A Neural Network Approach for Integrated Water Resource Management

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***Abstract*—**In arid regions, freshwater is scarce. The usual practice is to rely on desalinated seawater and ground water. For crop irrigation, desalinated water is an expensive option. A possible solution is to collect ground water, from different sources, into an integrated water resource that is supported by a blending mechanism capable of mixing collected water in a bid to optimize salinity levels with respect to irrigation crop requirements. Albeit, blending water of different salinity levels is a complex problem. In this paper, a neural network approach for managing the blending mechanism is proposed. This approach allows flexibility in water volume transfers among a network of water tanks in a bid to provide water with salinity levels optimized to meet specific crop requirements. The proposed method is illustrated through a case study. Results show that the neural network approach is a sound method for managing water blending in integrated water resources.

***Keywords*—**Integrated Water Resource Management, Optimization, Neural Networks, Desalination, Salinity Levels, Crop Yields.

I. Introduction

AGRICULTURE is fundamental to the economic growth and sustainable development of any country. However, agriculture heavily depends on freshwater supplies. In arid and semi-arid regions of the world, for example the gulf region, rainfall is very little. As a result, freshwater for irrigation, aquariums, poultry, livestock and human consumption is scarce. Although most of the gulf economies thrive on other natural resources such as abundant oil and gas, agriculture creates self-sufficiency and ensures food security. Albeit, the shortage of freshwater has been identified as one of the limiting factors hindering the future and sustainability of agricultural activities in the gulf region [1]. Therefore, the need for integrated water resource management methods, tools and techniques can never be over emphasized.

Due to the scarcity of rainfall in arid regions, alternative sources of water include; seawater desalination, ground water and reclaimed water. Alternative sources such as ground water and reclaimed water can be used effectively to promote agricultural developments and other non-human water uses. A major drawback in using alternative sources of water such as ground water for irrigation purposes is the issue of salinity. For example, it has been shown that crop yields are affected by the salinity levels in irrigation water [2]. Paradoxically, relatively little research has been done to support the sustainable use of saline water in irrigation, aquariums, poultry, or livestock [1]. Hence, there is a growing need to demonstrate the value and extent of applications of integrated saline water resources.

For human consumption, the usual practice in the gulf region is to desalinate seawater into freshwater. However, seawater desalination is an energy intensive process [3]. As such, this option is relatively expensive for uses other than human consumption. For large scale crop irrigation schemes, an alternative to desalinated water is ground water. Although ground water has been used effectively for irrigation purposes in other parts of the world [4], the salinity levels of such water need to be optimized with respect to specific crop requirements if significant crop yields are to be obtained. A possible solution that will be explored in this paper is to integrate ground water from different sources. Such integration means that the integrated water resource for supply and distribution consist of volumes of water with different salinity levels. Therefore, a blending system that can match and mix water of different salinity levels in a bid to optimize salinity levels with respect to irrigation crops is required.

A very important parameter in water salinity control is the electrical conductivity (EC). Optimum EC values for various crops have been determined by many researchers as cited in [5]. Therefore, optimizing salinity levels for specific irrigation crops is a sound method that has been proved to be viable and often leads to increased crop yields [6]. The logic followed in this work is as follows: ground water can be mixed in order to optimize the salinity levels for each crop under irrigation; since different sources of water have different salinity levels, mixing ground water from different sources can partially reduce salinity levels to an appreciable extent. This partial reduction of salinity is achieved by mixing different sources of ground water, which can then be further diluted by mixing with desalinated water in order to further reduce and hence optimize the salinity levels for irrigation crops. In this way, relatively smaller amounts of desalinated water will be used thus bringing down the cost of irrigation water. Therefore, the design and development of water storage and blending facilities have a significant contribution to both crop yields and the cost of irrigation water in arid regions.

Of more significance to the discussions in this paper are optimization methods and techniques required to handle the blending and optimization of salinity levels with respect to specific crop requirements and crop yields. To this end, a number of optimization tools and techniques have been developed to support the operations of integrated water resource management systems. A number of conventional optimization techniques have been developed to determine the optimal water allocation based on minimizing cost and

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maximizing water utilization [7]. In [7] a mixed integer linear programming model was developed and implemented to optimize an integrated water resource management system. In addition to the conventional methods of solutions, non-conventional optimization techniques and tools have also been applied to water allocation and water resource optimization problems. For example in [8], an expert system was used determine to the water requirements of irrigation crops. In [9], an optimization model for water allocation in agricultural water resources was proposed. Other optimization methods, techniques and tools that have been used for integrated water resource management systems include: simulate annealing [10], genetic algorithms [11], evolutionary algorithms [12] and neural networks [13]. In the public literature, a number of blending methods for integrated water resource management have also been suggested. For example in [14], the studies focused on analyzing the agronomic management requirements with respect to crop tolerance to salinity.

A close examination of the cited works shows that there are gaps in terms of establishing a practical monitoring, control and optimization system for the blending process. In addition, the issues of utilizing ground water, from different sources, and desalinated water in integrated water resource management systems for the purpose of optimizing salinity levels and crop yields with respect to irrigation crop tolerance and crop requirements have not been exhausted. This paper attempts to address the soft issues of creating a practical, effective and efficient integrated water resource management system that utilizes a blending method.

The aim of this paper is to develop a neural network approach for handling a blending system for an integrated water resource system for crop irrigation. The proposed approach takes into account deferent salinity levels of ground water from different sources and attempts to optimize salinity levels for different crops simultaneously with respect to crop yields and crop requirements. Since desalinated water is relatively expensive, a major constraint in the optimization process is minimal use of desalinated water. The objectives in developing the blending system are: (i) to minimize consumption of desalinated water in crop irrigation in arid regions, and (ii) to optimize the salinity levels of irrigation water with respect to crop requirements and crop yields.

In order to address these objectives, a case study of an irrigation scheme in the State of Qatar was used. In the following sections, a neural network model is developed and configured to manage a water blending system that allows flexibility in inter and intra volume transfers of water among a network of water tanks. The network of water tanks constitute the integrated water resource for irrigation purposes. The goal is to provide water with different salinity levels optimized to meet different standards, requirements and crop yields.

The remainder of the paper is organized as follows: in section 2, the water blending method is discussed and formulated, in section 3 a neural network method of solution is described, in section 4 obtained results are presented and discussed and finally concluding remarks are provided in section 5.

II WATER BLENDING MODEL

A. Problem Statement

In modeling the water blending process, the integrated water resource system for crop irrigation is cast as a network of tanks containing water of different salinity levels. In the supply tank network, one tank is assumed to be dedicated to the supply of water of the right quality and tolerable salinity level for a specific crop in the irrigation scheme. Depending on the number of crops to be irrigated, one or more tanks containing desalinated water will be part of the tank network. Since tanks are assumed to be inter and intra connected, volumes of water are inter and intra transferred among the tanks in the network in order to achieve the required salinity in the dedicated tanks. In this set-up, it is important to determine the volume transfers from other tanks in order to balance crop specific salinity levels. If each tank in the tank irrigation system (tank network) is connected to the other tanks and can send water to or take water from any tank then each tank can be source and/or a sink depending on the current requirements of the integrated water resource management system.

It is, however, noted that some of the activities and factors that lead to effective water blending depend on two issues, i.e. (i) the number of ways of arranging the tanks in a given tank network, and (ii) the number of ways of connecting the various tanks in a given tank network. For analytical purposes, these two aspects can be considered to be in different dimensions. Therefore, for ***n*** tanks, the number of possible ways for arrangements them is ***n!***, and the number of connections among ***n*** tanks is ***n(n-1).*** In this case, the tank connections will transfer water among the tanks until the required salinity levels are achieved. This type of tank system gives the highest degree of freedom to the irrigation system.

Due to practical reasons, some connections can be relaxed for analytical purposes. For example, it is reasonable to assume that the fresh water tank can only be a source i.e. it only supplies water to other tanks since it has the lowest salinity level. This is also true if among the other source tanks there are tanks with lower salinity levels. In this case it can be assumed that a tank with lower salinity level can be used to dilute the salinity levels of another tank with higher salinity level. While this assumption works only when the dedicated tanks are optimized individually, it helps us to develop an analytical model for the simultaneous optimization of the dedicated irrigation tanks.

On another note, suppose ***m*** tanks (with the lowest salinity levels among tanks under consideration) are used as source tanks only for blending saline water. These blending tanks would then have to be connected to at least one tank containing freshwater. On the other hand, suppose the number of ways for connecting ***n**** tanks, {i.e. ***n(n-1)***} for blending with ***m**** tanks containing fresh water and groundwater of the lower salinity levels are used among the various sources of water. In such a scenario we could have a subset of say ***n*** tanks to be blended by ***m*** tanks. The whole scenario can be approximated to a permutation problem for which the number of ways of blending ***n**** tanks with ***m**** tanks can be estimated as in (1).

$$P_{(n^*, \mathbf{m}^*)} = \frac{\{n(n-1)\}!}{(\{n(n-1)-(m \times n)\})!} \tag{1}$$

In light of these discussions, the problem statement for the water blending tank system for crop irrigation can be formally described as follows:

> Given a set of irrigation tanks for supplying water to crop fields after blending saline water in ***n*** tanks with fresh water from ***m*** blending tanks, the total number of feasible blending plans can be estimated mathematically as follows:
>
> *Let each crop require **Y** activities for blending, where **Y** is multidimensional. Let the **i**^th sub-activity have **y(i)** alternatives and let each crop require z_i elements in dimension **i** of **D** dimensions where **D** ∈ **Y**. Then the total number of feasible blending plans, Z, can be given by* (2)

$$Z = \prod_{i=2}^{D} \frac{\{n(n-1)\}!}{\{(n(n-1)-(m \times n)\}!} \sum_{i=1}^{n} \sum_{i=1}^{x} f(V) \tag{2}$$

where, $$f(V) = \left(\frac{\left(V_n - \sum_{i=1}^{k} V_{ni}\right) EC_n + \sum_{i=1}^{k} V_{in} EC_i}{V_n} \right) \tag{3}$$

and V_n is the tank volume and EC_n is the electrical conductivity of water in tank ***n***. From estimated representation in (2) and (3), it can be observed that it is difficult to numerically find solutions based on analytical equations. Therefore, a non-conventional solution method will be discussed in this paper.

B. Case Study

An irrigation farm in Qatar was used as a case study for this research. A physical pilot plant prototype was constructed at Qatar University for experimental purposes.

The irrigation system in the case study consists of four crops i.e. onion, tomato, squash and potato. This set of crops has a relatively higher tolerance of the hyper-arid environment in the State of Qatar. In the case study, the four crops were arranged in four plots that are supplied by four different tanks (crop dedicated) i.e. each crop has its irrigation tank that contains water with a salinity value suitable for the irrigation of that crop.

The irrigation system in the case study consists of a total of six tanks, i.e. four tanks to supply four different crops, and two blending tanks. One of the blending tanks contain fresh water (with an Electrical Conductivity (EC) = 0.7 dS/m) and the other contains saline groundwater of relatively low salinity level. The tanks that will feed the crop fields are initially filled with groundwater with different EC values ranging between 2.14-4.5 dS/m since they were collected from different sources of ground water. These values of EC were obtained experimentally by analyzing the characteristics of different groundwater sources in the State of Qatar.

III METHOD OF SOLUTION

A. Tank Systems

In developing the solution method, three experimental setups (or options) were designed in order to compare the total amount of fresh water used to reach the target salinity level for the crops. These options were later compared with a fourth option that represents the blending management system proposed in this paper. The target was to compare these four options and identify the option which uses the least amount of fresh water.

In option 1 and 2, two blending tanks were used to reach the target salinity level. In option 1, the blending tank, T1 contained fresh water with EC = 0.7 dS/m. The other four tanks (T2, T3, T4 and T5) were crop dedicated tanks. In option 2, the blending tank, T6, contained ground water of the least salinity ranging between 2.16-2.612 dS/m. The other four tanks (T2, T3, T4 and T5) were crop dedicated tanks.

Two blending tanks were used in options 3 and 4. In option 3, the two blending tanks contained, freshwater, T1, and ground water, T6. These two tanks were used blend the the crop dedicated tanks in a serial manner i.e. staring with T6 and followed by T1. Arrangement of tanks in option 4 was similar to that in option 3. Unlike the serial blending process in option 3, the blending process in option 4 was done simultaneously in an effort to conserve freshwater as much as possible.

The percentage yield was calculated at each range of water salinity for the tanks that will be used for irrigating the crops. The percentage yield was calculated using interpolation method since the relationship between water salinity and percentage yield can be assumed to be linear [15].

B. Experimental Setups(Options)

Experiments were configured based on the four options described in the previous subsection. Setup 1 is shown in Fig. 1. In setup 1, only the fresh water tank was used to reduce the water salinity level of the other four tanks to reach the target salinity level needed for the respective crops.

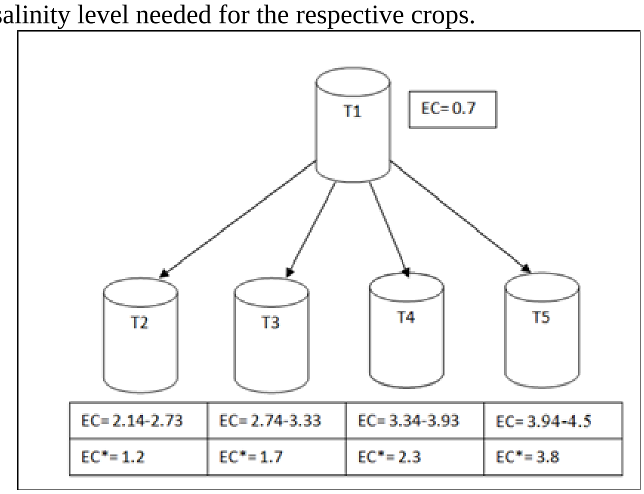

Fig. 1 Tank System for Option 1

In Fig. 1, the EC value of T1 is shown to be 0.7 (EC value for freshwater). Tanks T2, T3, T4 and T5 are crop dedicated tanks. Range of EC values of ground water in the other tanks are also indicated. In addition, the optimal crop specific EC value required in each of the dedicated tanks are also shown. The volume to be transferred from T1 to the dedicated tanks can be calculated using (4)

$$V_{1n} = V_n\left(\frac{EC_n - EC_n*}{EC_n* - EC_1}\right) \tag{4}$$

Where, n = tanks 2, 3, 4, or 5 and V_n is the volume of the tank n, V_{ni} represents the volume transfer from tank n to specific a tank i, V_{in} represents the volume transfers from tank i to tank n, EC_n represents the electrical conductivity of water in tank n and EC_n* is the electrical conductivity of water in tank n after blending.

Setup 2 is shown in Fig.2. In setup 2, T6 was used to reduce the water salinity level of the dedicated tanks to reach the target salinity level of that tank (i.e.T6). This limmitation is due to the fact that the resultant dilution can only approach the EC value of ground water in T6. Range of EC values of all tanks in setup 2 are also shown in Fig.2.

Fig. 2 Tank System for Option 2

It can be observed that mixing T6 with T5 will reduce the salinity level of T5 to a value below the target unless the volume transferred is carefully controlled. This situation illustrates the importance of optimal control in such and similar blending systems. Alternatively, a relatively small amount of freshwater can be transferred to T5 until the optimal EC value is reached. The required volume to be transferred from T6 to dedicated tanks were calculated using (5) and (6).

$$V_{6n} = V_n\left(\frac{EC_n}{EC_n*} - 1\right) \tag{5}$$

Where, n = tanks 2, 3, 4 only

$$V_{6n} = V_5\left(\frac{EC_5 - EC_5*}{EC_5* - EC_6}\right) \tag{6}$$

Step-up 3 is shown in Fig.3. In this setup, the freshwater tank (T1) is used with output volumes and EC levels from setup 2 in order to reach the target salinity level needed for the crops. This means that initially T6 was used to blend tanks T2, T3, T4 and T5. The T1 was used to further reduce the salinity levels according to specific crop requirements. This is done to reduce the amount of fresh water to be transferred to the dedicated tanks. The required volume to be transferred from T1 to the dedicated tanks was calculated using (4).

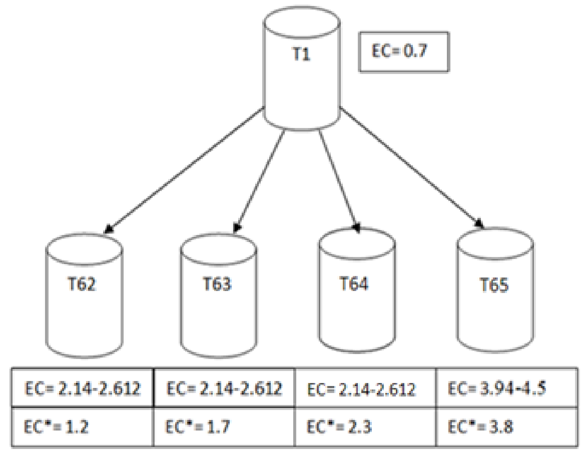

Fig. 3 Tank System for Option 3

Setup 4 is shown in Fig.4. In this setup, a complex network is formed by assuming that tanks in the system can either be a source or a sink. For practical reasons, it is important to assume that the fresh water tank and the tank with the lowest salinity level act as sources most of the time. The required volume to be transferred from source to sink tanks can be determined using (3), an implicit function. The EC values for setup 4 are shown in Table 1. The neural network model was used to predict the volumes to be transferred, the resultant EC values and the percentage yield.

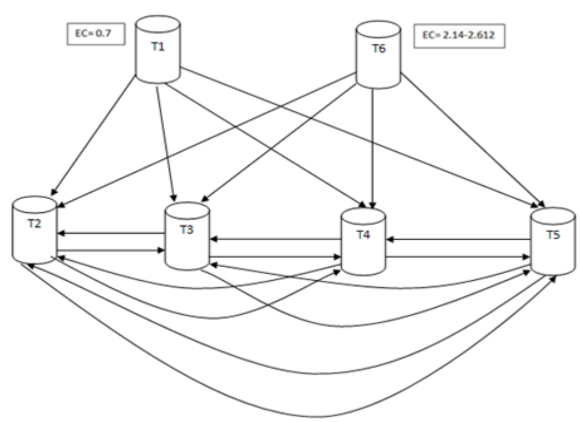

Fig. 4 Tank System for Option 4

TABLE 1
EC VALUES FOR TANK SYSTEM OPTION 4

EC_2 = 2.61-3.09	EC_3 = 3.09-3.56	EC_4 = 3.56-4.03	EC_5 = 4.03-4.5
EC_2* = 1.2	EC_3* = 1.7	EC_4* = 2.3	EC_5*

The logic behind the arrangement in tank system option 4 is that any tank can act as either a source or a sink.

The purpose of the neural network model developed in this paper was to predict the amount of water required to achieve certain salinity level (EC). That is, the amount of water needed to be blended in order to attain a desirable EC level. In real life, the decision to start irrigating is an expensive one – for example, water must be purchased, electricity or fuel must be purchased to operate pumps, and additional personnel may be required to monitor and maintain the irrigation system. Moreover, if the cropland is irrigated in a non-systematic way, the production yield will be affected, hence, revenue from the sale of crops will be lower than expected. Accordingly, being able to artificially predict the amount of water required serves to minimize the risk and will predict the amount of water needed beforehand. Subsequently an appropriate system can then be applied depending on the situation.

Clearly, the ability to accurately predict the amount of water can greatly improve the probability of having a good (therefore profitable) yield; accurate models can also help minimize variable operating costs through avoidance of unnecessary irrigation.

C. Feed Forward Neural Network Model

A non-linear feed-forward neural network model with cascade learning was trained and used in each of the four experimental setups discussed in section III part B. The neural network was trained to approximate the functional relationships between decision variables of the integrated water resource management system. The models for each experimental setup differed in terms of the inputs and outputs. The objective in these experiments was to predict the volume transfers, the optimal EC value and the associated percentage yield, given the initial values of EC for the integrated water resource system. Fig. 5, shows the general structure of the neural network model with seven inputsa and three outputs as implemented in this paper. The constructed neural network was composed of three layers: one input layer, one hidden layer (with 10 hidden nodes) and one output layer.

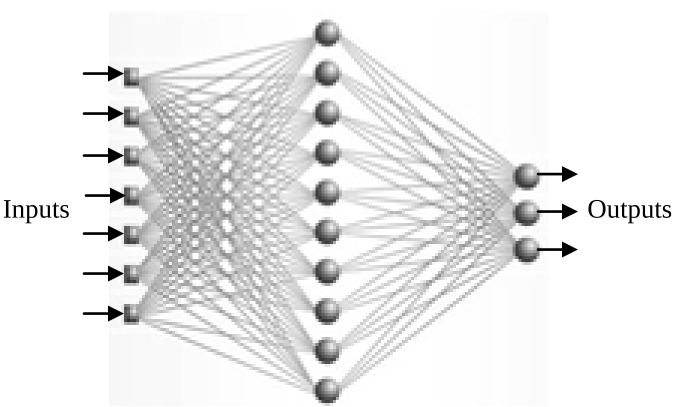

Fig. 5 General Neural Network Structure

For a two-tank system, e.g. blending T2 using T6, a total of seven input variables were used to predict three output parameters. For the two-tank system, examples of specific input variables were: the initial volumes of water in tanks T1 and T6, the initial EC values of the water in tanks T2 and T6, volume capacities for tanks T2 and T6 and the and the EC value required for best crop yield. The outputs from the neural network model (i.e. the predicted values) were; the volume to be transferred from T2 to T6, the final EC value of the water in the crop dedicated irrigation tank and the expected percentage crop yield.

In option 1 all tanks (T2, T3, T4 and T5) receive freshwater from T1 and the volume transfers, optimal EC values and percentage yield are predicted using the neural network model shown in Fig.5. In option 2 all tanks (T2, T3, T4 and T5) receive ground water from T6 and the volume transfers, optimal EC values and percentage yield are predicted using the neural network model shown in Fig.5. In option 3 all tanks (T2, T3, T4 and T5) initially receive ground water from T6 and further dilution to the required EC is done by transferring volumes of water from the freshwater tank, T1. The volume transfers, optimal EC values and percentage yield are predicted using the neural network model shown in Fig.5.

Option 4 is different from the other experiments in the sense that there are six inputs i.e. EC values of all tanks (T1, T2, T3, T4, T5 and T6). These inputs are used to predict the volume transfer to each of the dedicated tanks (T2, T3, T4 and T5), the optimal EC values for each of the dedicated tank and the associated percentage crop yields.

Fig.6 shows a graphical illustration of the plot of target values and neural network predicted values after successful training.

Fig. 6 Plot of the target and predicted values of volume transfers for one of the experimental options

Fig. 6 shows that the neural network predicted values and the target values are very close. Therefore, it can be inferred that the performance of the trained neural network model is good. Table 2 shows a statistical summary for neural network training process.

TABLE 2
STATISTICAL SUMMARY OF NEURAL NETWORK TRAINING

Output	R	Net-R	Avg. Abs.	Max. Abs.	RMS	Accuracy (20%)	Conf. Interval (95%)	Records
All	0.994	0.992	3.266	9.652	3.725	1	7.263	50
Train	0.994	0.993	3.590	9.516	3.968	1	7.746	35
Test	0.988	0.983	2.509	9.652	3.087	1	6.062	15
Valid	0.994	0.992	3.266	9.652	3.725	1	7.263	50

From Table 2 it can be observed that the **R** value was found to be 0.994 which indicates a good correlation between variables. Therefore, the developed neural network model is good. It can also be observed that the R values for the train and test data sets (0.994 and 0.988) differ by a small amount. This small difference suggests that the model is capable of generalizing and therefore is most likely to make accurate predictions.

IV Results And Discussions

After satisfactory training, the neural network models were used to predict the volume transfers, the optimal EC values for the dedicated tanks and the associated percentage yields. In the following paragraphs, summaries of the main results based on the neural network prediction are presented and discussed.

Each experiment discussed in section III part B required different amounts of fresh water and saline water. Consequently, each experiment is associated with different production yields and costs. The analysis for each experiment was based on the total volume of water required, the total cost of the water and the production yield predicted for each experiment. Table 3 summarizes the volumes of fresh water and saline water used in each of the four experiments.

In experiment 1, only fresh water was used for blending with the saline water. In experiment 2 only saline groundwater was used for blending. The third and fourth experiments incorporate both fresh water and saline groundwater. It is significant to mention that even if the total amount of water used in the fourth scenario is higher than the third, the usage of fresh water is less, accordingly, the fourth experimental setup gives better results.

TABLE 3
SUMMARY OF THE VOLUMES OF FRESH AND SALINE WATER USED IN THE EXPERIMENTAL SETUPS

Exp.	Fresh Water Volume(x100m^3)	Saline Water Volume(x100m^3)	Total Water Volume(x100m^3)
1	468	0.00	468
2	0.00	1 172	1 172
3	133	541	674
4	103	332	435

Fresh water is used in the first, third, and fourth experimental setups.

As can be observed in Fig. 7, the first setup requires more fresh water since fresh water is the only source for blending. On the other hand the highest volume of saline water is used in experiment 2 since only saline water is used to blend the dedicated tanks. Whereas, the usage of fresh water in the third experiment is significantly less than the first, it is the fourth experiments that consumes the least amount of fresh water. Overally, the results show that the largest amount of saline water was used in the second experiment since the blending was done using ground water of the lowest saline levels. Table 4 shows the various costs of freshwater and saline water based on assumptions of per unit volume costs as discussed in [16].

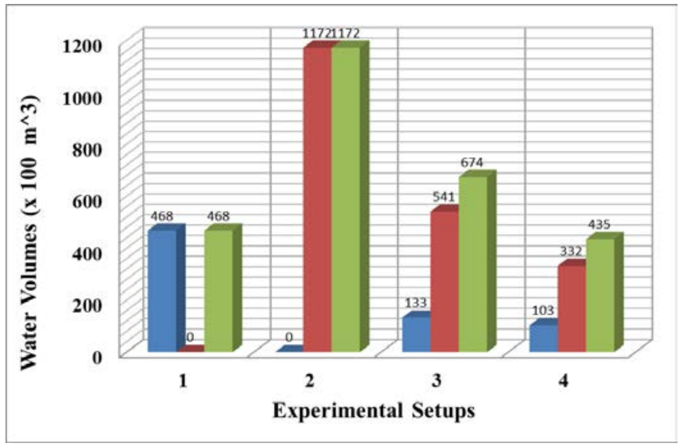

Fig. 7 Comparison of Fresh and Saline Water Requirements for the Four Options

TABLE 4
COSTS OF WATER USED IN EACH EXPERIMENTAL SETUP

	FW Volume	FW Costs	SW Volume	SW Costs	Total Volume	Total Costs
1	46800	313560	0	0	46800	313560
2	0	0	117200	42192	117300	42192
3	13300	89110	54100	19476	67400	108586
4	10300	69010	43200	15552	53500	84562

In Table 4, FW represents freshwater, and SW represents saline water. From Table 4, option 1, i.e. using freshwater for irrigation purposes, is the most expensive case, followed by option 3, option 4 and lastly option 2. Option 2 uses saline water only for blending. A comparison of the total costs of irrigation water associated with each option is shown in Fig. 8.

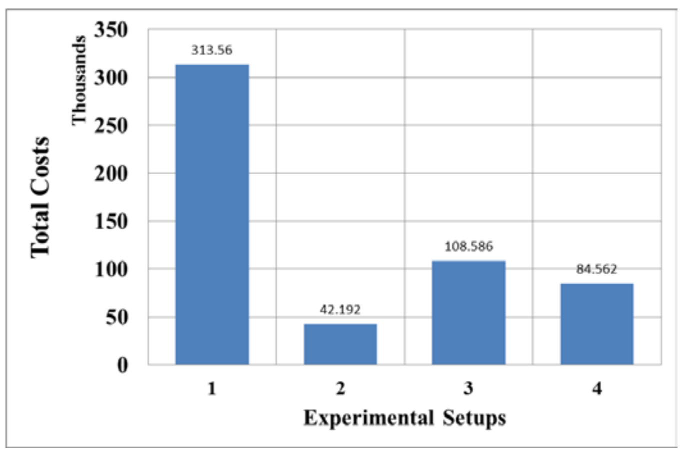

Fig. 8. Comparison of Total Costs of Irrigation Water for Each of the Experimental Setups

Although option 1 is the most expensive option, a cross comparison with the expected yields gives a clearer picture. Fig. 9 shows a comparison of the predicted crop yields under each of the experiment options.

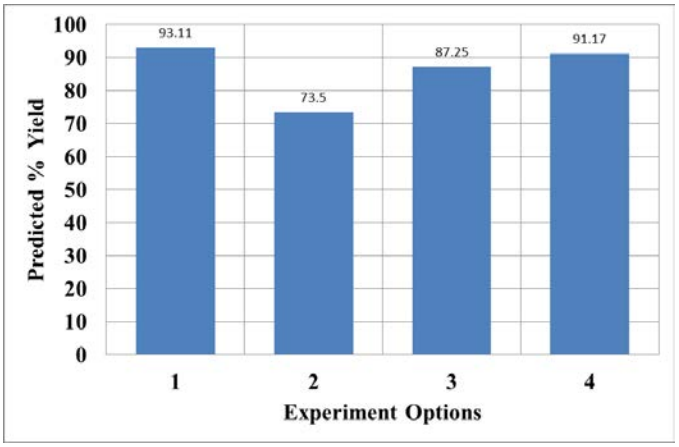

Fig. 9 Comparison of Predicted Percentage Crop Yield

In Fig. 9, the best yield is from option 1, followed by option 4, option 3 and option 2 in that order. It can be observed from Fig. 9 that although the saline water irrigation is the lowest cost option, the same option is associated with relatively low percentage yields. In addition, using saline water only for irrigation has other environmental consequences in the long run. For example, using saline water only will destroy the soil and will eventually deplete the groundwater basin as well as deteriorate the quality of the soil.

Overally, the fourth option is the best option for the following reasons: (i) relatively less fresh water will be used thus availing more fresh water for other critical uses such as human consumption, (ii) Although more expensive than the option to irrigate crops using saline water, option 4 is relatively less expensive in comparison to option 1 or option 3, (iii) Although option 1 has the highest yield, the differences in the yield when compared to option 4 is relatively small such that it is worthwhile to implement option 4 and, (iv) option 4 will have relatively little effect on the environment.

V Concluding Remarks

The aim of this paper was to develop a neural network approach for handling a blending system for an integrated water resource system for crop irrigation. To this end, a feed forward neural network was developed. The purpose of the neural network model was: (a) to predict the volume transfers, in the tank network required to reduce the salinity levels of irrigation water to levels that can be tolerated by irrigation crops, (b) to predict the optimal salinity levels that can be achieved by the blending system, and (c) to predict the crop yield based on the achieved salinity levels. The results of neural network training showed that a good correlationships was achieved between the training and test data sets. It was also established that the trained neural network was capable of generalizing the results. Hence, the trained neural network models were used to predict values for the optimal salinity levels, the required volume transfers and the probable crop percentage yields.

For experimental purposes, four options were discussed in which the first option was to use fresh water only for blending irrigation water. The second option was to use saline water only for blending irrigation water. The third option was to use both freshwater and saline water for blending the dedicated tanks in a serial manner. Finaly, the fourth option was to use both freshwater and saline water for blending the irrigation water in order to simultaneously achieve crop optimized salinity levels.

A major constraint in the fourth option was to conserve fresh water as much as possible. A comparative analysis was done based on the predicted values of: (1) total fresh water used, (2) total volumes of both fresh water and saline water used, (3) the total costs of irrigation water and (4) the expected crop yields. Cost benefit observations from the presented results indicated that in the long run the fourth option i.e. the option that uses fresh water conservatively has advantages over the other options.

It can, therefore, be inferred that the neural network approach provides data and information that can be used by decision makers in evaluating options to adopt under given conditions and constraints. As such, the neural network approach is a suitable candidate for managing the proposed blending system.

It can also be noted that using blended water (freshwater and saline ground water) is a viable option for water management and crop production, especially in an arid environment like that found in the State of Qatar. Although in a short term perspective it may not be economical to establish a saline water blending system for irrigation controlled artificially, in the long term it can prove to be a good solution for agricultural and irrigation problems in arid and semi-arid regions. In addition, this blending system can be used as a decision making tool since simulated data can be provided to assess a given situation.

References

[1] Jaradat, A. A., Saline agriculture in the Arabian Peninsula: Management of marginal lands. Journal of Food Agriculture & Environment , III, 2005.

[2] Haruvy, N. Reuse of Wastewater in Agriculture- Economic Assessment of Treatment and Supply Alternatives as Affecting Aquifer Pollution, In M. Benoit and L. Igor (eds), Environmental Security and Environmental Management: The Role of Risk Assessment, pp. 257-262, NATO Security through Science Series, Springer Netherlands, 2006.

[3] Veerapaneni, Srinivas (Vasu); Long, Bruce; Freeman, Scott; Bond, Rick, Reducing Energy Consumption for Seawater Desalination, Journal AWWA, 99(6) pp. 95-106, 2007.

[4] R Suleiman, The historical evolution of the water resources development in the Jordan river basin in Jordan, Retrieved January 14, 2012, From iwmi.cgiar.org

[5] Crop salt tolerance data in FAO corporate document repository, Agricultural Drainage Water Management in Arid and Semi-Arid Areas, Retrieved January 14, 2012, from FAO corporate document repository site: http://www.fao.org/docrep/005/Y4263E/y4263e0e.htm

[6] Kazumba, S., Gillarman, l., & Oron, G, Saline Agriculture in the Arabian Peninsula: Management of Marginal lands, 2005.

[7] E Xevi, S Khan, A multi-objective optimization approach to water management, Journal of Environmental Management, Volume: 77, Issue: 4, Pages: 269-27, 2005.

[8] Rafea, A., Tawfik, K., Ibrahim, E., & Khalil, M, Use of Expert Systems in Irrigation Practices. Retrieved December 3, 2011, From www.arc.sci.eg/NARIMS_upload/ CLAESFILES /3739.pdf

[9] Alex Mayer and Andrea Muñoz-Hernandez, Integrated Water Resources Optimization, Models: An Assessment of a Multidisciplinary Tool for Sustainable Water Resources

[10] Management Strategies, Geography Compass 3/3 1176–1195, 2009.

[11] Maria da Conceição Cunha and Joaquim Sousa, Water Distribution Network Design Optimization: Simulated Annealing Approach, Journal of Water Resources Planning and Management / Volume 125 / Issue 4, 125:4, 215-301, 1999.
[12] Wang, M. and Zheng, C, Ground Water Management Optimization Using Genetic Algorithms And Simulated Annealing: Formulation And Comparison. JAWRA Journal of the American Water Resources Association, 34: 519–530, 1998.
[13] Efstratiadis, A., and D. Koutsoyiannis, An evolutionary annealing-simplex algorithm for global optimization of water resource systems, Proceedings of the Fifth International Conference on Hydroinformatics, Cardiff, UK, 1423–1428, International Water Association, 2002.
[14] M. Shourian, S. Jamshid Mousavi, M. B. Menhaj and E. Jabbari, Neural-network-based simulation-optimization model for water allocation planning at basin scale, Journal of Hydroinformatics 10(4), pp 331-343, 2008.
[15] N. Katerji, J.W. van Hoorn, A. Hamdy, M. Mastrorilli, Salt tolerance classification of crops according to soil salinity and to water stress day index, Agricultural Water Management, 43, 2000 99-109, 2000.
[16] Maas E.V, Salt tolerance of plants. In: The Handbook of Plant Science in Agriculture. B.R. Christie (ed). CRC Press, Boca Raton, Florida, 1984.
[17] Hashim, M. A, Water, Agriculture and Environment in Arid lands: water and agricultural vision for Qatar by 2020. Doha, Qatar: Al Rayah Printing Press, 2009.