Water Usage Optimization of Smart Farm Automated Irrigation System Using Artificial Neural Network

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Abstract— **Limited water resources had become the main constraint to be considered in farming. Optimizing this has become one of the interests in researches relating to precision agriculture. In this paper, the researchers use Neural Network in optimizing the water usage in the smart farm by incorporating it to the proposed Smart Farm Automated Irrigation System (SFAIS) by implementing an expert system. Simulations were done using the MATLAB Neural Network toolbox and results show that neural network is a useful tool.**

Keywords— Water, Optimization, Smart Farm, Neural Network

I. INTRODUCTION

One of the most important factors in the country's economy is the state of its agriculture [1]. It is the backbone of food security in a country. The agricultural process itself requires a lot of investment to have a good yield, especially in preventing and mitigating effects of changing climatic conditions. One of the elements affected on it is the water resources. [2]

The two most common causes of withering in indoor and farm plants are overwatering and underwatering. Applying irrigation systems to farms can solve these watering problems. Irrigation is used to measure quantifiably and optimize efficiently the water supply of each crop. Thus, the primary objective of a proper and efficient irrigation system is to allocate the enough water resources for the plants [3]

Automated irrigation systems are not new. But the problem of efficiently allocating water resources to irrigate plants with just the right amount of water necessary for it still exists [3]. In some farms, especially those located in elevated areas far from rivers or lakes, underground water reservoirs are being utilized. But the problem of transporting it from underground to the surface requires the use of water pumps. Electric pumps are used, and require large amount of current and power. In a smart farm, independent power sources are used like solar panel systems. Therefore, proper allocation of power resources will become a problem. [4] This problem is the main goal of precision agriculture solutions, which is to improve the farming productivity by defining the farming needs and acting according to the inferences from experiences of farming and agriculture experts. [4] [5] [6]

In this paper, the researchers aim to provide the optimization of the water usage as part of the Smart Farm Automated Irrigation System in order to properly allocate the water resources.

II. SMART FARM AUTOMATIC IRRIGATION SYSTEM

The Smart Farm Automatic Irrigation System is the control system to be utilized in order to optimize the amount of water resources to be used in the smart farm. It is divided into three subsystems as shown in Fig. 1, namely Water Tank Monitoring and Control System, Open Irrigation Control System, and the Chamber Irrigation Control System. Each subsystem represents the control of the vital parts of the irrigation system.

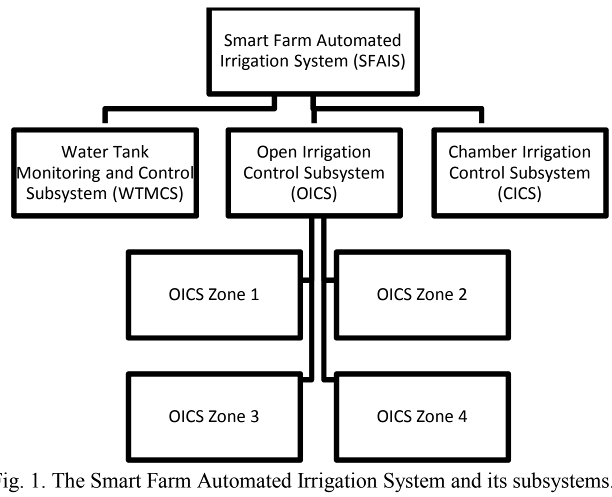

Fig. 1. The Smart Farm Automated Irrigation System and its subsystems.

The subsystem that is considered the most critical is the Water Tank Monitoring and Control System because this subsystem collects water from the underground reservoir

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through the motor pump and maintains the normal level of the water tank. Other subsystems are also critical in nature because these regulates the flow of water depending on the limiting parameters.

Each subsystem has its own corresponding inputs and outputs. Table I shows a summary of the input and output parameters of each subsystems for the whole system.

TABLE I.
SFAIS SUBSYSTEMS INPUTS AND OUTPUTS

Subsystem	Input(s)	Output(s)
WTMCS	L DL	PRIO
OICS	SM DSM	VP
CICS	H DH T DT SM DSM	VP

One of the algorithms to be used for the optimization is the Feed-forward Back-propagation Neural Network. Fig. 2 shows the block diagram of the SFAIS with the expert system incorporated.

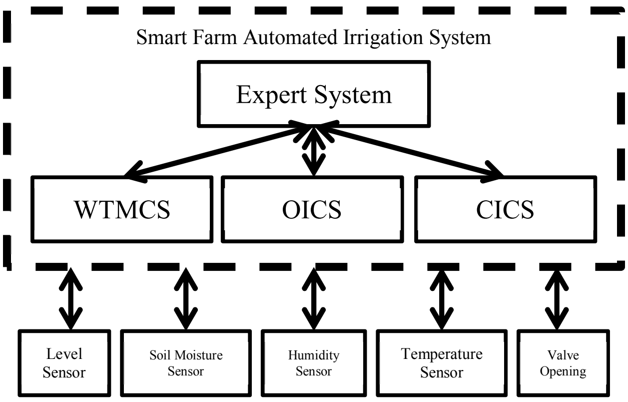

Fig. 2. SFAIS Block Diagram with the Expert System.

III. ARTIFICIAL NEURAL NETWORK

In artificial intelligence, artificial neural network or ANN is a learning technique used in diversity of tasks. It is analogous in structure of the neurological system of animals, which is made up of biological neural networks. [7]

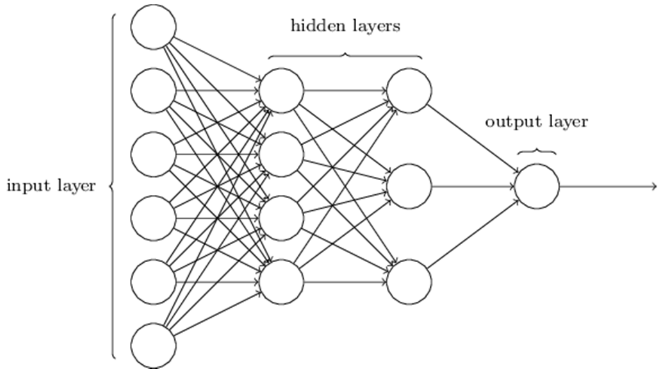

Fig. 3. Neural Network with different layers shown. For this example, there are 2 hidden layers.

For this paper, the expert system dedicated for the WTMCS (WTMCS Neural Network or WNN) will be used and simulated, since the WTMCS controls the main reservoir or storage of water. Fig. 4 shows the representation of the neural network used in the simulation. The WNN has two (2) input nodes indicating the inputs L and DL, and one (1) output node indicating the output PRIO. Twenty (20) hidden nodes were arbitrarily assigned by the researchers for the hidden layer.

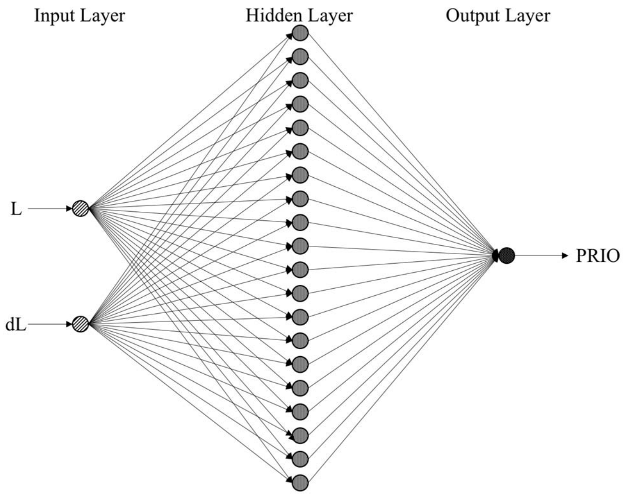

Fig. 4. Representation of Neural Networks for the WNN Expert System.

IV. METHODOLOGY

The simulation tool used for this paper is the MATLAB Neural Network Toolbox (*nntool*). Sample data used in this simulation was based on the normalized values gathered from the previous run without the Expert System or the neural network

TABLE II.
WTMCS ACTUAL AND NORMALIZED INPUTS AND OUTPUTS (TRAINING SAMPLES)

L	nL	DL	nDL	PRIO	nPRIO
24.9	0.249	8.6	0.573	6	0.6
55.4	0.554	7.2	0.48	5	0.5
43.8	0.438	11.8	0.787	5	0.5
71.6	0.716	8.2	0.547	5	0.5
3.3	0.033	11.7	0.78	9	0.9
73.2	0.732	5.5	0.367	5	0.5
39	0.39	13.8	0.92	5	0.5
18.7	0.187	12.9	0.86	7	0.7
12.6	0.126	4.5	0.3	9	0.9
80.7	0.807	11.8	0.787	7	0.7
3.7	0.037	8.1	0.54	9	0.9
0.7	0.007	3.9	0.26	9	0.9
44.4	0.444	4.3	0.287	5	0.5
43.9	0.439	14.1	0.94	5	0.5
51.1	0.511	13.4	0.894	5	0.5
19.9	0.199	0.9	0.06	7	0.7
65.7	0.657	7.5	0.5	5	0.5
75.3	0.753	1.5	0.1	1	0.1
48.4	0.484	8.7	0.58	5	0.5
19.4	0.194	2.9	0.193	6	0.6
54.7	0.547	14.7	0.98	5	0.5
76.4	0.764	11	0.733	6	0.6
73.2	0.732	5.3	0.353	5	0.5
91.6	0.916	7.2	0.48	5	0.5
1.6	0.016	3	0.2	9	0.9
54.7	0.547	8.1	0.54	5	0.5
52.5	0.525	2.6	0.173	4	0.4
99.4	0.994	7.9	0.527	5	0.5
82.3	0.823	11.8	0.787	7	0.7
98.9	0.989	7.2	0.48	5	0.5
16.3	0.163	0.1	0.007	8	0.8
27.3	0.273	13.2	0.88	6	0.6
64.4	0.644	5.2	0.347	5	0.5
30.2	0.302	4.4	0.293	6	0.6
41.3	0.413	13.5	0.9	5	0.5
89.4	0.894	12.9	0.86	9	0.9
25.9	0.259	13.2	0.88	6	0.6
58.9	0.589	8.1	0.54	5	0.5
26.7	0.267	2.1	0.14	5	0.5
62.4	0.624	13.2	0.88	5	0.5
46.9	0.469	10.2	0.68	5	0.5
5.4	0.054	8	0.533	9	0.9
2.8	0.028	14.4	0.96	9	0.9
52.5	0.525	12.2	0.813	5	0.5
7.5	0.075	14.8	0.987	9	0.9
56	0.56	9	0.6	5	0.5
92.2	0.922	4.5	0.3	5	0.5
34.9	0.349	7.1	0.473	5	0.5
1.3	0.013	11.2	0.747	9	0.9
6.9	0.069	3	0.2	9	0.9

Table II shows the actual and normalized inputs and outputs from the WTMCS for the first 20 out of 100 samples. The 1^{st}, 3^{rd}, and 5^{th} columns are the actual inputs and outputs obtained from the WTMCS. While the 2^{nd}, 4^{th}, and 6^{th} columns are the normalized inputs and outputs. The min-max normalization was done due to the difference of the minimum and maximum values of each variable by dividing the actual value by the maximum value particular to that variable. L and DL are in terms of the total volume percentage (%) in reference with the maximum number of liters. By normalizing the L and DL, the actual percentage was divided to the maximum percentage set. (L has a range of 0-100%, while DL has only 0-15%). For the PRIO, the actual priority was divided by the maximum priority level (priority level 10).

The normalized inputs (nL and nDL) will be the input data for the WNN and the normalized output (nPRIO) will be the target data for the training of the neural network. The training used is the Levenberg-Marquadt backpropagation technique (*trainlm)* and the performance is measured in terms of the mean squared error or MSE.

The first 50 of 100 samples will be used for training the network. As soon as the network was trained, simulations using the remaining 50 samples of input and output target data to confirm the difference between the output data provided by the WNN and the target data.

V. RESULTS AND ANALYSIS

Fig. 5, 6, and 7 show the overall performance of the WNN after training. The network's performance plot in Figure 5 shows that the training has reached 87 iterations or epoch before it stopped training. After it, the validation and testing was done and the best validation performance is at the 81^{st} iteration with MSE of 0.0027394. It can be seen that the difference training is far from the validation and testing, but validation and testing are almost equal after the point with best validation performance.

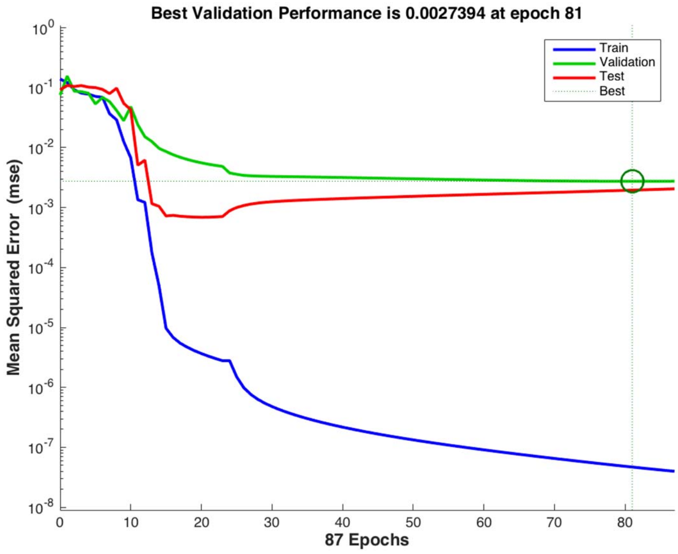

Fig. 5. Performance plot of WNN

The network training's plot in Fig. 6 shows the magnitude of gradient, mu value, and the validation checks after particular epoch. In the model, the training stopped at Epoch 87 where it reached the 6th failure in validation check, which was set as the maximum number of fails. The mu value is the control parameter in the network that directly affects the error convergence. In this model, the mu value reached $1\text{x}10^{-7}$ at Epoch 87.

Fig. 7 shows the regression plots of the network. The graphs show the regression plots for training, validation and testing data. The perfect fit for the network is being represented by the dashed line on each graph, while the best fit between the output and the target is represented by the solid line. R value denotes the linear relationship between the two values. The range of R value is between 0 to 1, where 1 means the relationship is exactly linear, while 0 mean no linear relationship. [9] [10] The value of R after the training is 1 for the training data, 0.94588 for the validation data, and 0.94559 for the test data, with an overall average of 0.98846. Since all the values are almost equal to 1, this indicates a good fit. The relationship of the output of the network and the target data is almost linear, meaning the network is accurate and additional training is not required.

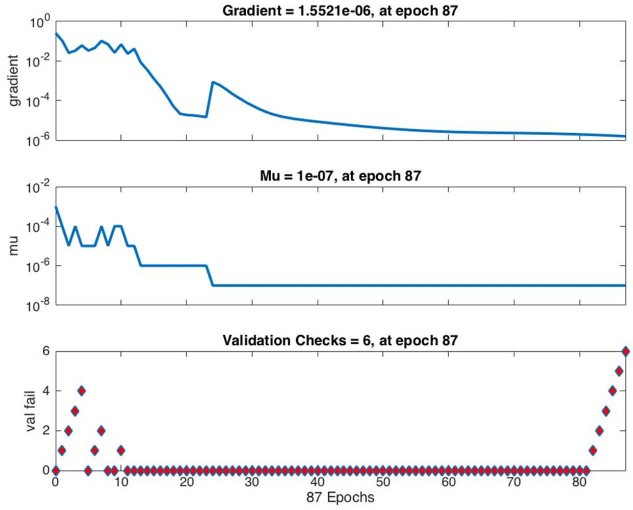

Fig. 6. Training plot for WNN

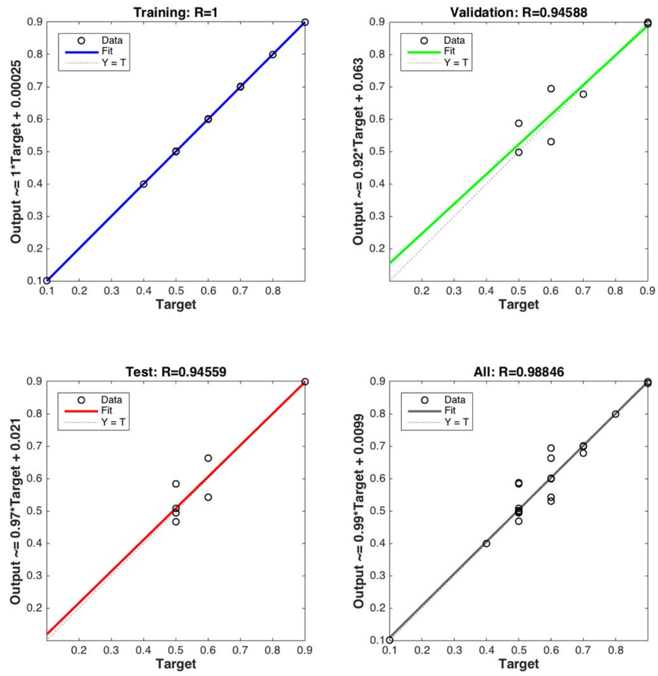

Fig. 7. Regression plots for WNN.

Fig. 8 shows the plot of the target data and output data

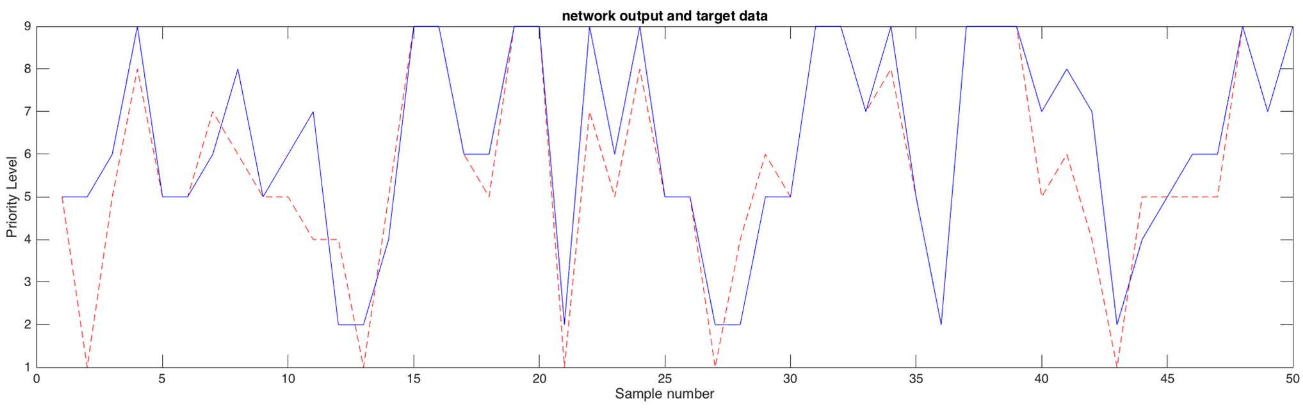

Fig. 8. Plot of Comparison of Target Data and Output Data

obtained from the WNN for the testing of network. The red dashed line represents the target data, while the blue solid line represents the output data of the WNN. It can be seen that at some points, there is a slight difference on the expected priority and the priority acquired from the network.

V. Conclusions

In the study, the priority level of the WTMCS that provides the were predicted using a feed-forward back-propagation ANN model with 2 nodes in the input layer, 20 nodes in the hidden layer, and 1 node in the output layer. Based on the results, it can be seen that the network provided a good response where though an almost linear relationship between the expected or target data and the output that was achieved from the network.

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