Evaluation of Smart Chip Technology
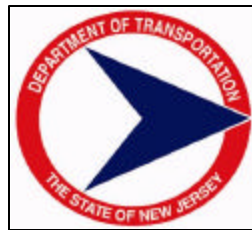
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Submitted
by

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16. Abstract

Gas recognition technology has seen tremendous progress recently, as a result of the wide spread utilization ranging from applications in the automotive industry to food processing to environmental engineering. The progress ranges from developing new sensors that have a faster reaction time and higher sensitivity to the targeted gas, to developing new signal processing techniques that takes an off-the-shelf sensor array as inputs and outputs an accurate, fast, and highly sensitive, repeatable reading. The latter approach utilizes relatively low cost sensors and an inexpensive, intelligent Very Large Scale Integration Application Specific Integrated Circuit (VLSI ASIC) to provide a high quality gas recognition system. Current instruments used for vehicle emission testing to quantify the amount of unwanted gases, although very sophisticated and can reliably measure as low as few parts per million, are very sensitive to environmental changes such as temperature, humidity, oxygen content, and sometimes any non-gaseous content and particulates. In this project, a type of signal processing technique called reinforcement artificial neural networks with an array of off-the-shelf sensors were used to enhance the output of vehicle emission instrument.

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ABSTRACT

Gas recognition technology has seen tremendous progress recently, as a result of the wide spread utilization ranging from applications in the automotive industry to food processing to environmental engineering. The progress ranges from developing new sensors that have a faster reaction time and higher sensitivity to the targeted gas, to developing new signal processing techniques that takes an off-the-shelf sensor array as inputs and outputs an accurate, fast, and highly sensitive, repeatable reading. The latter approach utilizes relatively low cost sensors and an inexpensive, intelligent Very Large Scale Integration Application Specific Integrated Circuit (VLSI ASIC) to provide a high quality gas recognition system. Current instruments used for vehicle emission testing to quantify the amount of unwanted gases, although very sophisticated and can reliably measure as low as few parts per million, are very sensitive to environmental changes such as temperature, humidity, oxygen content, and sometimes any non-gaseous content and particulates. In this project, a type of signal processing technique called reinforcement artificial neural networks with an array of off-the-shelf sensors were used to enhance the output of vehicle emission instrument.

INTRODUCTION

Artificial Neural Networks (ANN) represent collective, non-algorithmic, low-precision, nonlinear computing machines, which learn by training from examples and are data-controlled. They consist of massively interconnected networks with simple computational units (neurons, sometimes called "Processing Elements") as its nodes. Parallel processing and the ability to handle ill-defined problems are the two major advantages of ANN over typical sequential machines. The work in ANN has been inspired by the human brain and neural system. The ability of a human being to solve problems that do not have exact solutions due to insufficient information, and his ability to learn from experience, have motivated to proceed in accomplishing real world ANN.

The main objective of this project is to propose, build, and test a Very Large Scale Integration (VLSI) design and implementation of a Reinforcement Artificial Neural Network (RANN) that will improve vehicle emission testing and reduce external environmental effect. Consequently, we will be able to obtain more accurate and more repeatable results.

Figure 1 shows a simple processing element, which is the basic building block of any ANN. It consists of synapses, which are actually a number of multipliers, an accumulator that sums all the products, and a decision-making element. The decision-making element is a nonlinear function that operates on the output of the accumulator. A sigmoid function is a nonlinear smooth function that represents an example of such a function.

Figure 1 Basic Processing Element

Analog circuit implementation is the approach considered in this project. This approach is convenient for implementing ANN for many reasons. The following are some advantages of analog ANN:

    A. Area efficient: This is a very important feature of analog circuits because there is a need to fit as many neurons as possible on a chip.
    B. Truly real-time: All inputs are presented continuously and processed likewise.
    C. Does not require Analog to Digital Conversion / Digital to Analog Conversion (ADC/DAC) since most of the sensors and actuators which are connected to the ANN use analog signals
    D. The limited accuracy of analog circuits does not present a serious problem.
    E. Simple circuits
    F. High interconnectivity
    G. Time can be easily represented; hence, scaling and integration are possible.

Reinforcement Learning
Reinforcement learning is a method of learning for ANN, and it lies somewhere between supervised and unsupervised learning. Supervised learning is a way to train the ANN by associating actions to results. During the learning phase, the environment tells the ANN how good its action is, or how close the action is to the expected one. Unsupervised learning lies on the other side of the spectrum, where the environment does not know what to expect. The ANN adjusts itself in such a way as to minimize a certain function or criterion. In a reinforcement system, there is no desired output is known to compare with; instead the system is only given a signal from the environment indicating whether it is doing **well** or **poorly**. The system uses stochastic methods to explore the environment, and tries to maximize the reward reinforcement signal.

METAL OXIDE SEMICONDUCTOR (MOS) FULLY ANALOG REINFORCEMENT NEURAL NETWORK CHIP

As mentioned earlier, Artificial Neural Networks (ANN) are nonlinear computing machines which learn by training from examples. They consist of synapses and neurons. The synapse applies weighting to all inputs and provides results to the simple processing elements called neurons, where all weighted inputs are accumulated. The sum of all weighted inputs is introduced to a decision-making element. A decision must be made as to whether or not the stimulus is strong enough to fire the neuron. ANN draws their power from the fact that the choice of the weights and the interconnections between simple identical elements enable them to solve different kinds of problems. Changing the interconnections and/or the weights enables the same networks to be used in different applications. In addition, modeling the environment or modeling the system is not needed to solve problems. This makes ANN attractive in applications where modeling of the system is difficult or impossible.

Analog Circuit Implementation

Analog circuit implementation is one approach that can be used to easily implement ANN for many reasons, as outlined earlier in this report. It is area efficient; hence, we can fit many neurons on a single chip and achieve massive interconnectivity.

The computation is truly real-time. All inputs are presented continuously and processed likewise. Contrary to digital implementation, analog implementation does not require Analog to Digital Conversion / Digital to Analog Conversion (ADC/DAC) since most of the sensors and actuators that are connected to the ANN use analog signals. Despite these advantages, analog implementation still faces many challenges. The lack of analog standard cells is a major obstacle. Every time we need to build an ANN, we must start from basic principles. In addition, available circuits such as multipliers and adders are usually incompatible, and they hardly work together without I/V or V/I converters. This section uses the already designed analog standard cells such as the analog multiplier, adder, and sigmoid function in order to design a Reinforcement Artificial Neural Network (RANN) as shown in Figure 2.

Figure 2 Block Diagram of the Reinforcement Artificial Neural Network (RANN)

The circuits are designed such that they are all in voltage mode, which eliminates the need for I/V or V/I converters. They have been optimized for minimum size and wider input range so that they are capable of handling the wide variations of different sensors.

P-type Metal Oxide Semiconductor (PMOS) Analog Multiplier
A compact four quadrant PMOS analog multiplier was designed as illustrated in Figure 3. The circuit consists of twelve P-type Metal Oxide Semiconductor (PMOS) and two N-type Metal Oxide Semiconductor (NMOS) transistors. The output signal of this multiplier is voltage, which makes it easy to interface with other analog circuits. In addition, the output common mode voltage is positive, which matches those needed in many applications such as ANN. In such applications, multipliers must interface with analog adders to provide the neurons with synaptic signals. The output voltage of the multiplier is perfectly compatible with the input voltage of the adder circuit and this will be discussed.

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Figure 3 Four-Quadrant Analog Multiplier

Note that:

    A. All of the transistors are biased so that they operate in the linear region except M5a, M5b, M5c, M5d, M7a, and M7b.

    B. Current sources bias voltage V_{bias} is equal and opposite in sign to the threshold voltage of the PMOS transistor V_{tp}.

    C. The value of V_{tp} is equal and opposite to the input voltage common mode voltage V_S.

Hence, the output voltage will be

$$V_{o1}-V_{o2} =1/(k_3)*\left((2kW_1W_3^2)/(W^2)+(2kW_3^2W_1(V_{o1}+V_{o2}))/(W(4WW_5V_{dd}^2)^{.5})-(kW_1W_3)/(W)\right)V_1V_2$$

The effect of k, which is now in the range of 1/3, reduces the nonlinear effect of the first and third terms above and improves circuit linearity. Although the aspect ratios of the transistors are important, they are not critical to the functionality of the circuit. The multiplier's two inputs are the input signal from the chemical sensor and the weights for each input. The input range of the multiplier is capable of handling the dynamic range of the sensor. Using PMOS transistors in place of NMOS reduces nonlinearity errors and provides a circuit that is not sensitive to transistor process parameters or aspect ratios. This is a result of the process transconductance parameter of the PMOS transistors being smaller than that of an NMOS transistor, which reduces the effect of unwanted terms in the multiplication equation.

The circuit was designed using 1.5 µm n-well technology and occupied 100 x 150 µm^2 of silicon. The input/output characteristics of the PMOS multiplier are shown in Figure 3.

Multi-input Metal Oxide Semiconductor (MOS) Analog Adder

A novel multi-input Metal Oxide Semiconductor (MOS) analog adder has been designed and fabricated. It consists of *2n+2* NMOS transistors, where *n* is the number of inputs as shown in Figure 4. Inputs, as well as outputs, are balanced differential voltage signals.
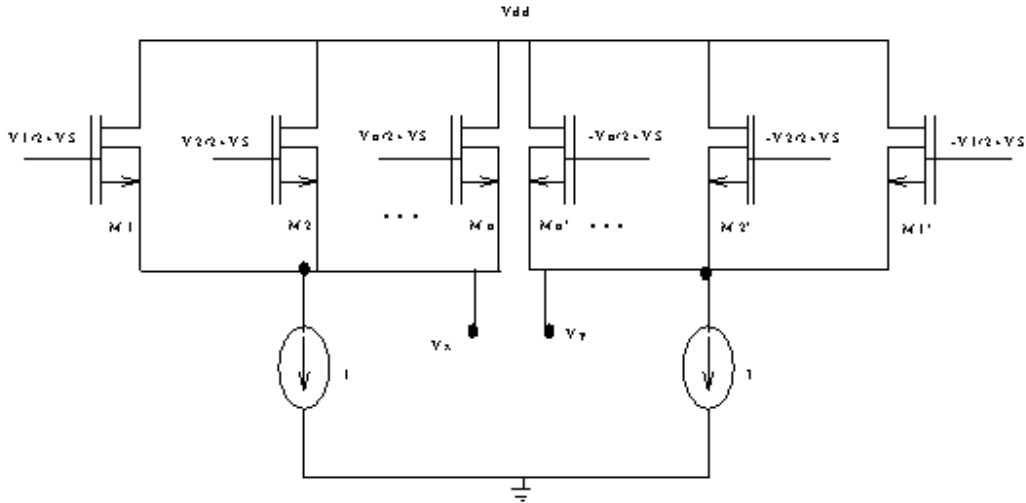

Figure 4 A 3-input Analog Adder

The output voltage is given by

$$V_x - V_y = (V_1 + V_2 + ... + V_n)/(n)$$

The characteristics of this circuit make it the perfect adder cell for neural network applications. Multiple inputs can be added simultaneously without the need for sequential adder circuits. Unused inputs can be connected to V_{ss} in order to turn their corresponding transistors off. This allows for the design of one multi-input core that may be used in many different applications. The fact that the summation function, as shown above, is attenuated by the number of inputs, guarantees that the output will never saturate and that the input signals are not restricted by the number of inputs. A 3-input analog adder has been designed and Very Large Scale Integration Circuit (VLSIC) implemented as part of a Reinforcement Artificial Neural Network (RANN) as shown in Figure 2.

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Sigmoid Function Circuit

Bipolar sigmoid function is the most popular activation function used in neural networks. It is used as a decision-making device as to whether or not to activate the output neuron. If the input voltage is less than -1.5 V, its output is low. But if the input is higher than 1.5 V, the output is high. A mathematical function that represents a sigmoid function may be written as:

$$F(x)= (1-a*e^{-x})/(1+a*e^{-x})$$

where *a* controls the steepness of the transition area in the function.

This is preferred over a threshold function because it is differentiable at all points. The sigmoid function generator is realized by cascading two simple inverting amplifiers with feedback resistors (active transistors operating in linear region). The control voltages, V_{TH_P} and V_{TH_N} are used to reduce the offset voltage of the circuit due to process-induced variations. Their values can be set during initialization phase. V_{R1} and V_{R2} control the output gain of the circuit.

The sigmoid function generator has been implemented using MAGIC 6.5 tools. It consists of 8 NMOS transistors and 4 PMOS transistors. It occupies 178 X 137 μm^2 of silicon area. It has one input pad, one output pad, four other DC biasing signals, and two pads for the supply voltages. The implemented circuit parameters have been extracted. Figure 5 shows this chip.

Additional Analog Circuits

In order to interface the balanced differential output of the 3-input adder with the single-ended sigmoid circuit, a simple differential circuit was designed. It consists of a current mirror, two input transistors, and a constant current source. The output is equal to the differential input. This circuit also amplifies the output of the adder circuit in order to partially compensate for the attenuation in the adder and the multiplier. Input of the differential amplifier is the differential output of the adder. The differential amplifier provides a total gain in the range of 60 dB. A similar circuit with a steep transition between the two output extremes can be used as a comparator. This can be achieved by adjusting the aspect ratios of the transistors.

Inputs of the comparators are the output of the sigmoid function circuit and a reference value that will be described in the next section. Two analog comparators are required in the RANN because the reference values can be adjusted externally. These reference values determine the lower/upper levels of the neuron output, which indicate the existence of the targeted gas. The output has two distinct values. The neuron output is either higher or lower than the reference value.

Analog Reinforcement Artificial Neural Network (RANN) System

All aforementioned circuits have been designed and VLSI implemented to be used in different applications. This section focuses on utilizing these cells to design a Reinforcement Neural Network that will be used as a signal-processing unit for vehicle emission evaluation. Figure 2 shows the block diagram of the RANN. In a 2.2 X 2.25 mm^2 Tiny Chip, two neurons with their associated comparators were implemented. Limitation on the number of neurons was due to the number of available pads and not due to the silicon area. Each neuron module occupies an area of 450 x 450 λ^2, which allows for about 16 neurons in one Tiny Chip.

Inspection of Figure 2 demonstrates that it is possible to divide the network into modular parts. Each has a neuron and all possible comparators. This allows for using a chipset to implement the RANN and consequently expand the network as needed. It is very clear that more neurons could have been added if we had more input/output pads. In order to verify the operation of the designed system, using three weights represented by three DC voltage sources, namely 1V, -2 V, and 3 V, stimulates it.
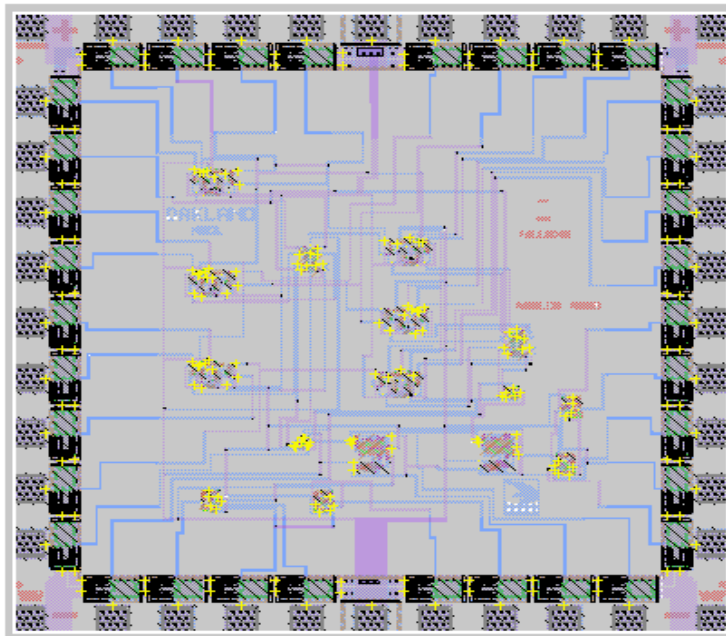

Figure 5 Analog Implemented Reinforcement Artificial Neural Network (RANN)

REINFORCEMENT ARTIFICIAL NEURAL NETWORK (RANN) SYSTEM TRAINING AND EVALUATION

One objective of this project is to develop a VLSI system that is capable of recognizing a number of organic/non-organic volatile chemicals and to quantify them. Considering the wide spectrum of chemicals that need to be analyzed and recognized, it would be prohibitively expensive to design a sensor that targets one and only one of all of the volatile chemicals that exist in the environment around us. Instead, researchers took a simpler approach by using a set of elements of relatively broad, overlapping selectivity profiles. A set of sensors provides a pattern that can be interpreted as an indication of the existence of certain chemicals in the environment. Again, this approach was inspired by animal behavior, such as selecting types of food to eat, establishing territories, and many other applications.

Reading from the NDIR System

Fast Accurate Robust/Repeatable Measurement

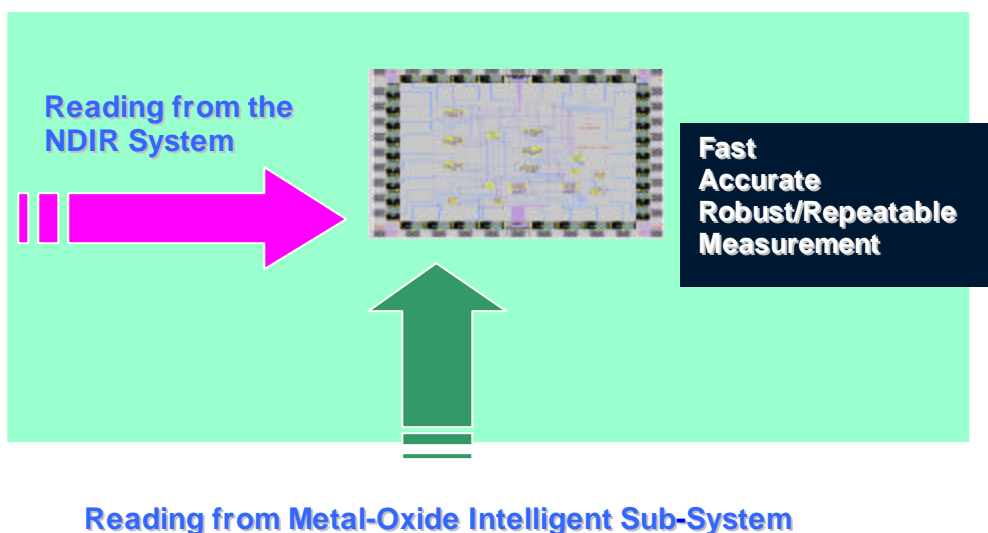**Reading from Metal-Oxide Intelligent Sub-System**

Figure 6 Vehicle Emission Enhancement System

These wide response sensors must be interfaced to an electronic system that conditions the input signals, improves the signal-to-noise ratio, and subsequently employs a pattern recognition algorithm to determine to which volatile chemical the set of sensors are exposed. Figure 6 depicts the system block diagram. Fuzzy assisted feature extracting technique is also used, and commercially available.

Artificial Neural Networks (ANN) have received more attention recently in the field of gas recognition because they offer a number of advantages such as learning by example instead of using a modeled environment and handling noise and sensor fluctuations. Most of the recent work in gas recognition by ANN has undergone experimentation using computer software. Back-propagation has been used in a number of applications. Reinforcement

learning has proven to be more appropriate for gas recognition based on the behavior of biological systems. Over a period of time, the animal builds a database that consists of the olfactory system response and the chemical name. Once it is exposed to an unknown volatile chemical, it selects a gas from this list, say gas A, and the environment provides a simple feedback; the choice was "right" or "wrong".

The system under investigation for measuring fuel exhaust emissions consists of three off-the-shelf volatile organic sensors that are commercially available, and a VLSI digital RANN described in another project, trained and architected specifically for these sensors and for measuring the compounds required for fuel exhaust emissions testing. The chemicals being measured include NO_x, carbon monoxide, carbon dioxide, and appropriate hydrocarbons.

Recognition System
The recognition system shown in Figure 7 consists of three sensors that monitor the environment.

The outputs of these sensors are fed to the RANN, which is trained to perform the required task. The objective of the system is to recognize the existence of any of the gases and to quantify the gas concentration in order to enhance the State of New Jersey vehicle emission test results.
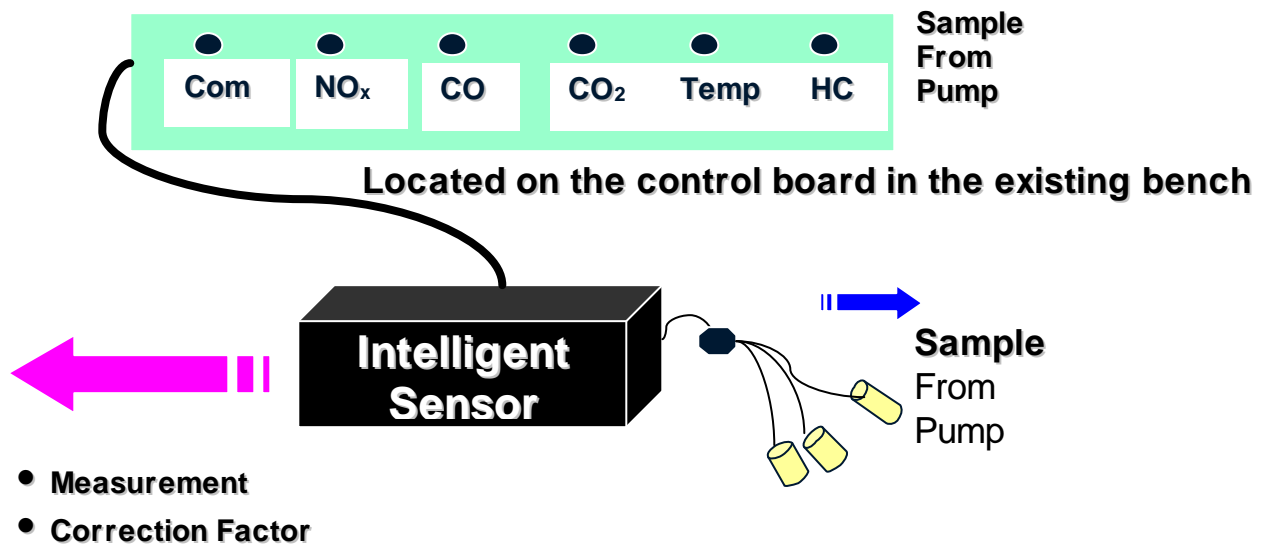

Figure 7 Gas Sensing Enhancement System

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Chemical Sensors

In order to demonstrate the ability of the ANN technique in providing the required discrimination and recognition using some off-the-shelf sensors, three sensors were selected. These sensors are TGS813, TGS203, and TGS2620. TGS813 is a general-purpose gas sensor with sensitivity towards a wide range of combustible gases. It has high sensitivity to methane, propane, and butane. It has the ability to detect between a few hundred to 10000 parts per million (ppm) of these gases. Measurement is affected by humidity and temperature. TGS203 is a Carbon monoxide sensor. This sensor is insensitive to combustible gases. Sensitivity is affected by hydrogen molecules and hydrogen sulfide. Sensor can detect as low as 10 ppm and as high as 10000 ppm. Humidity change has little effect on measurement if kept above 40%. TGS2620 is a general purpose sensor that is for detecting alcohols. The sensor responds to methane and carbon monoxide but somewhat differently from the above sensors. The sensitivity for the TGS2620 is between 50 ppm to 5000 ppm.
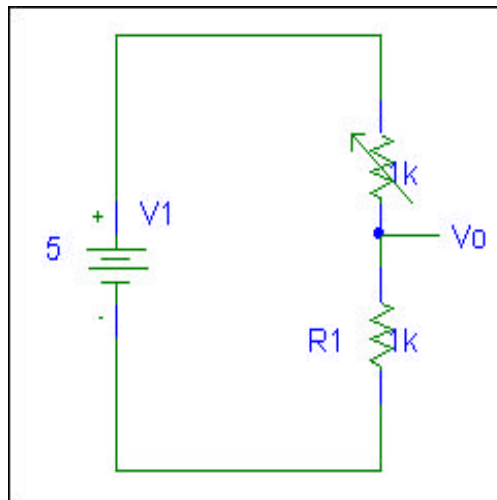

Figure 8 Voltage Divider used to Operate the Sensors

Humidity sensor NH-03 was also used to rectify any variation due to humidity. The existing New Jersey Emissions Testing System did not take into account humidity at all. Our studies showed that humidity was an important factor that contributed to the accuracy of several of the gas measurements. These sensors were selected because they provide slightly different responses to different inputs. It should be emphasized here that the sensors' responses are similar and sometimes overlapping, but they all respond to all of the gases. These sensors are resistive sensors made of tin-oxide, SnO_2. The sensitive element reduces its resistance when exposed to certain chemicals. The sensitivity is a function of the tin-oxide structure in the sensor and the nature of the target. In clean air, oxygen, which traps electrons by its electron affinity, is adsorbed onto the Tin dioxide forming SnO_{2-x} at the boundary of the grain, which consequently forms a potential barrier. When the sensor is exposed to a reducing gas, the tin dioxide adsorbs these gas molecules causing oxidation. This lowers the barrier potential and reduces the resistance to the flow of electrons between

the two sides of the barrier. The sensor has a heating element that heats the sensing element to 400-600° C. High temperature improves the sensitivity of the sensor and reduces the effect of the environment temperature variation on the sensor's output. In order to sense the change in the resistance of the sensor, a voltage divider as shown in Figure 8 was designed. The value of the load resistance was chosen so that the steady state output voltage is about 0.5 V when none of the targeted gases is present in the sample.

The Controlled Environment
A semi-sealed box with 235mm x 180mm x 210 mm dimensions and effective volume of about 5400 cc was used as the controlled environment. The box contains a small fan to ensure a more homogeneous concentration of the contents. The three selected sensors were attached to the box cover as shown in Figure 9 below.
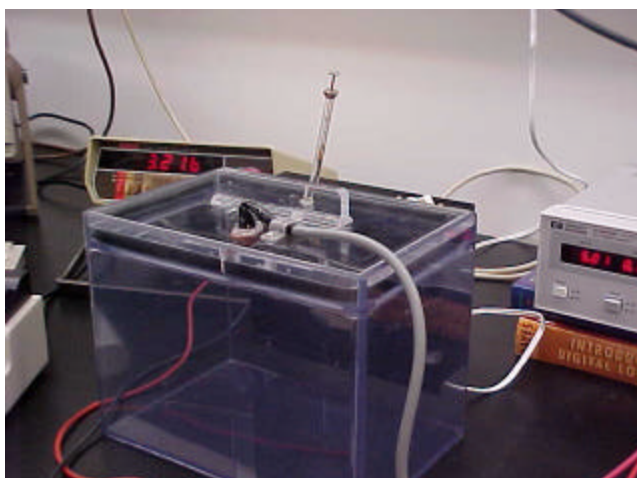

Figure 9 The Testing Controlled Environment

Before injecting any chemicals, the system was powered up and sensors were allowed to reach their steady state temperature before starting the experiment. This is done by monitoring the output voltage of the sensor using a voltmeter.

Training the System

As mentioned earlier, ANN learn by examples or experience and are data-controlled. In order to train our RANN, a set of examples has been prepared. The following procedure describes how the data was collected.

A. Power the system up with TGS813, TGS203, and TGS2620 and wait for the steady state condition by monitoring the output voltage of the sensors to reach its steady state voltage.
B. Inject the standard low gas levels (corresponds to low vehicle emission) into the box.
C. Wait for system to reach steady state voltages.
D. Read the output voltages of the sensors.
E. Flush the system using pure nitrogen (zero gas).
F. Repeat steps A-E with target gas concentrations mid1, mid2, and high.

Table 1 Output voltage of the three sensors when exposed to target gases

	TGS813	TGS203	TGS2620
Zero Gas	0.944	0.76	0.80
Low Gas	2.49	1.95	1.55
Mid1 Gas	3.11	2.5	2.81
Mid2 Gas	4.64	3.9	3.5
High Gas	4.64	4.75	4.2

The contents of each gas concentration are shown in Table 2.

Table 2 Content of each gas level used in the experiment

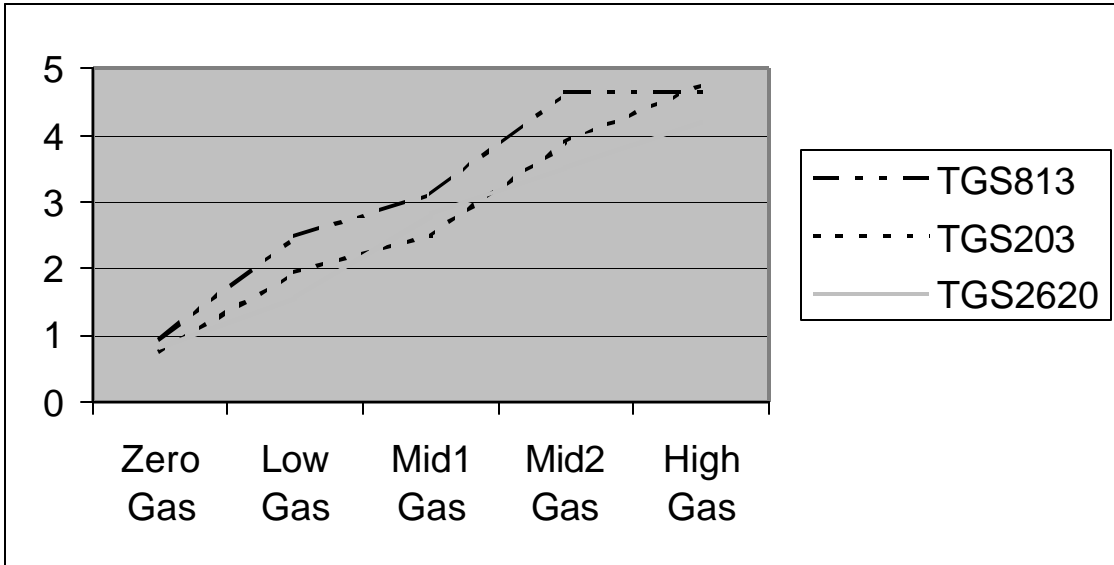|	Propane PPM	CO %	CO_2 %	NO_x PPM
Zero Gas	Zero	Zero	Zero	Zero
Low Gas	150	1.5	3.75	Zero
Mid 1 Gas	960	2.42	3.6	880
Mid 2 Gas	1925	4.81	7.2	1807
High Gas	3210	7.97	12.0	2988

Figure 10 Variation in Sensors Response to Each Mixture

From Figure 8 above, for each mixture of the ones tested or any mixture of the same ratios of the contents of CO, NO_x, and Propane, it proved to be easy to find out the concentration X by the three readings we got from the sensors, with variations to the ratios of gas concentration, the sensors respond differently. The difference is the most valuable output of the system. The RANN was trained using Matrix Laboratory (Matlab). The following weight adjustment equation has been used to find out the proper weight matrix.

$?W_{ij}=?((G_i-W_{ij})r_i+?(G_i-W_{ij})p_i)$

where $?W_{ij}$ is the change in the weight of the jth synapse to the ith neuron.

G_i is the output of the ith neuron. r_i and p_i are the reward and the penalty rates. Matlab training provided the following weight matrix to the network. It also provided a bias value for each neuron.

G = F [1 -0.7 2.1, 1 –2.1 1.5, 1 –1.5 –0.5] +[1.9 2.78 2.35]

CONCLUSIONS

Voltage mode, all-MOS, compact, and analog computational standard cells for neural network applications have been utilized to design an analog RANN. The RANN has been designed and VLSI implemented using 1.5 μm technology. The interfacing between these circuits has been discussed. It was clearly shown that these circuits are compatible, which eliminates the need for additional matching circuitry, reduces silicon area, and improves system performance, accuracy, and repeatability. The implemented analog Reinforcement Artificial Neural Network was used in this gas recognition application successfully. The number of pads limited the number of neurons in the Tiny Chip to two.

The proposed RNN has been successfully trained and was able to positively recognize three volatile organic compounds, namely Propane, Carbon monoxide, and Nitric oxide. Training was performed off-line due to silicon area limitations on training algorithm implementation. Training showed that three sensors are adequate to recognize three gases. In addition, a bias factor applied to each neuron is also important for successful operation.