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A Compact, Accurate, Low-Power ASIC Implementation for Sensor Data Augmentation for Economically Sustainable Water Quality Monitoring.

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Abstract - Water pollution caused by industrial and waste-water discharges, agricultural activities, and human activities is a major concern. This paper presents a hardware implementation of data augmentation ASIC design for a low-power, low-cost Water Quality Indexing application. The design has been developed using a Multilayer Perceptron (MLP) feedforward network with backpropagation learning to predict the data of DO and EC using pH and ORP as the input vector. This eliminates the need for expensive sensor electrodes, thereby reducing the cost of the design. The Augmentation ANN achieves 98% in the prediction of DO and EC. The results have been presented and compared with standard WQI devices.

Keywords: data augmentation; ASIC; Artificial Neural Networks; Water Quality; Water Pollution; Water usage optimization;

1 INTRODUCTION

Water is one of the most basic resources that is required to sustain life along with food and air. Thus, the availability of safe drinking water is major concern. Water pollution caused by industrial and municipal wastewater discharges, agricultural and urban runoff, and other human activities is a major concern on a global scale.

Conventional water quality measurement techniques include on-site sampling and subsequent laboratory-based tests; both are labor-intensive and cost-intensive processes. The measurements are not in real-time.

We have chosen four parameters to measure water quality, pH, ORP, DO, and EC, to reduce the cost of a real-time in-situ WQI device. Measurement of pH and ORP can be done easily but DO and EC require expensive electrodes. Data augmentation is used to predict DO and EC values, reducing the cost of the device.

Historically, data enhancement has been performed using mathematical methods. Nonetheless, ANN has shown to be more accurate when there are no mathematical relationships between input and output characteristics.

2 METHODOLOGY FOR DATA AUGMENTATION

Data Augmentation is necessary for WQI devices for in-situ application due to the high cost of measurement. Two primary approaches to data augmentation are the mathematical approach and the ANN based approach. Mathematical approaches based on Linear Interpolation, Multilinear Regression, Bayesian Regression model and

Watershed Models are not efficient models and limited in their application (Wilkin R. T., McNeil, Adair, & Wilson, 2007) (Patulea, Baran, & Calusaru, 2012) (Jones, 2002).

3 ANN APPROACH

The artificial neural network (ANN) technique can learn complicated water quality variable correlations and integrate nonlinearities to supplement input data. It is adaptable and can be extended to multivariate instances and adjusted by changing the network design (Kim, Seo, Jang, & Kim, 2021). ANNs have been used to estimate dissolved oxygen (DO) in a wide variety of environments (He & Takase, 2006), and their performance has been superior to other statistical techniques (Hirsch, Moyer, & Archfield, 2010). The use of ANN methods to predict environmental water quality has increased rapidly and can be applied to augment Water Quality parameter data and improve prediction accuracy.

4 ANN-BASED DATA AUGMENTATION

The complete methodology of the Augmentation ANN ASIC Implementation is broken down into the following steps:

- Water sample collection
- Measurement of parameters using standard lab-based methods
- Measurement of pH and ORP using Arduino Uno
- Prediction of DO and EC values using Data Augmentation ANN (A-ANN)
- Hardware Implementation of A-ANN

4.1 Water Sample Collection for Training, testing, and validation of ANN

1806 Ground and surface water samples have been collected from various locations in and around Pilani, Rajasthan, India. Based on knowledge, each sample was marked into one of the three categories – potable, agricultural, and wastewater.

4.2 Lab-based parameter measurement and Collection of Training and Validation data set for Data Augmentation

1806 samples were tested for pH, ORP, DO, and conductivity using titration, spectroscopy, and solution chemistry. A-ANN and C-ANN training, testing, and validation data were used. Arduino Uno was used as the sensing circuit, and sensing and conditioning circuits were removed to save costs. Sensor accuracy was adjusted by ANN for classification. Figure 1 exhibits the concept of digitization of pH and ORP using Arduino Uno.

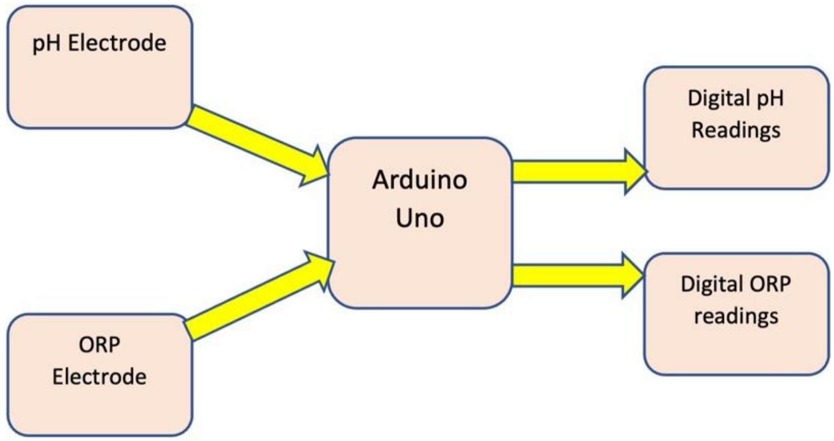

Figure 1: Block diagram for taking pH and ORP readings using Arduino Uno

4.3 Hardware Implementation of A-ANN

ASIC (Application Specific Integrated Circuit) design approach has been used to implement A-ANN on hardware.

Figure 2 shows the Accuracy and Mean Square error for various architectures that were tested for the A-ANN. The ANNs were designed on MATLAB with chosen input and output vectors. The number of layers and number of neurons in each layer are varied and the accuracy and mean square error of the output are plotted using in-built functions of MATLAB.

From figure 2 and Figure 3 we can conclude that the most suitable architecture is with 3 hidden layers with 32 neurons each because it give maximum accuracy and minimum Mean Square Error.

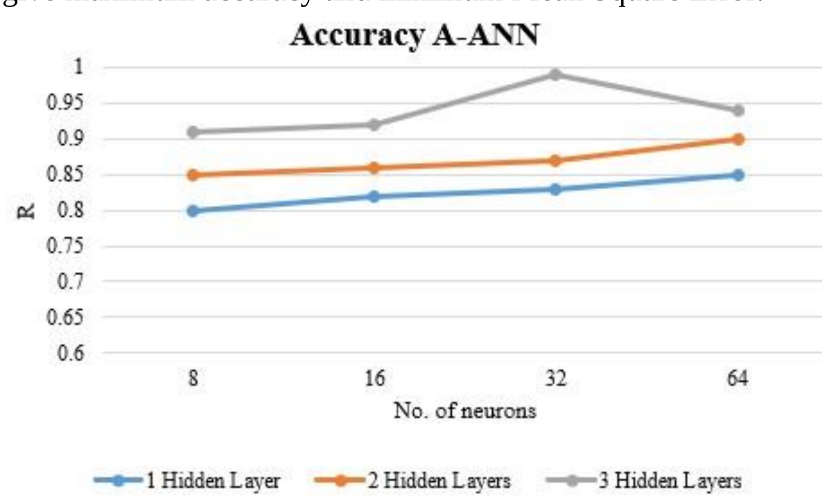

Figure 2: Accuracy of A-ANN

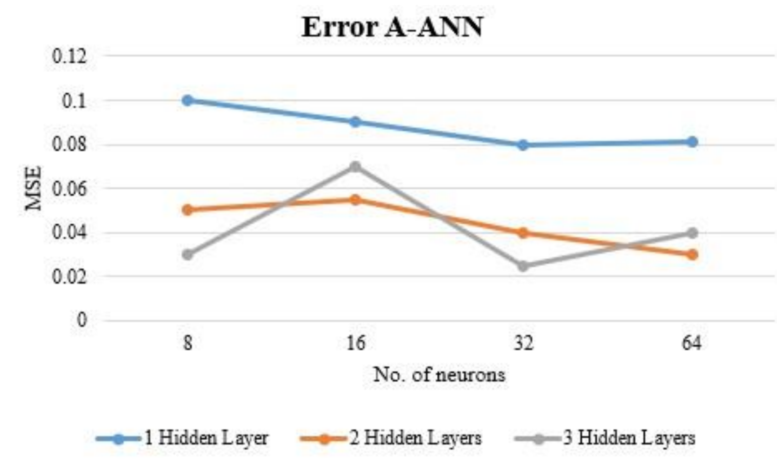

Figure 3: Mean Square error for A-ANN

4.3.1 ASIC Design

The ASIC approach involves the use of an Arduino and an IC designed using Verilog HDL and TSMC 180nm Standard cell library. A block level representation of the system is shown in Figure 7.

A-ANN is coded using Verilog HDL based on the Posit floating point number representation system, using an Arduino Uno microcontroller. The pH and ORP readings are converted into Posit format before being transferred to an in-chip memory, where they are accessed by the A-ANN coded in Verilog. The Verilog code predicts the values of DO and EC in Posit format. ASICs are economical, power efficient, and suitable for portable devices. They also have on-chip connections, leading to more reliable connections and lesser loosely connected wires. However, they provide a reliable device at the cost of repairability.

Table 1: Comparison of Hardware Implementation of Augmentation ANN using IEEE 754 and Posit Number Representation system.

Parameter	IEEE 754 implementation	Posit Implementation
Standard Cell Library Resources	264580	95170
Area (micro metre squared)	2.409368	0.697938
Power (uW)	10396.62351	112.969682
Critical Path Delay (ps)	66711	12653

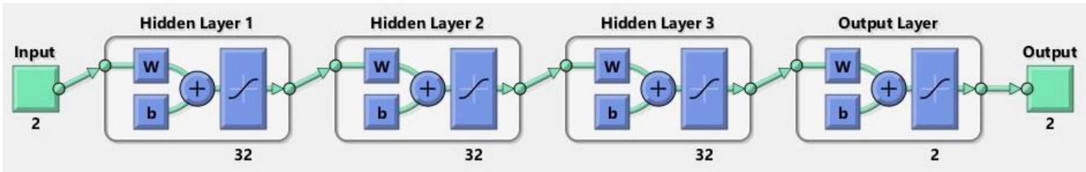

Figure 4: Augmentation ANN Architecture

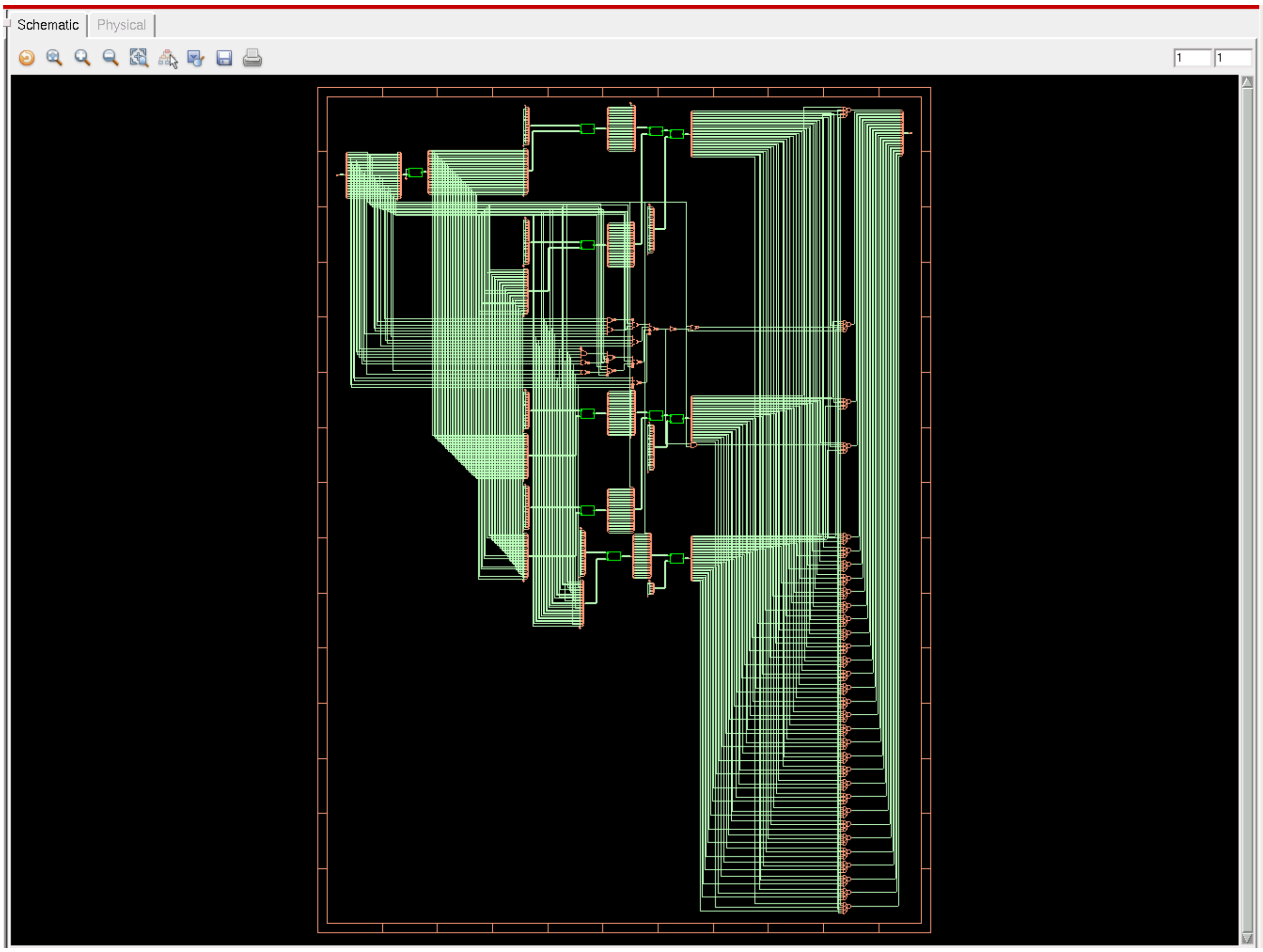

Figure 5: Snapshot of Augmentation ANN Synthesis using Cadence RTL Encounter with TSMC 180nm Standard Cell Library

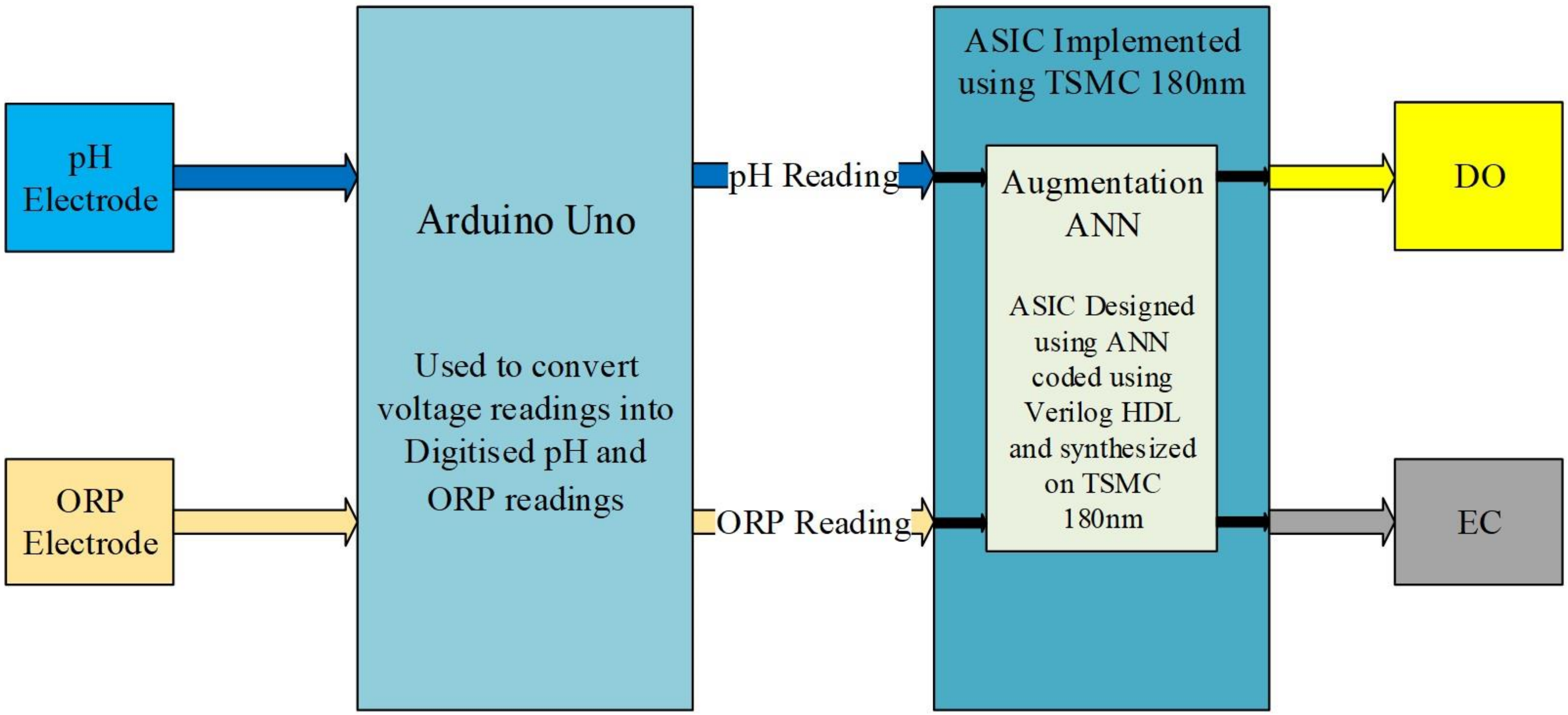

Figure 6: Block diagram of WQI device using ASIC implemented Augmentation ANN

4.3.2 Results of Prediction Accuracy of A-ANN for ASIC approaches.

A total of 14 training functions are tested. From these 14 functions, only one training function (trainLM), has finished the work of regression plot and error plots. Using the Lavenberg-Marquardt training function and a sigmoidal activation function (logistic function), A-ANN with 2 hidden layers and 16 neurons in each layer was optimised (logistic function).

Figures 7 and 8 exhibit A-ANN's DO and EC response plots. It is observed that DO and EC have above 97% accuracy. A-ANN architecture yields 0.98 R2 at 0.00232 RMSE.

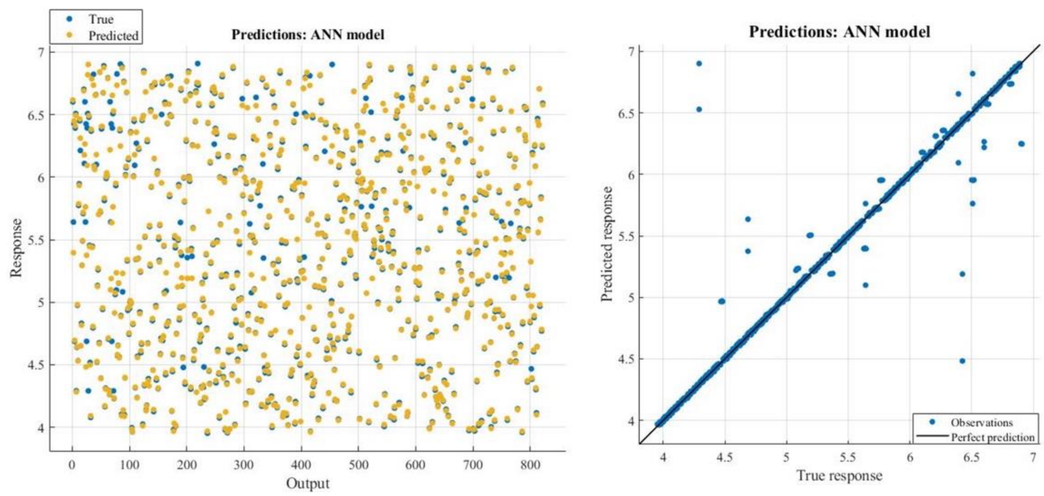

Figure 7: a) Response plot of A-ANN, b) Actual vs. predicted DO value using A-ANN

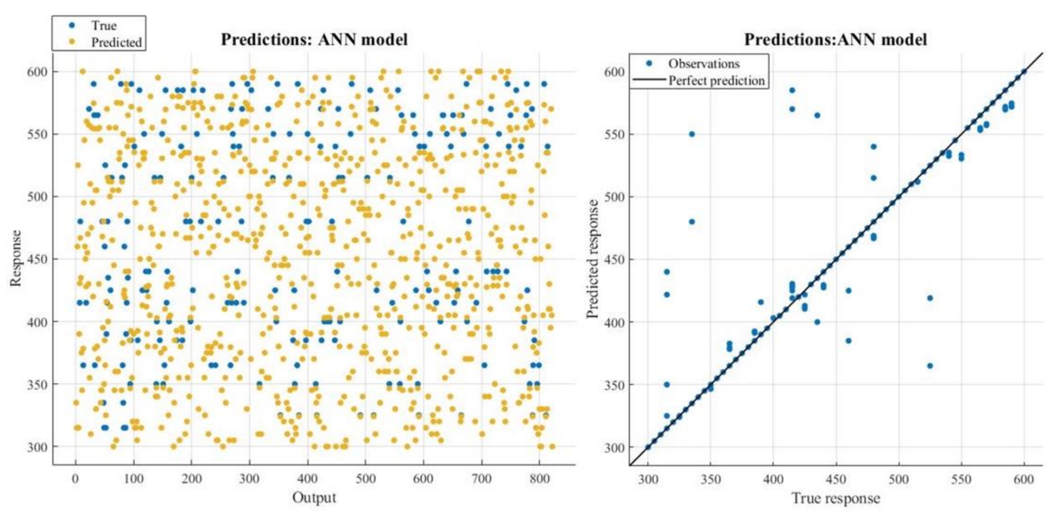

Figure 8: a) Response plot of A-ANN, b) Actual vs. predicted EC value using A-ANN.

Table 2 compares the predicted values of 15 water samples with actual laboratory measured values. The comparison validates the accuracy of 97%.

Table 2: Validation of proposed device for real-time water quality measurement

Sample No	DO (Experimental)	DO (Predicted using A-ANN)	EC (Experimental)	EC (Predicted Using A-ANN)
1	9.36	9.3	1777	1745
2	9.32	9.4	1407	1398
3	9.35	9.5	912	918
4	9.36	9.3	1450	1540
5	3.81	3.3	1640	1640
6	7.36	7.4	928	908
7	6.82	7	1482	1502
8	7.89	7.8	915	915
9	7.13	7.3	1525	1500
10	5.82	6	1225	1325
11	6.34	6.3	1560	1524
12	5.56	6	857	857
13	7.31	7.3	1362	1362
14	5.18	5.2	1090	1000
15	8.13	8.1	1402	1492

Cost Comparison

Table 3: Cost reduction achieved in the proposed device

Component Name	Measured Parameter	Cost (Conventional Atlas Scientific Kit)	Cost (Proposed ASIC WQI Device)
Atlas Scientific DO Probe	Dissolved Oxygen	INR 21,240 (Atlas Scientific, n.d.)	Mass produces VLSI design is much cheaper compared to Atlas Scientific Lab kit
Atlas Scientific DO Sensor	Dissolved Oxygen	INR 4,299 (Atlas Scientific, n.d.)	
Atlas Scientific EC Electrode	Electrical Conductivity	INR 11,200 (Atlas Scientific, n.d.)	
Atlas Scientific EC Sensor	Electrical Conductivity	INR 5,600 (Atlas Scientific, n.d.)	
Cost reduction achieved		**INR 42,339/-**	

5 CONCLUSIONS

In this paper we have designed a Multi-Layer Perceptron architecture with 3 hidden layers, each with 32 neurons. This ANN is used for DO and EC sensor data augmentation. It gives us optimum accuracy and the least Mean Square Error.

The hardware implementation of the Augmentation ANN design achieves 97% accuracy and yields an R^2 of 0.98 at 0.00232 Root Mean Square Error in the prediction of Dissolved Oxygen and Electrical conductivity using pH and ORP input data.

The Augmentation ANN helps reduce cost by eliminating the need for expensive sensor electrodes. Also, when mass-produced, the cost per chip is very minimal. When this augmentation ANN is used along with a classification ANN, a complete low-cost compact VLSI design for the Water Quality Indexing device can be achieved.

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