R-based neural networks decision model for water air cooler system

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ABSTRACT

Water air cooler is a process that uses an evaporative system. In its first generation, there was no temperature sensor, and its fan was turned by an electric motor in an open loop system with a fixed speed. As well, the water's flow and level in the tank are governed by a mechanical system, which is generally a floating ball attached to a shaft. In order to ameliorate this classical system with more advantages and performances, many ideas are included in subsequent generations such the integration of embedded systems, intelligent control and components of manufacturing materials. In this paper, the current study aims to integrate an intelligent system, which is the neural networks by using R language to give a smart decision model to command relays switching dedicated to control the electric motors, where the first one is tied up with a fan and the other to an electro-pump. The HC-SR04 ultrasonic and DHT11 sensors supervise the two desired parameters control, water level in the tank and the outside temperature successively.

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1. INTRODUCTION

In summer or in the last days of spring season, many areas have an environment temperature more than 25 degrees, which leads to the use of any system capable to reduce this temperature rise, such as the water-based air conditioner. This last, its main operation is based on the exploitation of the interaction between the air expelled outside by the power force of the electric motor of the fan through the filters humidified by water. The air ventilation system that uses water is a process where the air circulates from the outside to the inside, then to the outside in another direction [1]. The work [2] has presented a design and analysis of a hybrid air and water cooler, where it has discussed the utilization of a desert cooler for cooling air as well as water. The study in [3] has touched the increasing evaporative cooler efficiency by controlling water pump run and off times.

In this paper, we aim to generate a temperature and water level neural networks [4]–[8] decision model for water air cooler system by using R language [8]–[11], where this control supervises the two relays [12], [13] switching mode. The first one is dedicated to turn ON or OFF the electric motor attached to the air fan, and the other is reserved the water electro-pump. Our proposed temperature and water level neural networks decision model for water air cooler is illustrated in Figure 1, and its conception is shown in Figure 2. This process is characterized by two inputs to the desired neural networks model, which are the outside process temperature (T°) and the water level (L cm) in its tank. The outputs of this artificial intelligence are focused to command the two relays, which control the electric motors inside this water air cooler.

The proposed main operation of this water-air system is based on the closed loop measurement of the outside temperature with the DHT11 sensor [14], [15] and of the water level with the HC-SR04 sensor [16], [17]. For the first parameter, which is the temperature, a threshold is fixed as a reference (T_{ref} = 18°). For the second measurement which is the level (L (cm)), it is fixed on an interval ($L_{min} < L < L_{max}$), where L_{min} is the HC-SR04 sensor's safe distance from the maximum water level (D (cm)) in the tank with several leaky holes, and beyond the maximum measured distance L_{max}, the water electro-pump is in forced OFF mode.

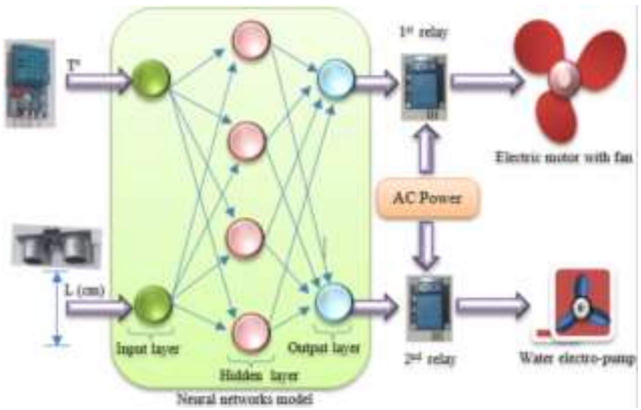

Figure 1. The proposed temperature and water level neural networks decision model for water air cooler

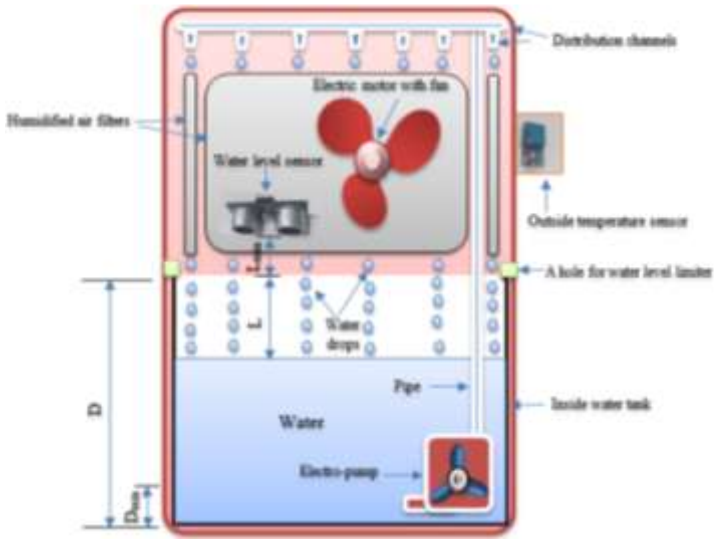

Figure 2. The proposed conception for water air cooler

2. METHOD

The proposed main operation of this water-air system is based on the closed loop measurement of the outside temperature with the DHT11 sensor and the water level with the HC-SR04 sensor. For the first parameter, which is the temperature, a threshold is fixed as a reference by T_{ref} =20°. For the second measurement which is the level (L (cm)), we have fixed the L_{min} ($L_{min} \leq L$), which is the HC-SR04 sensor's safe distance from the maximum water level (D (cm)) in the tank, and beyond L_{max} ($L_{max} = D - D_{min}$) which is the max water level, the emerged electro-pump [18] is on OFF mode. A secured system for maximum water level is presented by the leakage holes, and the two relays are the elements responsible for operating the two electric motors by their states on switching interactions modes with the two sensors control decision.

The classification modes for the outside temperature and the level of the water tank are given by the organigram based on the Arduino embedded [19]–[21] system, illustrated in Figure 3. For any value of the exterior temperature greater than or equal to T_{REF} = 18 °, it will be assigned to 1, else it will be assigned to 0. Likewise, for those to the water level measured by HC-SR04 sensor, if L is lower or equal to L_{max}, it will be assigned to 1, else it will be assigned to 0. The general proposed parameters are D = 30 cm, D_{min}= 3 cm and L_{min} = 5 cm.

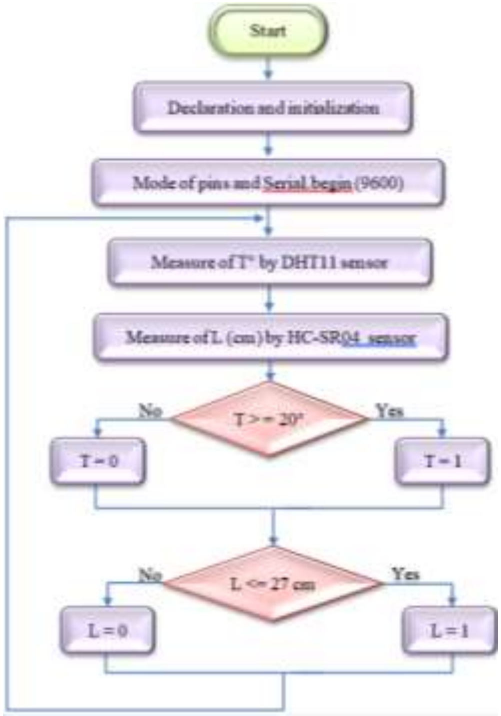

Figure 3. The proposed organigram classification of outside temperature and water tank level

3. NEURAL NETWORKS DECISION MODEL USING R LANGUAGE

Artificial neural networks is one of the famous areas application in several problems related to engineering and sciences, where its principal structures were developed and inspired from known models of biological nervous systems and the human brain itself [22], [23]. In this work, our proposed neural networks is structured by two inputs, which are the outside temperature and the water tank level. One hidden layer, which contains neurons with a sigmoidal activation function. In the output layer, we have two decisions with a linear activation function. The first one is dedicated to turn ON or OFF the relay, which controls the electric motor attached to the air fan, and the other is reserved to manage the water electro-pump's relay switching.

Two cases are proposed for the general states control interactions between the both input sensors and the two relays in output. The first case, which is represented in Table 1 and by binary classification in Table 2, the 1st relay is in ON mode, which is similar to 1 in binary classification, only where the outside temperature is upper or equal to 20°. As the same, the 2nd relay is in ON mode, which is similar to 1 in binary classification, only where the water level is lower or equal to 27 cm. For the second case, which is illustrated in Table 3 and by binary classification in Table 4, the both of relays are in ON mode, which is similar to 1 in binary classification, only in one state, in which the outside temperature is upper or equal to 20° and the water level is lower or equal to 27 cm.

Table 1. The general interaction states control between the both inputs and two outputs for the 1st case

Neural networks inputs states		Neural networks outputs states	
Outside temperature T°	Water tank level L(cm)	1st relay	2nd relay
$T < 20$	$L > 27$	OFF	OFF
$T \geq 20$	$L > 27$	ON	OFF
$T < 20$	$L \leq 27$	OFF	ON
$T \geq 20$	$L \leq 27$	ON	ON

Table 2. The general interaction states control between the inputs and outputs with binary classification for the 1st case

Neural networks inputs states		Neural networks Outputs states	
Outside temperature T°	Water tank level L(cm)	1st relay	2nd relay
0	0	0	0
1	0	1	0
0	1	0	1
1	1	1	1

Table 3. The general interaction states control between the both inputs and two outputs for the 2nd case

Neural networks inputs states		Neural networks Outputs states	
Outside temperature T°	Water tank level L(cm)	1st relay	2nd relay
$T < 20$	$L > 27$	OFF	OFF
$T \geq 20$	$L > 27$	OFF	OFF
$T < 20$	$L \leq 27$	OFF	OFF
$T \geq 20$	$L \leq 27$	ON	ON

Table 4. The general interaction states control between the inputs and outputs with binary classification for the 2nd case

Neural networks inputs states		Neural networks Outputs states	
Outside temperature T°	Water tank level L(cm)	1st relay	2nd relay
0	0	0	0
1	0	0	0
0	1	0	0
1	1	1	1

Our study in this article is realized by using neural net package on R language, where its training is based on the backpropagation, resilient backpropagation with or without weight backtracking or the modified globally convergent version. The package allows flexible settings through custom-choice of error and activation function. Furthermore, the calculation of generalized weights is implemented [24], [25]. The proposed organigram to simulate the temperature and water level neural networks decision model, for water air cooler system by using R language, is shown in Figure 4.

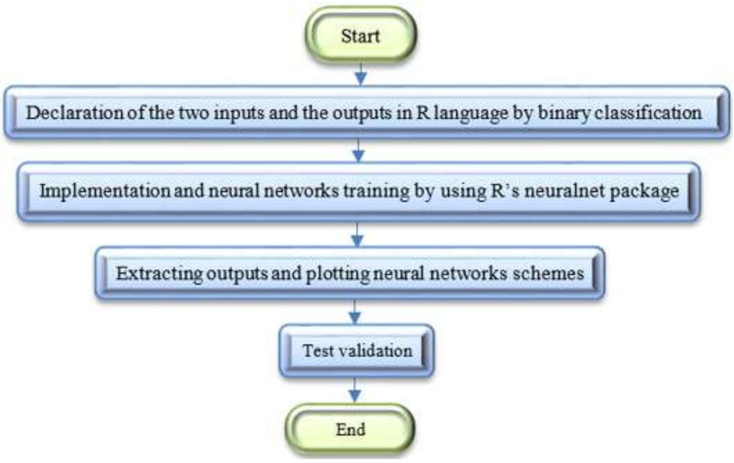

Figure 4. The proposed organigram to simulate the temperature and water level neural networks decision model for water air cooler system by using R language

4. RESULTS AND DISCUSSION

The simulation results by using R's neuralnet package for the both proposed cases of the temperature and water level neural networks decision model for water air cooler system, with inputs and the outputs in binary classification, are presented in two cases. The first one is illustrated with two different neural networks models on Figures 5 and 6, where the both of these models are structured by two nodes in input layer (outside temperature and water tank level) and two nodes in output layer (1st relay and 2nd relay decisions). However, they have only the different in hidden layer, where one model has two nodes and the other has three nodes. After the neural networks simulation and training for these both models, the results of weights, bias, steps, and errors are shown on Figures 5 and 6.

The second case is also has two different neural networks models, which are similar in inputs and inputs numbers and types of the first case, but have also the different in hidden layer, where a model has one node and the other has two nodes. After the neural networks simulation and training for these both models, the results of weights, bias, steps and errors are shown on Figures 7 and 8. A collection of the obtained results for the proposed decision model on temperature and water level neural networks for water-air cooling system using R language simulation is presented in Table 5.

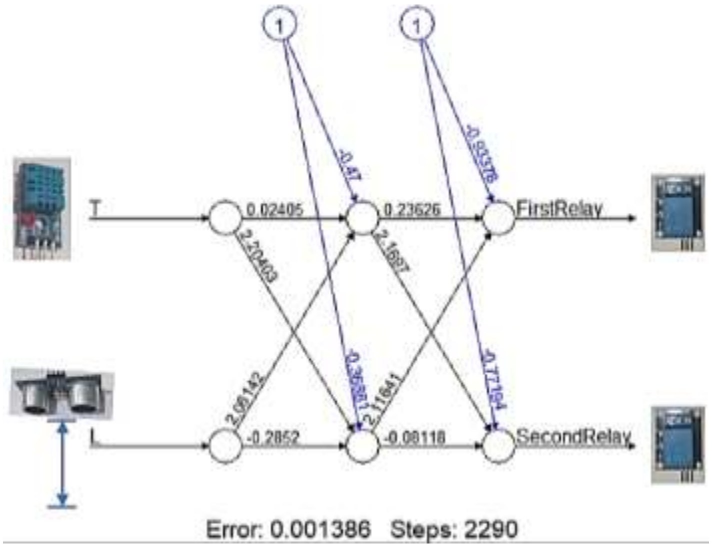

Figure 5. Temperature and water level neural networks decision model for water air cooler system by using R language for the first case (hidden layer with two nodes)

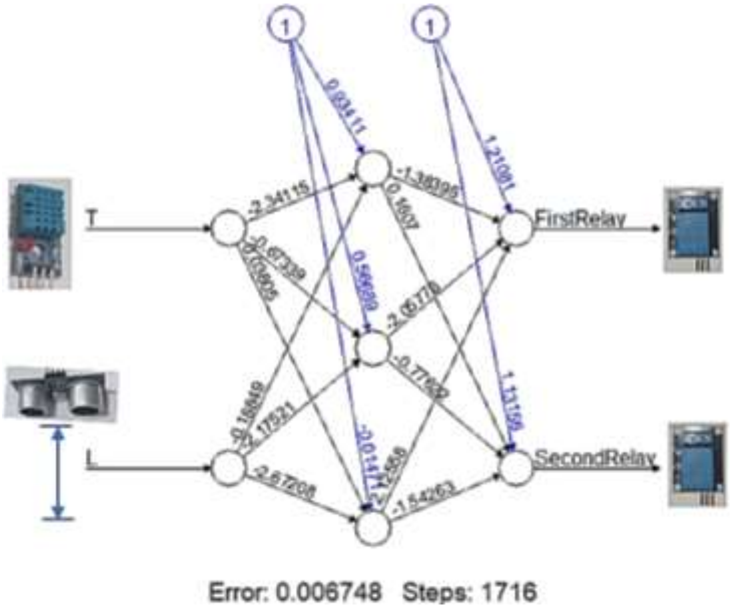

Figure 6. Temperature and water level neural networks decision model for water air cooler system by using R language the first case (hidden layer with three nodes)

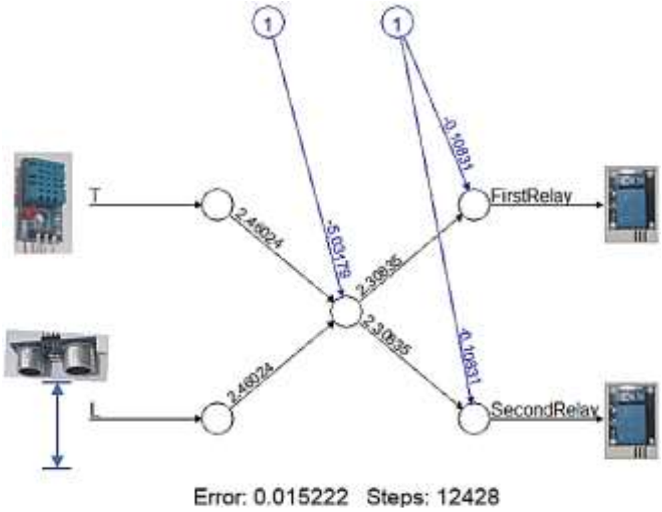

Figure 7. Temperature and water level neural networks decision model for water air cooler system by using R language for the second case (hidden layer with one node)

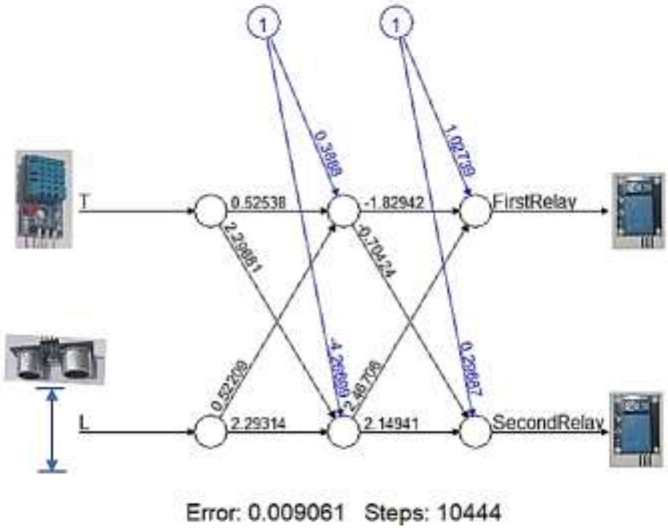

Figure 8. Temperature and water level neural networks decision model for water air cooler system by using R language for the second case (hidden layer with two nodes)

Table 5. Neural networks training results

Proposed neural model decision	Number of nodes in input layer	Number of nodes in hidden layer	Number of nodes in output layer	Simulation steps	Simulation error
1st case	2	2	2	2290	0.001386
	2	3	2	1716	0.006748
2nd case	2	1	2	12428	0.015222
	2	2	2	10444	0.009061

The simulation results by using R's neuralnet package for the both proposed cases, which are designed to the temperature and water level neural networks decision model for water air cooler system, are presented in Table 5. For the first case, the two proposed schemes are similar in the number of nodes in input and output layers, which is fixed to 2. However, the major difference is figured in the number of nodes in their hidden layers. For the first scheme where we have proposed 2 nodes, the results are obtained by neural network training simulation after 2290 steps with an error equal to 0.001386. For the second scheme, which is adapted with 3 nodes, the results are obtained by neural network training simulation after 1716 steps with an error equal to 0.006748.

As for the second case, the two proposed schemes also have two nodes in the input and output layers, which is set to 2. The major difference lies in the number of hidden nodes in each layer. For the first scheme where we have proposed 2 nodes, the results are obtained by neural network training simulation after 12428 steps with an error equal to 0.015222. An error rate of 0.009061 is obtained after 10444 steps of neural network training simulation for the second scheme, which is adapted with 3 nodes. The four proposed binary decision models based on neural networks are valid for controlling in closed loop the two relays switching modes desired to the water electro-pump and the fan's electric motor for the water air cooler system.

5. CONCLUSION

In this paper, we have touched the implementation of the artificial intelligence in the classical water air cooler system by using neural networks decision. A binary classification has modeled and implemented on Arduino embedded system for the outside temperature with the DHT11 sensor and the water level with the HC-SR04. However, two cases by four binary decision models based on neural networks are proposed for controlling the two relays switching modes, which are desired to command the two electric motors implemented in the classical water air cooler system. For these four models, the both of neural input nodes are the outside temperature and the water tank level. The output layer is represented by to switching decisions for the two relays, where the first one is dedicated to the electric motor, which turns the air fan, and the second is reserved to control the emerged electro-pump. The simulation accomplished by using R's language neuralnet package for the proposed binary classifications and decisions, has yielded a satisfactory result.

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