality parameters when exceeding a fixed threshold value. The algorithm was able to numerically and graphically indicate the possibility of a quality fault based on single and multiple measured water quality time series. The authors, however, stated that the model's performance needed improvement and a dynamic threshold method should be analysed. Arad *et al.* (2013) aimed to improve the study by Perelman and colleagues. Even though the same type of ANN and input variables were used (Table 1), Arad *et al.* (2013) included online and offline data and implemented the dynamic threshold method by utilizing a genetic algorithm (GA), whereafter Bayesian analysis was used to detect contamination event probability. The study concluded that with appropriate preparation, the method may be implemented at any water distribution system and may also provide statistical and visual indications of contaminant events. It was also noted that the dynamic threshold method was superior to the fixed threshold method.

## ORGANIC AND INORGANIC POLLUTANTS

In the study by Cauchi *et al.* (2011), three polynuclear aromatic hydrocarbons and three heavy metals were quantified and predicted using a feed-forward neural network (Table 1). These parameters were selected due to their use in industrial processes and correlation with industrial sites. Their presence in water is of great concern as they have various health effects (Cauchi *et al.* 2011). When a water sample is measured with an analytical instrument, it is possible for pollutants with similar properties to have overlapping peaks, which makes it difficult to distinguish between them. To overcome this problem, Cauchi and colleagues applied a feed-forward ANN. Results indicated that the ANN was able to accurately quantify and predict these pollutants simultaneously.

## RESIDUAL ALUMINIUM, COST AND PERFORMANCE EFFICIENCY OF A WATER TREATMENT PLANT

MLP networks have also been applied to predict residual aluminium levels, to determine the construction cost as well as the performance efficiency of water treatment plants (Table 1). Water treatment plants can use aluminium salts as a coagulation chemical. High levels of residual aluminium may have several health effects (World Health Organization 2003). Tomperi *et al.* (2013) compared MLR and MLP models for the prediction of residual aluminium (Table 1). Even though both models were able to predict residual aluminium levels fairly accurately, the MLR model outperformed the MLP model. It was also concluded that raw water temperature, $KMnO_4$ and PAC/$KMnO_4$-ratio had the highest correlation with residual aluminium. The authors suggested the models could be used to create an

early-warning system to give additional information to process operators.

With construction of a new water treatment plant, preliminary information on the costs is not always available. In Egypt, stakeholders often need to estimate construction costs which leads to high estimation variability (Marzouk & Elkadi 2016). Therefore, Marzouk & Elkadi (2016) used a MLP network to model construction costs (Table 1). Various models were developed and the model with the lowest MAPE was chosen. In this case, the best model had a MAPE value of 21.18%, which is considered reasonable for cost estimation. The study concluded that the ANN was able to successfully predict the cost estimation, which may reduce the resources and time spent on the estimation process. The authors also suggested that detailed estimates could be compared by using this model as a benchmark.

Poor water quality and water shortages are two major challenges that India is continually facing. The optimization of water treatment processes and the prediction of water quality plays an important role in ensuring good quality water is supplied to consumers (Saha *et al.* 2017). Therefore, Saha *et al.* (2017) used a Non-structural Fuzzy Decision Support System (NSFDSS) as well as a neural network to determine the performance efficiency of a water treatment plant (Table 1). A NSFDSS is a multi-criteria decision making method (MCDM) which determines the comparative weight between parameters. In this study, the aim was not to compare the NSFDSS with the neural network, but rather to use the neural network to determine the index weights by training the model after which the model output was predicted. Results indicated that the ANN was able to successfully predict the model output. The study concluded that the efficiency of the clariflocculator was the most significant parameter.

## APPLICATION OF ANNS IN THE WATER SECTOR: SCENARIO IN SOUTH AFRICA

In South Africa, the application of ANNs in the water sector is very limited, especially in the drinking water sector. Studies pertaining to environmental water include the prediction of: streamflow (Ilunga & Stephenson 2005; Katambara & Ndiritu 2009; Kagoda *et al.* 2010; Van Vliet *et al.* 2012; Onyari & Ilunga 2013; Oyebode *et al.* 2015); reservoir capacity (Adeloye & De Munari 2006; Adeloye 2009); rainfall data (Hughes *et al.* 2006; Nkuna & Odiyo 2011); river-runoff (Steynor *et al.* 2009); water demand (Msiza *et al.* 2007) and water temperature (Van Vliet *et al.* 2012). Studies relevant to drinking water only include the prediction of chemical dosing which was performed by Naidoo & van der Walt (2013). In their study, a feed-forward network was used to determine the chemical dosing in order to improve budgeting, accuracy and reliability of the distribution plant (Table 1). This was a case study that was undertaken by the water company, Rand Water, in South Africa. Results indicated that the ANN was able to correctly predict the chemical dosing levels for lime, polymer and chlorine, even during periods where raw water quality spikes in turbidity, pH, alkalinity and colour levels were experienced. Limited ANN studies highlight the research gap regarding the application of ANNs in South African water purification facilities.

## CONCLUSION

The limitations of end product testing are becoming more evident in the water sector around the world (Okeyo *et al.* 2011). Where deterioration in available raw water quality takes place, it is often difficult to identify which step in the water purification step is not working up to standard (Okeyo *et al.* 2011). The cost of advanced treatment may be unaffordable to some water purification facilities (Brookes *et al.* 2014). Modelling and future projections, on the other hand, may not only help to improve water quality, but may also help to determine which other treatment options will be worth the investment (Brookes *et al.* 2014). Modelling techniques are increasingly playing important roles when it comes to water management decisions (Scholten *et al.* 2007; Salami Shahid & Ehteshami 2016).

This review indicates that ANNs are efficient forecasting tools in the water sector. From the literature, it was evident that the most popular neural network was MLP. However, it was also observed that ANNs were mainly used as prediction tools or studies were performed in order to compare or improve modelling techniques. None of the studies developed these models to be a

decision-making tool, except Al-Barqawi & Zayed (2008) with the development of a web-based condition rating tool, and Griffiths & Andrews (2011) with the development of a software package to monitor filtration conditions. It was also evident that the applications of ANNs in the water sector of South Africa are limited. With the current drought as well as pollution, the quality of environmental water in South Africa is deteriorating. It may thus be to the advantage of drinking water production facilities to use statistical approaches to ensure that safe drinking water of good potable quality is produced. In addition, based on international examples, there are opportunities for employing ANNs as a tool in decision-making.

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