Quantitative Assessment of Channel Seepage Using the Artificial Neural Network (ANN) Approach

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EXTENDED ABSTRACT

Channel seepage has been identified as a significant loss from the irrigation channels from both water quantity and environmental degradation perspectives. Recent studies have indicated that estimates of channel seepage are an essential component in the management of earthen channel systems. Seepage losses from channel or drains must be located and quantified to establish their economic and environmental importance. Because of drought scenarios and environmental concerns, there is much pressure on existing water resources in Australia. Seepage from earthen channels has therefore become an important issue in Australia for several reasons including the loss of an economically valuable resource and of channel assets and accession to groundwater.

Artificial Neural Networks (ANNs) have been recently employed for the solution of many hydraulic, hydrologic, and water resources problems but ANNs do not seem to have been applied for analysis of seepage from irrigation channels. In the present study ANNs have been applied to analyse channel seepage in the Murrumbidgee region of New South Wales, Australia. It is predicted by ANN that if channel seepage is not remediated, over 42 GL of water can be lost from 500 kilometres of channel in the Murrumbidgee Irrigation Area (MIA) each year as seepage and 12.5 GL will be lost through evaporation for the measured length of the channels. The traditional seepage estimate methods such as inflow-outflow and ponding tests are only useful in providing bulk estimates of losses from the studied channel reaches. The distributed qualitative methods using EM-31 and local quantitative methods using the Idaho seepage meter were an improvement in the estimation of seepage losses. However, due to varying soil properties and underlying groundwater characteristics it was not possible to effectively determine spatial distribution of channel seepage which is necessary for cost-effective lining of channels. Due to the complexity and the non-linearity of the seepage phenomenon and impossibility of building linear relationship between seepage and EM data an ANN method was developed to overcome this limitation. This helped spatially map the seepage extent along the supply channels of the MIA and therefore guide the most cost effective investments for reducing seepage losses.

Results from this study clearly show that ANNs can be successfully applied to analyse distributed channel seepage by using key input variables since the ANN method is capable of handling non-linearity due to quick adaptation and parallel computation power. The channel seepage study in the Murrumbidgee Irrigation Area in Australia indicates that most significant seepage (> 20 mm/day per unit area) occurs in less than 32 percent of the surveyed channel length, therefore it is important to initially target channel lining investments to the leakiest parts, “hotspots” of the channel system. The approach using ANNs has proven its advantages in this paper, it may be the most effective way of ascertaining seepage hotspots.

1. INTRODUCTION

Australia is the driest inhabited continent (in terms of runoff per unit area) on the planet and requires most efficient water use management due to highly variable rainfall and runoff. Agriculture is the primary consumer of water in Australia much of it through irrigation. Irrigated agriculture contributes approximately 50% of the total net returns from agriculture each year on less than 0.5 percent of the total area under agriculture. In producing these returns, it consumes over 70% of the total water use. Because of recurring droughts and growing environmental concerns, there is much pressure on existing water users to improve their productivity per unit of water consumption. The available surface water resources are being used to meet the competing consumptive water demands, and most river basins, e.g. Murray Darling Basin, are now at the limit of meeting all such water demands. There is thus a growing scarcity and competition for water among agricultural, industrial, commercial and residential sectors forcing water resources to be used more efficiently or reallocated through trading mechanisms. Since the existing resources are virtually fully committed, minimising any losses may be the only fair way to find water to reallocate. In 2007 the Prime Minister of Australia announced the Commonwealth's $10 billion National Plan for Water Security. The plan aims to improve water efficiency and to address the over-allocation of water in rural Australia, particularly in the Murray-Darling Basin. In particular this plan aims to invest $6b to save on-farm and off-farm water losses including reduction in channel seepage. There is need for "hotspots" analysis using innovative techniques such as the one described in this paper which can become prerequisites for targeting infrastructure upgrades in the leakiest parts of the irrigation areas.

The main mechanism for the conveyance of water to farms is through earthen channels. Recent surveys have indicated that a significant amount of water (10 to 30 percent) is lost in conveyance to farm (ANCID, 2006). Losses from on-farm channel systems to the ground water system have been variously estimated to contribute about 15-25 % of total ground water accessions (Van der Lely, 1995). Watts and Thompson (2001) estimated seepage loss along the Mulwala 20 channel in Victoria Australia, which diverts water from the main Mulwala Supply Canal, was 81 ML over three seasons (807 days). Akbar (2003) carried out a study on seepage from on-farm channels and drains, where he concluded that 1 to 4% of the allocated water to a farm is lost through seepage.

The studies above indicate that the estimates of channel seepage are an essential component in the management of earthen channel systems and there is a need to identify and quantify off-farm and on-farm channel seepage and deep drainage under the farm. This paper deals with the channel seepage analysis.

Channel seepage is hard to analyse and model using conventional techniques due to its non-linearity, rapid change in amount of seepage along the channels and complexity. ANN's capability of handling non-linear relationships make them suitable for complex applications such as forecasting water allocations, industrial control systems, financial forecasting, pattern and voice recognition, and in the health sector, where linear relationships do not exist. 'Neural network practitioners generally tackle more complex problems, the dimensionality of the models tends to be much higher, and methodologies are hand tailored to particular applications' (Holger et al, 2000). Artificial Neural Networks (ANNs) have been recently employed for the solution of many hydraulic, hydrologic, and water resources problems (Tayfur et al, 2005). Tokar and Johnson (1999) and Rajurkar et al. (2002) applied ANNs for rainfall runoff while Jain (2001), Tayfur (2002) and Nagy et al. (2002) applied them to sediment transport and Aziz and Wong (1992) and Lu et al. (1998) applied them to solute transport studies. Tayfur et al (2005) applied ANNs for predicting seepage through the body of the Jeziorsko earthfill dam in Poland. However, ANNs do not seem to have been applied for analysis of seepage from irrigation channels. In the present study ANNs were applied to analyse channel seepage in the Murrumbidgee region of New South Wales.

2. DESCRIPTION OF STUDY AREA

The Murrumbidgee River (Figure 1) has a catchment area of around 84,000 km^2 and a length of 1600 km from its source in the Snowy Mountains to its junction with the Murray River. The geographic boundaries of the Murrumbidgee catchment include the Great Dividing Range in the east, the Lachlan River Valley to the north and the Murray River Valley to the south.

The main irrigation areas in the Murrumbidgee catchment are the Murrumbidgee Irrigation Area (MIA), Coleambally Irrigation Area (CIA) and the Lowbidgee Irrigation Area (Figure 1). The MIA consists of the Yanco, Mirrool, Benerembah, Wah Wah and Tabbita irrigation districts. The natural drainage-way of the MIA is the Mirrool Creek. The topography is a flat open plain at an elevation of 100-135 m above sea level. Water for the MIA is diverted from the Murrumbidgee River at Berembed Weir and further downstream at Gogeldrie weir. From Berembed Weir water moves into Bundidgery storage which is the start of the system owned and maintained by Murrumbidgee Irrigation Ltd. Water is measured onto farm properties and farmers pay for the water supply charges. From Gogeldrie Weir water is directed to the Sturt canal to supply farms on the western side of the MIA. Drainage water from irrigation farms flows through Mirrool Creek to Barren Box Swamp and then flows into the irrigation districts of Benerembah, Tabbita and Wah Wah.

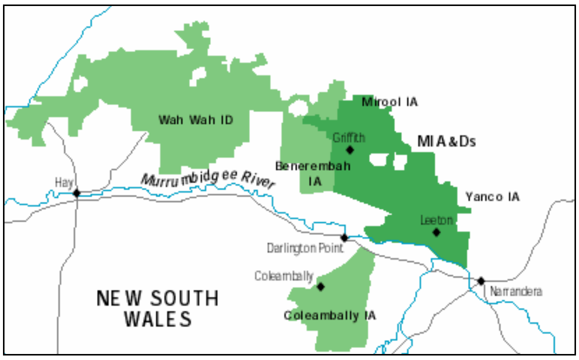

Figure 1. Location of the Murrumbidgee Irrigation Area (MIA) and Coleambally Irrigation Area (CIA)

3. METHODOLOGY

Commonly used methods for identifying seepage are:

- Local quantitative seepage estimates using the Idaho seepage meter;
- Ponding test to determine bulk seepage from a canal reach; and
- Inflow-outflow tests to determine bulk seepage from channel reaches.

A problem with these methods is their labour intensive nature and inability to quantify distributed seepage losses along the length of canal. An alternative to these approaches is the use of geophysical techniques (Electromagnetic – EM and electrical resistivity - ER) for qualitative distributed assessment of relative seepage along the channels. These qualitative measurements combined with the local quantitative seepage estimates (as described in dot points 1 to 3 above) allows the development of a workable distributed quantitative technique as described in this paper.

Some of the reasons why ANNs was used as a preferred technique are given below (Cancelliere et. al, 2002):

- In opposition to Artificial Intelligence approach, ANNs require no programming: they can be trained directly from the data;
- ANNs are massively parallel: this allows them to gain high speed performance in decision making;
- ANNs have, under some hypotheses, the ability to generalize, i.e. to extend their decision making to novel data not seen by the network during the training.

ANNs can be successfully applied when multi-criteria decision support is required: for example in classification or pattern recognition.

The ANNs could learn from a range of input variables against seepage for a range of soil properties since the ANN method is capable of handling non-linearity due to quick adaptation and parallel computation power. The study conducted in the Murrumbidgee Irrigation Area for monitoring seepage losses in irrigation channels involved four phases:

- Electromagnetic (EM 31) survey of the channels for identifying critical sections of the irrigation supply channel system, for qualitative seepage analysis.
- Water flow measurements (using Flow Tracker) in selected channels to determine bulk water losses, including evaporation, leakage and seepage. Inflow-Outflow methods were used to measure bulk water losses in measured lengths of channels.
- Quantitative measurement of local seepage rate using an Idaho Seepage Meter at selected spots, particularly the spots identified as having potentially high seepage because of low electromagnetic conductivity. These spots were likely “hotspots” because of higher water losses in these sections reflected by Inflow-Outflow measurements.

“Training” of an ANN model by using all the data collected by the above methods. EM31 data (surrogate for the bulk response of the porus media), hydraulic conductivity, salinity and depth to watertable are inputs into the model with actual seepage results from the Idaho seepage meter compared to predicted seepage rate as outputs. The trained ANN was subsequently used to convert qualitative distributed seepage data (collected in step-1) to quantitative distribute seepage rates.

Channels of the Murrumbidgee Irrigation system were surveyed using a combination of methods to measure seepage, identify seepage sites and quantify the extent of the losses as described above. The data collected were also used to determine statistical relationships between EM and local seepage rates. Measurements were made over 700 kms of channel, which when accounting for overlapped measurement comprised over 500 kilometres length of reaches for loss detection. The measurements were taken from the larger channels in MIA, CIA and the Lowbidgee districts covering 80% of the total flow in the system. The selected channels were surveyed using EM31 meters in a boat. These meters use electromagnetic induction to measure the average electrical conductivity of the soil from the surface to a depth of 6 metres including the water layer. This average reading is known as "apparent conductivity" (ECa). This meter provides a quick way of gathering a large amount of data without any ground intrusion but is susceptible to electrical or magnetic interference. Low conductivities indicate potential seepage sites. Once the EM31 surveys were completed, maps were prepared using SURFER 8 from the imaging data using GPS references (Figure 2).

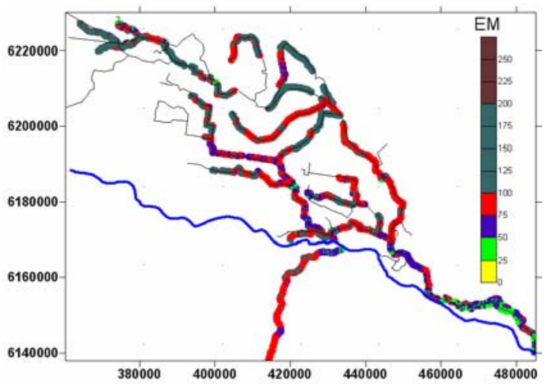

Figure 2. EM31 Map of surveyed channels in the Murrumbidgee Irrigation Area (MIA)

These maps helped to identify the parts of channels with low EM values where higher seepage was likely to be occurring. Doppler flow meters were then used to measure inflow and outflow of particular reaches of channels to determine gross water losses. Large differences in flows at each end of the channels indicated seepage losses. For a range of channel EM values Idaho seepage meters tests were conducted. A relationship was determined between measured seepage rates and ECa values using EM31 surveys (Figure 3) to quantify the seepage rates along the surveyed sections of the system. A preliminary approximation was obtained using this relationship recognising that the accuracy of such estimated seepage rates has limitations.

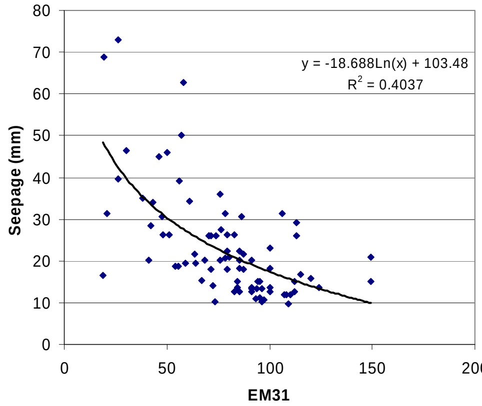

Figure 3. Correlation of Seepage measurements and EM31 results for the surveyed channels in the Murrumbidgee Irrigation Area (MIA)

All the data collected was used to "train" a model known as an ANN model (Figure 4). The particular ANN architecture of 4 hidden layers was chosen to solve the non-linearity within 4 inputs (EM31 data, hydraulic conductivity, salinity and depth to watertable) and output.

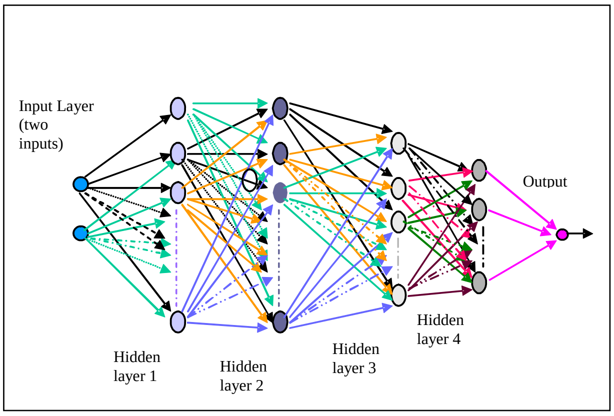

Figure 4. A typical neural network with 4 hidden layers. Each layer has one or more processing elements

3.1. Artificial Neural Network (Ann) Model for Seepage Studies

EM31 data, hydraulic conductivity, salinity and depth to watertable were used as inputs into the model with actual point seepage results from the Idaho seepage meter provided as outputs. These data were collected from across the region and was used to train and develop the ANN network.

Data was organised into row and columnar wise matrices labelling input and desired columns followed by setting up training and cross validation data files. The training data file was assigned for network learning whilst the cross validation data was designated to prevent possible over training, which may result in abnormal learning behaviour. A test data file was used to test the validity and performance of the learnt network. A data set of 470 input and output records was obtained from different channels in the Murrumbidgee region, these were used to train and develop a suitable network. The entire dataset was divided into 3 sets 70%, 20% and 10% for the training, cross validation and testing respectively. Neural networks with different topologies were attempted and at last a hybrid network called Radial Basis Function (RBF) was found to be most suitable for the training purposes. The established network was trained by several iterations.

Prediction from this network, has given promising results providing a correlation of 0.86 between actual and predicted seepage values as shown in Figure 5.

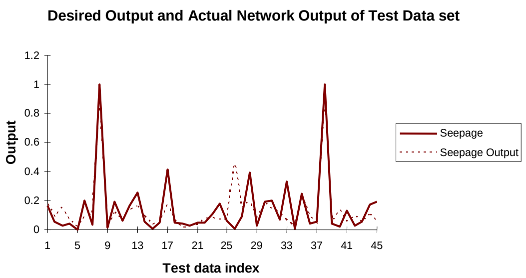

Figure 5. Performance of the test dataset that was used by the trained network

The results in Figure 6 show the capabilities of a network in learning and predicting by using the entire data set. The correlation coefficient between actual and forecast seepage values has been improved to 88%.

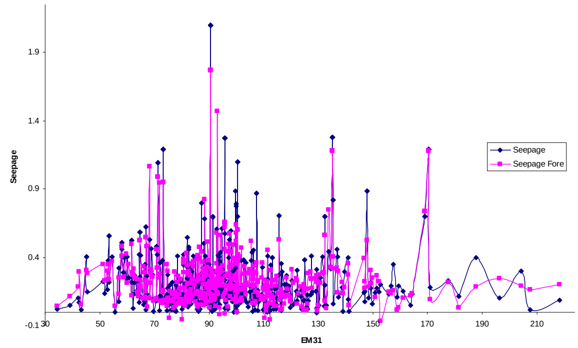

Figure 6. Comparison between actual and forecast seepage values used in the training and cross validation data sets

4. RESULTS AND DISCUSSION

Using the ANN the estimated total losses from 509.5 km of channels are 54.3GL over 270 days, of which 41.7 GL can be attributed to seepage (Table 1).

The ANN predicted seepage data was plotted to map seepage extent to show the spatial variations of seepage rates (Figure 7). The calculated seepage data was also analysed to present the distribution of seepage rate classes across the irrigation area (Table 2). This analysis shows that around 7% of seepage losses occurred at the rate of 30-70 mm/day, 25% of seepage losses occurred at a rate of 20-30 mm/day, 46% of seepage losses occurred at a rate of 10-20 mm/day while remaining 22% of seepage losses occurred at a rate of less than 10 mm/day.

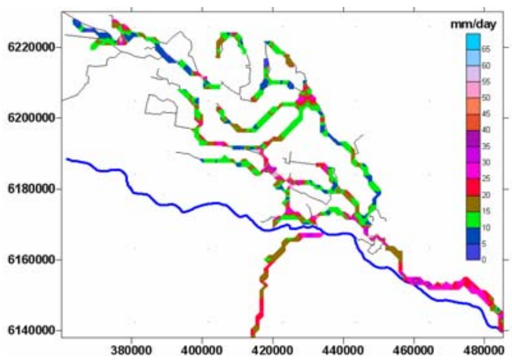

Figure 7. ANN predicted Seepage Map of channels in the MIA (mm/day)

This analysis clearly indicates that most significant seepage (> 20 mm/day) occurs in less than 32 percent of the surveyed channel length (Figure 7), therefore it is most important to target investments to this area which is the leakiest parts of the channel system.

Table 1. Seepage Losses using ANN

Location	**Length** (km)	**Seepage** (ML/270d)	**Evaporation** (ML/270d)	**Total Loss** (ML/270d)
Benerembah Channel 2	15.7	765	225	991
Northern Branch Canal	36.6	1422	568	1990
North Kooba	24.1	1368	343	1711
Sturt Canal	36.8	3528	773	4301
Benerembah Canal	18.7	1256	387	1643
Gogeldrie Channel No. 3	11.2	386	156	542
Lake View Canal	16.8	576	281	858
Gogeldrie Main + Gogeldrie Branch 2	33.2	2431	752	3183
Lateral 235	12.5	468	186	654
Lateral 284	26.8	1281	421	1701
Mirrool Creek Branch Canal	31.9	1740	550	2290
South Gogeldrie	16.7	1106	290	1397
Warburn	18.4	823	237	1060
Wah Wah	29.4	1150	460	1609
Channel No. 1	13.9	659	205	864
Channel 3, 10 and 18	14.0	312	205	517
MIA Main Canal (Start - Bundidgerry Reg)	42.3	8345	1810	10156
MIA Main Canal (Narrandera – Nonells Reg)	52.8	8476	2635	11111
MIA Main Canal (Nonells Reg - East Mirrool Reg)	34.1	3594	1315	4908
MIA Main Canal (East Mirrool Reg- Penfolds)	23.6	2070	775	2845
Total MIA	**509.5**	**41756**	**12574**	**54330**

Table 2. Proportion of ANN predicted seepage rate

Seepage Range	**%age**	**Seepage (Ml/270d)**	**Assoc. Channel Length (Km)**
Less than 10 mm/day	22.76	9504	134.14
10 - 20 mm/day	46.33	19347	257.68
20 - 30 mm/day	24.15	10083	85.89
30 - 40 mm/day	1.74	725	8.39
40 - 50 mm/day	0.95	396	5.05
50 - 70 mm/day	4.08	1702	18.32

5. CONCLUSIONS

The traditional seepage estimate methods such as inflow-outflow and ponding tests are only useful in providing bulk estimates of losses from the studied channel reaches. The distributed qualitative methods using EM-31 and local quantitative methods using the Idaho seepage meter were an improvement in the estimation of seepage losses. However, due to varying soil properties and underlying groundwater characteristics it was not possible to effectively determine spatial distribution of channel seepage which is necessary for cost-effective lining of channels. Due to the complexity and the non-linearity of the seepage phenomenon and impossibility of building linear relationship between seepage and EM data an ANN method was developed to overcome this limitation. This helped spatially map the seepage extent along the supply channels of the MIA and therefore guide the most cost effective investments for reducing seepage losses.

Results from this study clearly show that ANNs can be successfully applied to analyse distributed channel seepage by using key input variables since the ANN method is capable of handling non-linearity due to quick adaptation and parallel computation power. The channel seepage study in the Murrumbidgee Irrigation Area in Australia indicates that most significant seepage (> 20 mm/day per unit area) occurs in less than 32 percent of the surveyed channel length, therefore it is important to initially target channel lining investments to the leakiest parts, “hotspots” of the channel system. The approach using ANNs proven advantages in this paper may be the most effective way of ascertaining these hotspots.

6. ACKNOWLEMENT

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7. REFERENCES

Akbar S (2003) Measurement of Losses from On-Farm Channels and Drains, Annual Report, Cooperative Research Centre for Sustainable Rice Production http://www.ricecrc.org/

ANCID (Australian National Committee on Irrigation and Drainage)(2000) Open Channel Seepage and Control – Vol 1.2 Current Knowledge of Channel Seepage Issues and Measurement in the Australian Rural Water Industry, Prepared by Sinclair Knight Merz, August 2000.

Aziz A R A, and Wong K F V (1992) Neural network approach to the determination of aquifer parameters, *Ground Water*, 30(2), pp. 164– 166.

Cancelliere, A., G. Giuliano, A. Ancarani and G. Rossi (2002), A neural networks approach for deriving irrigation reservoir operating rules, *Water Res. Mgmt.*, 16 (1), pp. 71 – 88.

Jain S K (2001) Development of integrated sediment rating curves using ANNs, *J. Hydraul. Eng.*, 127(1), pp. 30–37.

Holger, R.M and G.C. Dandy (2000), Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environmental Modelling & Software, 15, 101 – 124, Department Civil and Environmental Engineering, The University of Adelaide, S.A. 5005, Australia.

Lu R-S, Lai J-L and Lo S-L (1998) Predicting solute transfer to surface runoff using neural networks, *Water Sci. Technol.*, 38(10), pp. 173-180

Nagy H M, Watanabe K and Hirano M (2002) Prediction of sediment load concentration in rivers using artificial neural network model, *J. Hydraul. Eng.*, 128(6), pp. 588–595.

Rajurkar M P, Kothyari U C and Chaube U C (2002) Artificial neural networks for daily rainfall-runoff modelling, *Hydrol. Sci. J.*, 47(6), pp. 865–878.

Tayfur G, Swiatek D, Wita A and Singh V P (2005) Case Study: Finite Element Method and Artificial Neural Network Models for Flow through Jeziorsko Earthfill Dam in Poland, ASCE *Journal of Hydraulic Engineering*, 131(6), pp. 431-440

Tayfur G (2002) Artificial neural networks for sheet sediment transport, *Hydrol. Sci. J.*, 47(6), pp. 879–892.

Tokar A S and Johnson P A (1999) Rainfall-runoff modeling using artificial neural networks, J. Hydrologic Eng., 4(3), pp. 232–239.

Van der Lely A (1994) Cited, Coleambally Draft Land and Water Management Plan November, 1995.

Watts D and Thompson P (2001) Improving Hydraulic Efficiency of Irrigation and Drainage Systems through Benchmarking, Final Report, Murray Irrigation Limited.