SDR Input Power Estimation Algorithms

Janette C. Briones
NASA Glenn Research Center
21000 Brookpark Road MS 54-1
Cleveland, OH 44135
216-433-3382
Janette.C.Briones@nasa.gov

Jennifer M. Nappier
NASA Glenn Research Center
21000 Brookpark Road MS 54-1
Cleveland, OH 44135
216-433-6521
Jennifer.M.Nappier@nasa.gov

Abstract—**The General Dynamics (GD) S-Band software defined radio (SDR) in the Space Communications and Navigation (SCAN) Testbed on the International Space Station (ISS) provides experimenters an opportunity to develop and demonstrate experimental waveforms in space. The SDR has an analog and a digital automatic gain control (AGC) and the response of the AGCs to changes in SDR input power and temperature was characterized prior to the launch and installation of the SCAN Testbed on the ISS. The AGCs were used to estimate the SDR input power and SNR of the received signal and the characterization results showed a nonlinear response to SDR input power and temperature. In order to estimate the SDR input from the AGCs, three algorithms were developed and implemented on the ground software of the SCAN Testbed. The algorithms include a linear straight line estimator, which used the digital AGC and the temperature to estimate the SDR input power over a narrower section of the SDR input power range. There is a linear adaptive filter algorithm that uses both AGCs and the temperature to estimate the SDR input power over a wide input power range. Finally, an algorithm that uses neural networks was designed to estimate the input power over a wide range. This paper describes the algorithms in detail and their associated performance in estimating the SDR input power.**

TABLE OF CONTENTS

1. INTRODUCTION 1
2. STRAIGHT LINE ESTIMATOR 2
3. ADAPTIVE LINEAR COMBINER ESTIMATOR 3
4. NEURAL NETWORK ESTIMATOR 5
4. SNR CALCULATION 7
5. RESULTS 8
6. SUMMARY 9
REFERENCES 9

1. INTRODUCTION

The General Dynamics (GD) S-Band software defined radio (SDR) in the Space Communications and Navigation (SCaN) Testbed [1] on the ISS provides experimenters an opportunity to develop and demonstrate experimental waveforms in space. The initial GD SDR receive waveform includes three reconfigurable parameters – data rate, coding on/off, and center frequency. The receive waveform is a spread signal and is compatible with the Tracking Relay Data Satellite System (TDRSS) [2]. The S-Band RF center frequency can be changed to operate with the TDRSS Single Access (SA) or Multiple Access (MA) modes. The receive waveform can be configured to operate at two data rates – 18 and 72 kbps. The Viterbi decoder for forward error correction can be enabled and disabled. These three parameters lead to the eight different receive waveform combinations that are found in Table 1.

The GD SDR has an analog and a digital automatic gain control (AGC) that adjust the received RF power to a constant level for receive signal processing. The response of the AGCs to changes in SDR input power (from -130 dBm to -90 dBm) and temperature (from -20 °C to +60 °C) for all eight receive waveform configurations was characterized prior to the launch and installation of the SCaN Testbed on the ISS. The characterization results [3] showed a nonlinear response to SDR input power and temperature. The AGCs respond differently for all eight SDR receive waveforms. The AGCs scale based on total received RF power, so varying noise conditions or the present of interferers will affect the AGC output.

A desirable function of an SDR is to estimate the received signal input power in order to better understand and predict link performance. The AGCs on the GD SDR will be used to estimate the SDR input power of the received signal. In order to estimate the SDR input from the AGCs for all eight receive waveforms, three algorithms were developed and implemented on the ground software of the SCaN Testbed. In sections 2-4 the algorithms are described in detail and their associated performance in estimating the SDR input power. Initial performance results of the SDR input power estimators from on-orbit operations are discussed in section 5.

Table 1. GD SDR Receive Waveform Description

Waveform ID	Data Rate (kbps)	Forward Error Correction	Frequency
1	18	Uncoded	SA
2	18	Coded	SA
3	18	Uncoded	MA
4	18	Coded	MA
5	72	Uncoded	SA
6	72	Coded	SA
7	72	Uncoded	MA
8	72	Coded	MA

978-1-4673-1813-6/13/$31.00 ©2013 IEEE

2. STRAIGHT LINE ESTIMATOR

The straight line estimator uses the digital AGC and the baseplate temperature to estimate the SDR input power over a smaller section of the SDR input power range. The SDR input power range in which the straight-line estimator is valid is listed in Table 2. This is the linear range of the digital AGC.

Table 2. Straight Line Estimator Power Range

Waveform	Minimum SDR Input Power (dBm)	Maximum SDR Input Power (dBm)
SA/MA, uncoded, 18 kbps	-124.0	-111.0
SA/MA, coded, 18 kbps	-122.0	-107.5
SA/MA, uncoded, 72 kbps	-118.0	-105.5
SA/MA, coded, 72 kbps	-116.0	-103.0

Straight Line Algorithm Description

The straight-line estimator is the simplest estimator. Straight-line equations for the SDR input power as a function of the digital AGC were created using the Microsoft Excel function LINEST. In order to compensate for the differences over temperature, the baseplate temperature was divided into three bins, <10 °C (cold), 10-35 °C (ambient), and > 35 °C (hot). The digital AGC characterization results showed that the digital AGC performance was only dependent on the data rate and coding status, not the center frequency. Therefore, only four different sets of equations were created for the eight different waveform combinations described in Table 1. For example, the 18 kbps, uncoded SA and MA waveforms have the same equations for computing SDR input power from the digital AGC. Each set of equations consists of three equations (ambient, cold, and hot). Figure 1 shows the equations for the SA and MA frequencies, 72kbps, uncoded waveforms at the three different temperatures.

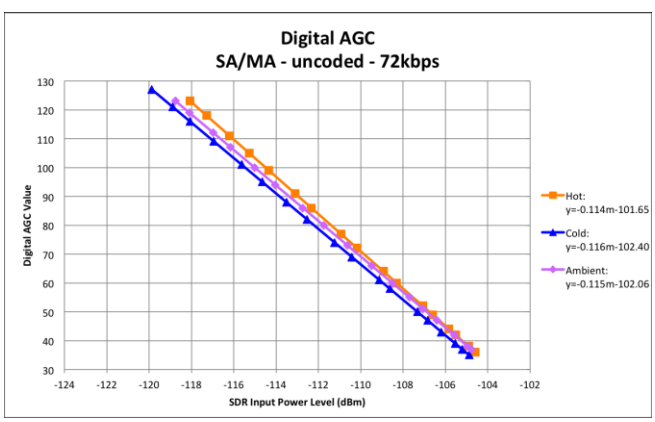

Figure 1 - Equations for Straight Line Estimator

Error Analysis

The digital AGC is only linear for SDR input power levels specified in Table 2 or less. Therefore, the straight line estimator is not valid for SDR input power levels higher than those listed in Table 2 because there will be a lot more error. The error histograms within the valid power ranges for this estimator are shown in Figure 2. A regression plot for all eight waveforms is shown in Figure 3.

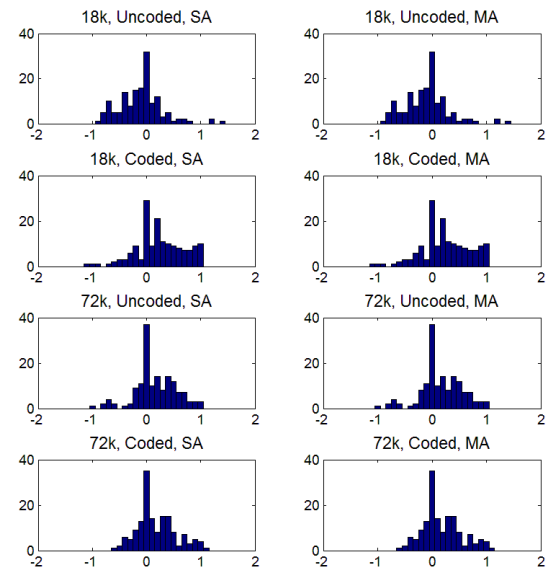

Figure 2 - Straight Line Estimator Error Histograms

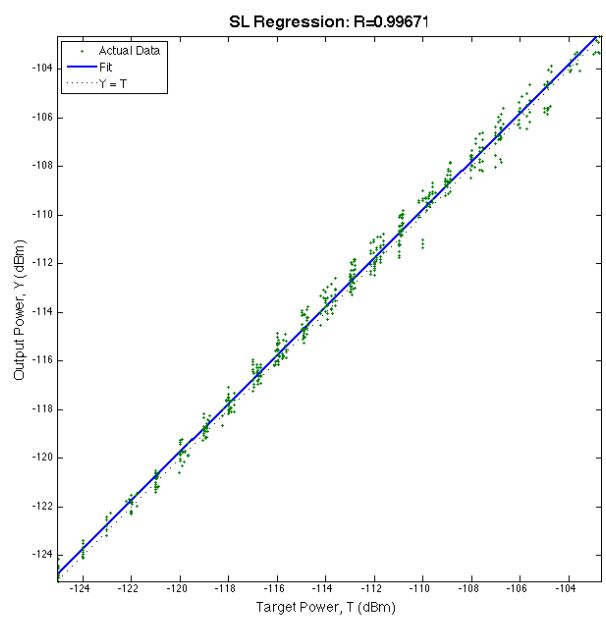

Figure 3 – Straight Line Estimator Regression Plot

3. ADAPTIVE LINEAR COMBINER ESTIMATOR

The adaptive linear combiner [4] estimator uses the digital and analog AGCs, the GD SDR baseplate temperature, and a constant to estimate the SDR input power over a wide input power range from -130 dBm to -90 dBm. The adaptive linear combiner estimator is based on the adaptive linear combiner shown in Figure 4. The inputs consisting of the digital AGC, analog AGC, baseplate temperature and a constant are multiplied by a weight vector to create the SDR input power estimate. The constant was inserted to act as the DC offset and it decreases the estimator error. During training, the SDR input power error is calculated and the weight vector is updated with the least mean square algorithm shown in equation 1. After the weight vector has been computed, the estimated SDR input power can be calculated as shown in equation 2.

$$W_{n+1} = W_n + \alpha[A_n - W_n X_n]X_n' = Wn\,X \tag{1}$$

$$Y_n = W_n X \tag{2}$$

$$W = \begin{bmatrix} W_{DAGC} \\ W_{AAGC} \\ W_{TEMP} \\ W_{const} \end{bmatrix} \tag{3}$$

$$X = [DAGC\ AAGC\ Temp\ 50] \tag{4}$$

where

W = weight vector

X = digital AGC, analog AGC, baseplate temperature, and a constant

A = actual measured SDR Input Power

Y = estimated SDR input power

α = loop update gain factor

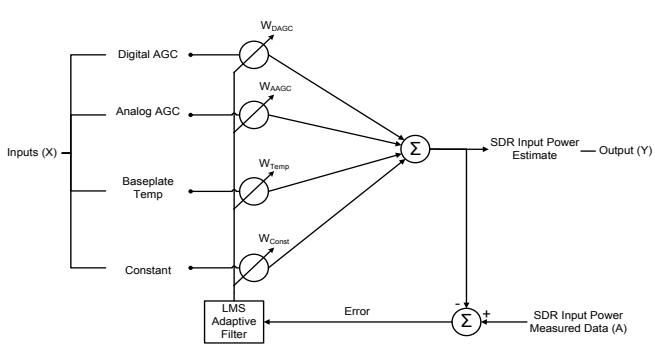

Figure 4 - Adaptive Linear Combiner

Adaptive Linear Combiner Algorithm Description

A general outline of the adaptive linear combiner training algorithm is listed below:

(1) Input the training data set, which consists of the digital AGC, analog AGC, baseplate temperature, and measured SDR input power.

(2) Sort the data into 3 temperature bins (<10 °C - cold, 10 °C – 35 °C –ambient, >35 °C – hot). These temperature bins were chosen based on the linear regions of the training data.

(3) Randomize the data in each bin in order to eliminate trends that might be created by sorting by SDR input power or temperature.

(4) Initialize the weight vector, W.

(5) Compute the weight vector for each temperature bin.

(6) Repeat the previous step using the last value for the weight vector as the initial value for the next weight vector until the weight vector converges.

(7) Calculate the estimated output power, Y, using the weight vector and analyze the error.

Temperature Membership Functions

In a nonlinear system, a set of linear equations can be used to approximate the nonlinear system if the system is divided into smaller linear segments. In this system, the response of the AGCs to changes in temperature is nonlinear so the data set was divided into three temperature bins and weight vectors were calculated for each bin (Wc, Wa, Wh). The temperature bin were <10 °C (cold), 10-35 °C (ambient), and > 35 °C (hot). In order to smooth the output power calculation when transitioning between the temperature bins, triangular membership functions were created. A membership function is a way of classifying the probability that a particular data point is within a given range. In this case, the temperature was divided into three bins and membership functions were chosen subjectively. The membership functions are shown in Figure 5. If membership functions were not used, there would be a discontinuity when the temperature crosses the bin boundaries. If the temperature falls between the ambient and the cold temperature bins, the estimated SDR input power is a function of both the cold (Wc) and the ambient (Wa) weight vectors. For example, if the temperature is 17.5 °C, the estimated SDR input power is shown in equation 5.

$$Y = .2W_c X + .8W_a X + 0W_b = +.2W_c X\ Wn\ X \tag{5}$$

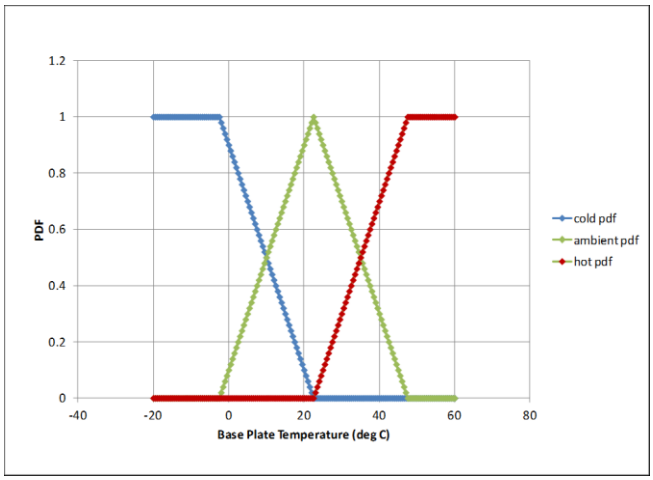

Figure 5 - Temperature Membership Functions

Randomized Input Data

The data set used to compute the weight vector was randomized. If the data set was sorted by SDR input power before computing the weight vector, the weight vector would change with the SDR input power and never converge to an average value. The goal was to achieve an average weight vector over all SDR input powers, and this requires a randomized data set.

Weight Vector Convergence and α

The weight vector, W, is computed through many loop iterations of equation 1. The mean square error of the estimated SDR input power error is minimized while computing W. In each loop iteration, W is updated with a gain factor, α. A larger α will lead W to converge to a final value faster. Less loop iterations are needed with a larger α. However, a larger α will also lead to larger standing oscillations in W. Large standing oscillations in W can be a source of error bias in the output of the estimator. Since the data is randomized differently each time W is calculated from the data set, a large standing oscillation could lead to a different W and a different error bias. This problem can be solved by choosing an α (and corresponding number of loop iterations – a smaller α will need more loop iterations) small enough so that the error bias will not produce a significant fluctuation in the output.

For this estimator, the peak to peak amplitude of the W vector oscillation must be in the 10-4 decade or less. This will produce less than .1 dB of variation in the SDR ouput power estimate every time W is calculated. The peak to peak amplitude of the last 100 iterations in the W calculation is shown in Figure 6. The peak to peak amplitude also varies due to the sources of error from the data collection. The weight vectors with the highest peak to peak amplitude are from the waveforms in which the most data was collected (18k, uncoded, SA & MA), and thus the most variation.

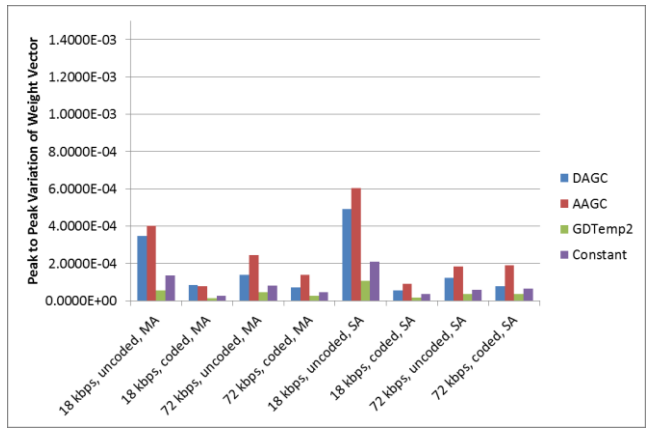

Figure 6 - Ambient Weight Vector Variation

Error Analysis

The goal for the estimator error is to be within +/- 1 dB of the actual measured SDR input power for SDR input power between -130 dBm to -90 dBm. Histograms of the error for each waveform are shown in Figure 7. The two waveforms with the most error (18k, uncoded, SA & MA) are the waveforms in which the data set was the largest. This error is attributed to variation in test setup and the measured SDR input power calculation. Another source of error is due to the fact that the digital AGC will vary +/- 3 units for a constant SDR input power. A regression plot of all eight waveforms is shown in Figure 8.

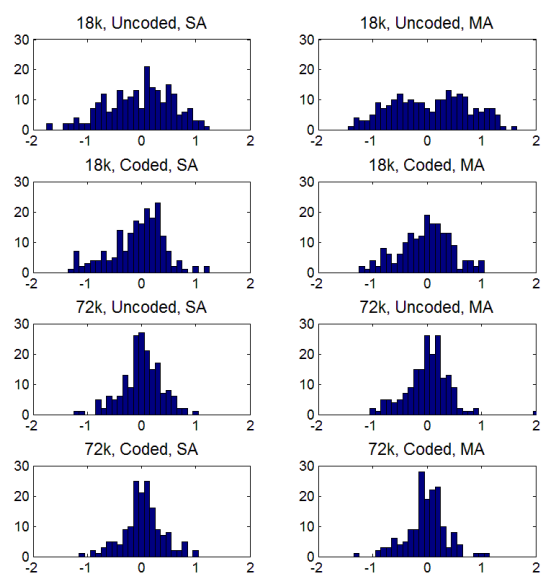

Figure 7 - Adaptive Linear Combiner Estimator Error Histograms

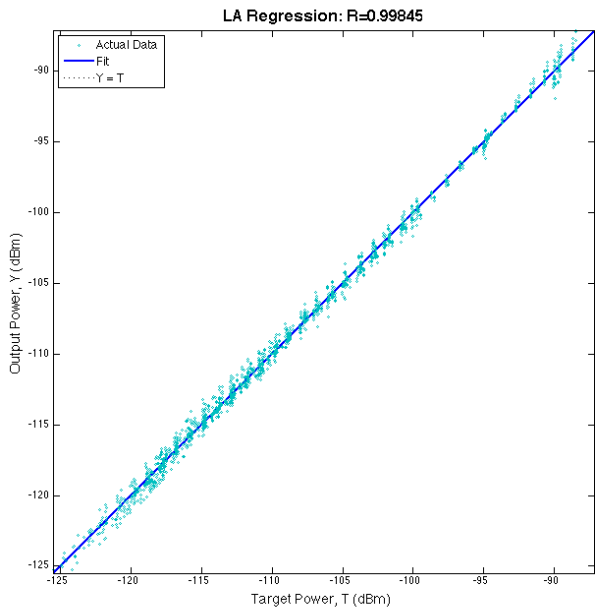

Figure 8 - Adaptive Linear Combiner Estimator Regression Plot

4. NEURAL NETWORK ESTIMATOR

The neural network estimator uses the digital and analog AGCs, the GD SDR baseplate temperature, and a waveform ID to estimate the SDR input power over an input power range from -130 dBm to -90 dBm. A block diagram of the neural network estimator is shown in Figure 9. The neural network estimator is based on a feed-forward neural network as described in [5]. The neural network is based on a feed-forward neural network, shown in Figure 10 which consists of a single hidden layer with 20 neurons in one hidden layer, with the tangent sigmoid as the transfer function in the hidden layer and a linear transfer function in the output layer. The network has one output neuron, because there is only one target value associated with each input vector. The input vector consists of the digital AGC, analog AGC, the SDR baseplate temperature, and the waveform ID. The target vector is the measured SDR input power. The neural network estimator was implemented in Excel to mimic the neural network estimator model so it could be implemented in the ground software for the SCaN Testbed.

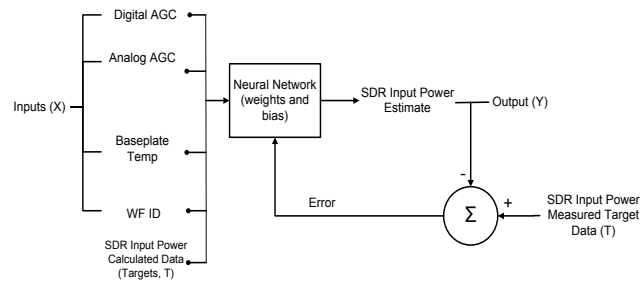

Figure 9 - Neural Network Estimator

Neural Network Estimator Algorithm Description

A general outline of the neural network estimator is listed below:

(1) Input the training data set, which consists of the digital AGC, analog AGC, baseplate temperature, waveform ID (X) and measured SDR input power (T).

(2) Create feed-forward neural network

   a. Train the neural network.

   b. Simulate the neural network.

   c. Obtained weights and bias.

(3) Normalize the input and target vector by obtaining the max and the min values, using equation 6.

For steps 4 through 6 see Figure 10.

(4) Calculate the sum of the weighted inputs and the bias, Sm using equation 7.

(5) Calculate the output to the tangent sigmoid transfer function, a, based on output from step 4, using equation 8.

(6) Calculate the sum of the layered weighted inputs and the bias, yn, using equation 9.

(7) Denormalize the vectors using equation 10.

(8) Calculate the estimated SDR input power, Y, as shown in equation 11, using the weights and bias obtained from the neural network.

(9) Compare the output (Y) to SDR input power measured target data, T.

(10) Analyze the error; train and simulate the neural network to obtained new weights and bias if necessary.

Weight and Bias Vectors Description

The feed-forwad neural network was implemented in a Matlab function to obtain the weights (*IW, LW*) and bias ($bias_1$, $bias_2$) vectors to be used in the neural network estimator algorithm. The weights and bias were iteratively updated to minimize the mean square error function between the target and the SDR input power estimate and to obtained the optimal weights vector. The weights and bias vectors have been input in the ground software for the SCaN Testbed and are used to calculate the SDR input power in real time.

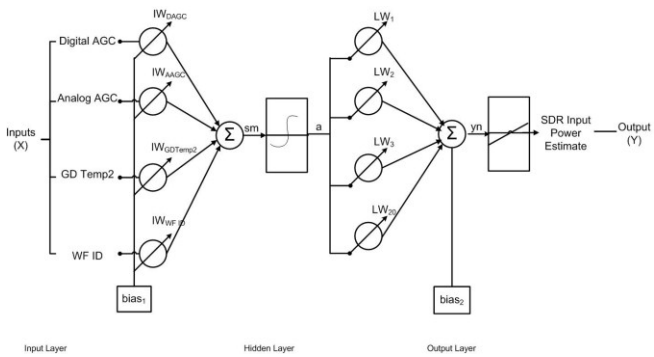

Figure 10 – Feed-forward Neural Network

$$X_n = \frac{\left(\frac{(X_n - \min X_n)}{(\max X_n - \min X_n)} - 0.5\right)}{0.5} \tag{6}$$

where

n = Number of inputs

X_1 = Digital AGC

X_2 = Analog AGC

X_3 = GD Temp2

X_4 = WFID listed in Table 1

$$S_m = \sum_{X-1}^{n} X'_n * IW' + bias_1 \tag{7}$$

$$a = \left(\frac{2}{(1 + e^{-2*sm})}\right) - 1 \tag{8}$$

$$y_n = \sum_{1}^{n} a' LW' + bias_2 \tag{9}$$

$$X = 0.5(y_n + 1) * (\max t - \min t) + \min t \tag{10}$$

$$Y = m * x + b \tag{11}$$

Training and Simulation

After the network was created and all weights and biases have been initialized, the neural network was trained, so that a particular input lead to a specific target output, the SDR input power measured data.

The network used the Levenberg-Marquardt algorithm for training. The algorithm is performed in such a way to minimize the mean square error between the SDR input power estimate and the target value, the SDR input power measure data, and the weight correction. The mean square error of the SDR input power error is minimized while the network is trained to search for the optimal weights vector. Equation 12 is used to update the weights. The learning rate, which is multiplied by the negative of the gradient, determines the changes to the weights and biases. If the learning rate is set too large, the algorithm is unstable and if is set too small, the algorithm take a longer time to converge.

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \tag{12}$$

where Δwij is the weight modification term weights, this term is added to the weight at the weight updating, and η is the learning rate.

The function randomly divides input vectors and target vectors into three sets as follows: 60% are used for training, 20% are used to validate that the network is generalizing. The last 20% are used as a completely independent test of network generalization.

The Levenberg-Marquardt algorithm was used for faster convergence and because is able to obtain lower mean square errors.

After the network is trained, a simulation process is performed to check that the SDR input power estimate has low error with respect to the measured SDR input power. If the simulation reveals data outside the fit line as shown in Figure 11, that randomness indicates that the model does not properly fit the data and since the goal is to extract the weights and the bias vectors from this simulation, then it is important that the model reflects a good fit. The data outside the fit line is the difference between the measured SDR input power data and the values that the neural network model predicts, estimated SDR input power data. This training process is repeated until there is a good fit so it can provide a more reliable estimate. The Target in the x-axis of Figure 9 is the measured SDR input power data and the Output on the y-axis is the output generated by the neural network (estimated SDR input power). Figure 12 is the final result of the training process and it shows that there is a good fit between the measured and estimated SDR input power and therefore, low error. It indicates that the weights and the bias vectors are the final set to be used in the algorithm for estimating SDR input power.

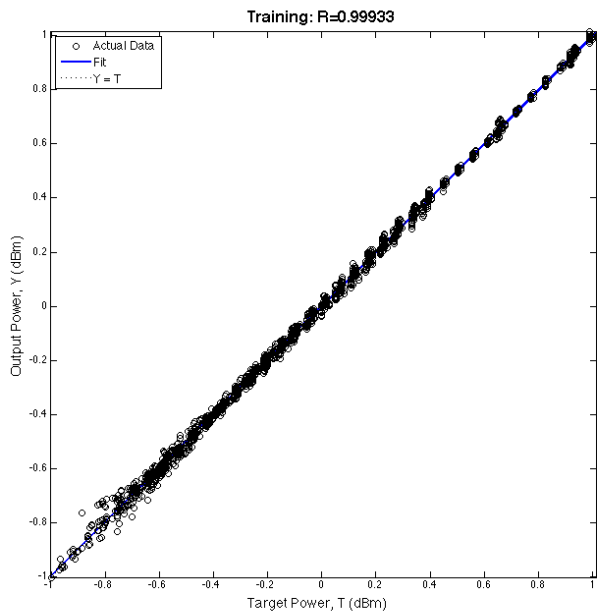

Figure 11 – Neural Network Estimator Regression Plot (Training)

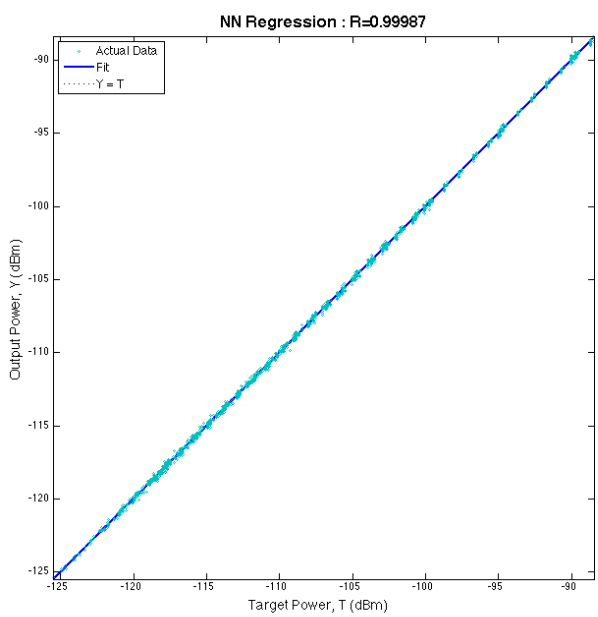

Figure 12 – Neural Network Estimator Regression Plot (Final)

Error Analysis

The goal for the estimator error is to be within +/-.5 dB of the actual measured SDR input power for SDR input power between -130 dBm and -90 dBm. Histograms of the error for each waveform are shown in Figure 13.

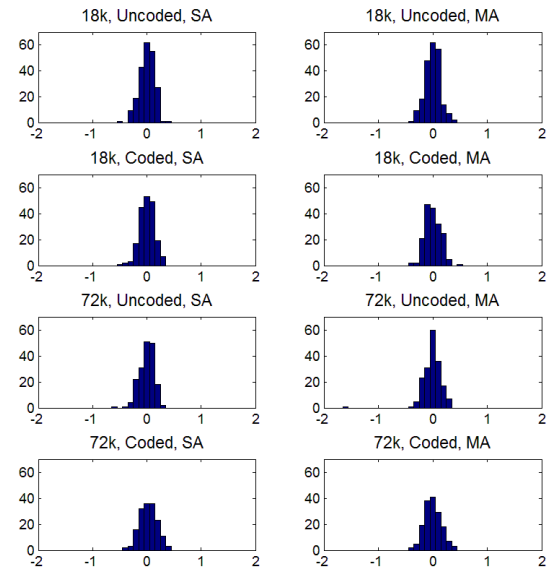

Figure 13 - Neural Network Estimator Error Histograms

4. SNR CALCULATION

The SNR can be calculated from the estimated SDR input power. The equations used in this test to calculate the SNR are listed below in equations 13-15. This method assumes a constant noise floor and was used extensively during the pre-launch testing phase on the ground for the SCaN Testbed. Since the AGCs detect total SDR input power, if the noise conditions change or there are interferers present, this method of computing the SNR may not be valid in those situations. It will be used in the coming months to calculate the SNR and create bit error rate (BER) curves while characterizing the GD SDR receiver performance on the ISS in a variety of noise and interferer conditions. This data will be used to determine if and or when these equations can be used to calculation the SNR.

$$E_b = P_{in} - 10log10(Data\ Rate) \tag{13}$$

$$N_o = -\frac{174dBm}{Hz} + NF \tag{14}$$

$$SNR = E_b - N_o \tag{15}$$

where

E_b = Energy per bit

N_o = Noise power spectral density

P_{in} = SDR calculated input power from AGCs

-174dBm/Hz = Theoretical noise floor

NF = Receiver noise figure

Data Rate = 18000 or 72000

5. RESULTS

Implementation in Ground Software

Each SDR input power estimator was implemented in the ground software for the SCaN Testbed. The benefit of implementing the estimators in ground software over flight avionics software or radio software is that the estimators are much easier to update and they do not use the limited flight resources. The varying parameters for each estimator were placed in a configuration file, so when the parameters need to be updated, all that needs to be done is edit the configuration file. This implementation keeps with the spirit of design for software defined radios. If a new waveform is developed, the ground software configuration file can be updated with the new waveform, but no code changes to the SDR input power estimator algorithms will be necessary.

The AGC telemetry from the GD SDR will vary slightly with the constant SDR input power. This variation can lead to a variation of several dB in the SDR input power estimator. In order to minimize this variation to less than .5 dB, a moving average filter of 5 samples was implemented in the SCaN Testbed ground software. The AGCs and temperature telemetry are sent to the moving average filter before being input into the SDR input power estimator. This leads to a much more stable, yet still responsive power estimate.

Initial Results from Operation on the International Space Station

The GD SDR input power estimators were first used during the initial installation checkout of the SCaN Test on the ISS in September 2012. During checkout, the operation of all subsystems on the SCaN Testbed was verified. The GD SDR input power was predicted using Satellite Tool Kit (STK) models and the input power estimators were used to estimate the GD SDR input power during communication passes with TDRSS. The 18 kbps, uncoded, SA receive waveform was used because the most data was collected for this GD SDR waveform. Three passes were completed in September 2012 with GD SDR baseplate temperatures ranging from +4 to +9 °C. Initial results are shown in Figure 14 to Figure 16.

The tests that were completed on 09/13/12 show that the linear adaptive and the neural network estimators are within 2 dB of the predicted power. The SDR input power was higher than the valid range for the straight line estimator and this accounts for the error. In the middle of the first pass, an unknown interferer began and this can be seen in the variation of the input power estimate. The test completed on 09/26/12 shows that all three SDR input power estimators are within 2 dB of the predicted power.

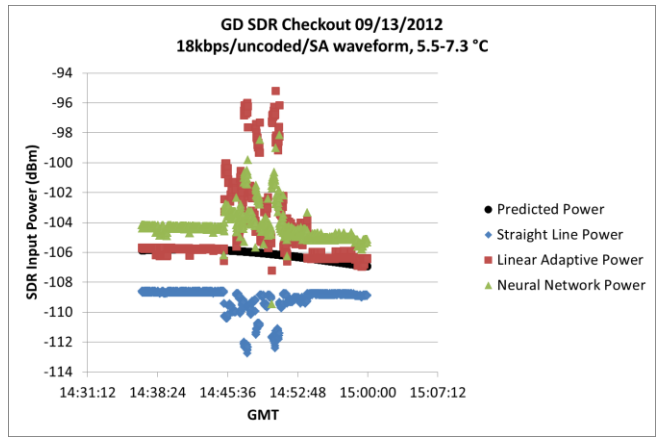

Figure 14 - GD SDR Checkout 09/13/12 Pass 1

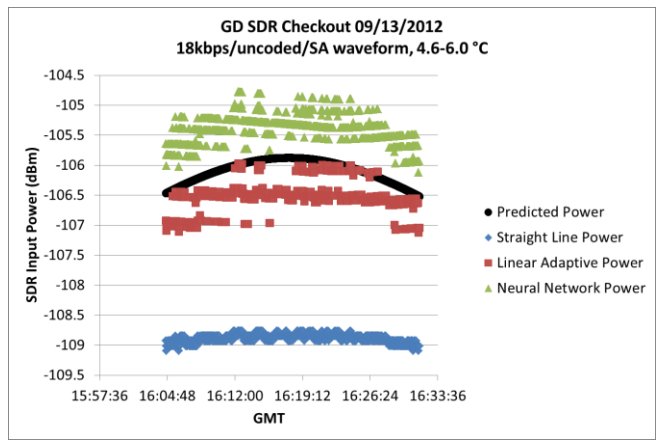

Figure 15 - GD SDR Checkout 09/13/12 Pass 2

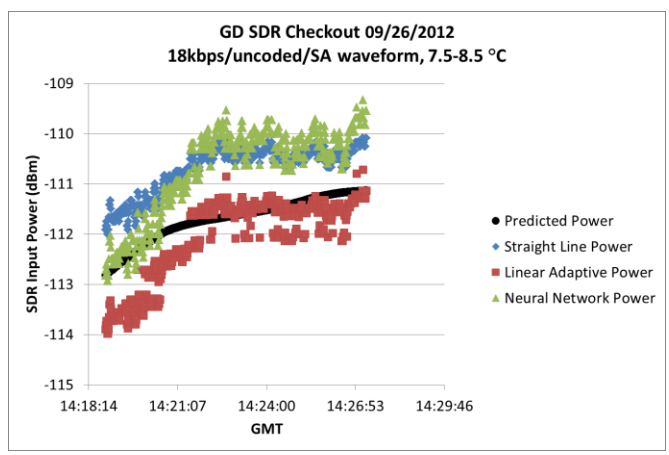

Figure 16 - GD SDR Checkout 09/26/12

6. SUMMARY

Three SDR input power estimators have been created to calculate the SDR input power from the digital AGC, analog AGC, and baseplate temperature. The estimators include a straight line estimator, an adaptive linear estimator, and a neural network estimator. This paper describes each algorithm in detail. Initial on-orbit test results indicate that the estimators perform within 2 dB of the predicted SDR input power for the 18 kbps, uncoded, SA receive waveform. In the future, the three SDR input power estimators will be characterized on orbit for all eight waveforms over a wider operating temperature range and many different SDR input power levels. Recommendations will be made on which algorithm is better for particular operating conditions. The SNR estimation method will also be characterized to determine the conditions under which it can be used.

REFERENCES

[1] S. Johnson, R. Reinhart, and T. Kacpura. "CoNNeCT's Approach for the Development of Three Software Defined Radios for Space Application," presented at the IEEE Aerospace Conference, March 2012.

[2] Space Network (SN) User's Guide, 450-SNUG (Revision 9, August 2007).

[3] J. Nappier and J. Briones. "GD SDR Automatic Gain Control Characterization Testing," to be presented at the Wireless Innovation Conference in Washington, D. C., January 2013.

[4] B. Widrow and M. Lehr. "30 Years of Adaptive Neural Networks: Perceptron, Madaline, and Backpropogation." Proceedings of the IEEE, vol. 78, no. 9, pp. 1415-1442, September 1990.

[5] S. Haykin. "Neural Networks A Comprehensive Foundation." Second Edition. Prentice-Hall Inc, 1999.

Biographies

Janette C. Briones *received a M.S. in Computer Engineering from University of Texas at El Paso, El Paso in 2005. She has been with NASA Glenn for more than 6 years and is currently working on the GD SDR S-Band Experiment for the SCaN Testbed Project.*

Jennifer M. Nappier *received a B.S. in Electrical and Computer Engineering from Ohio State University in 2006 and a M.S. in System and Controls Engineering from Case Western Reserve University in 2009. She has worked for NASA Glenn for 7 years and is currently the GD SDR S-Band Experiment Lead on the SCaN Testbed Project.*