Neural Networks Based Approach to Enhance Space Hardware Reliability

Ricardo S. Zebulum* Anilkumar Thakoor Thomas Lu

Lauro Franco Tsung Han Lin S. S. McClure

Jet Propulsion Laboratory
California Institute of Technology
Pasadena CA 91109

08/04/2011

Outline

- Background
- Motivations
- Artificial Neural Networks Applied to Device Modeling and SPICE Integration
- Case Studies:
  - Zener 1N6634;
  - Bipolar transistor 2N2222;
  - Voltage regulator IS1009 2.5V;
  - Diode 1N6642
  - OpAmps AD8138 and LT1499;
- Convergence Issues;
- Conclusions.

Device Modeling - Background

- As a critical step in the Flight hardware design process, the Worst Case Analysis (WCA) of electronic hardware provides a quantitative assessment of circuit performance, accounting for the manufacturing tolerances as well as the mission-specific environmental, aging, and radiation effects.

- Essential for the WCA is the availability of accurate SPICE models for electronic components used in the circuits, which are usually of limited accuracy or not available. Current solutions to these problems are device modeling by specialists; or the use of extreme conservative analysis such as EVAs. The former is costly and time consuming; and the later usually leads to over-design.

Motivations

- This works proposes the use of Artificial Neural Networks as an alternative solution to device modeling;

- Artificial Neural Networks (ANN) are computational models loosely based in the nervous system, successfully used in applications such as pattern recognition, series forecasting and others;

- Can be used as an autonomous modeling tool for electronic components that will produce and deliver accurate SPICE (*Simulation Program with Integrated Circuit Emphasis*) models of virtually any component at a variety of environmental conditions from limited or incomplete test data;

- ANNs are able to learn from measured/screening data from a specific component lot and could generalize its response as it is exposed to unseen patterns;

- *Deliver more accurate simulation models, which will also be tunable to Mission environment;*

Artificial Neural Networks For Device Modeling

- ANNs can be trained to learn non-linear relationships from corresponding device I/O data, even if they are incomplete:
  - Measured data;
  - Screening data;
  - Worst Case Database (WCDB) specific for the particular Mission environment.

- This presentation demonstrates the use of ANNs for device modeling:
  - Generate a device SPICE model from scratch;
  - Improve upon existing device SPICE models provided by manufacturers;
  - Generate/Improve simulation models that accounts for Mission critical variables not accurately modeled conventionally, mainly temperature, initial device tolerance and radiation effects of Total Ionization Dose (TID).

Biological Neuron

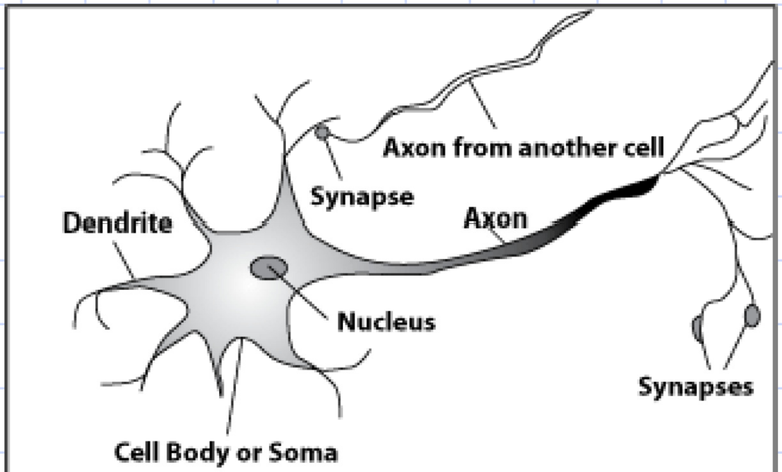
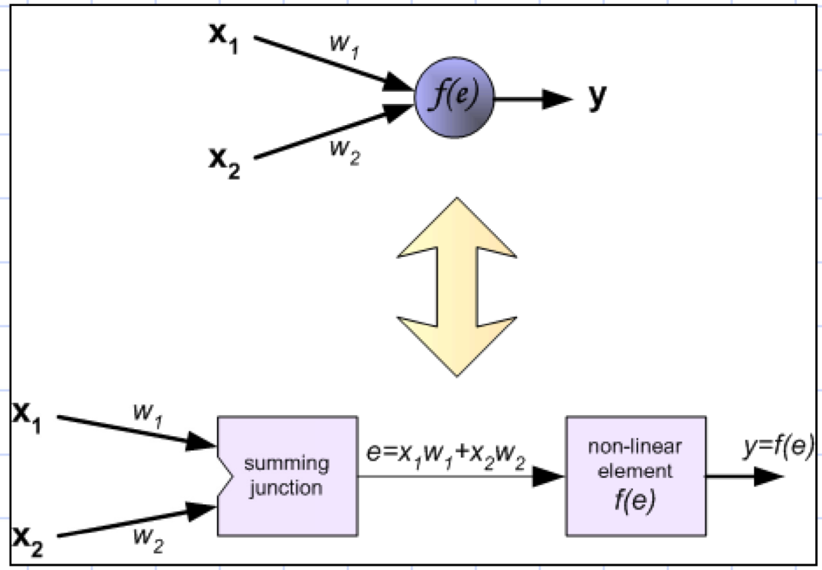
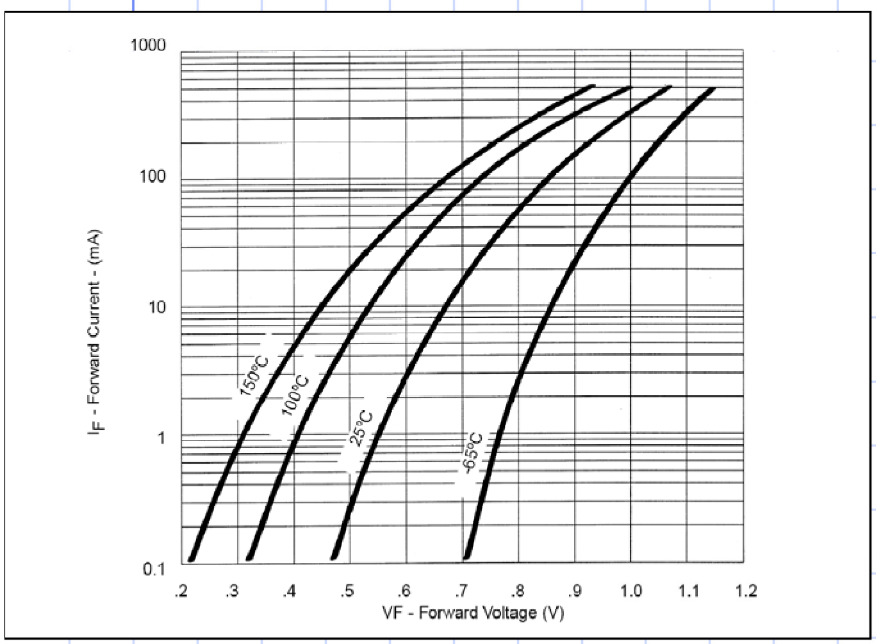


Figure 1: A Biological Neuron

Artificial Neuron





Typical diode response over temperature provided by Spec as a candidate for ANN modeling.

Integration of ANN Models into SPICE

- Instead of physical modeling , ANNs generate behavioral models for electronic devices;
- The ANN derived models are defined as a set of non-linear equations and real-valued coefficients or weights;
- These mathematical models can be seamlessly to used to define the controlled sources;
- Typical ANN model for a diode as written in SPICE format:

```
.subckt ann_diode 100 200

Gdiode1 100 200 VALUE =  {(V(95) )}

E1 1 0 VALUE = {( (V(100,200) + 5)/10 )}
V2 2 0 0.0V

E21 21 0  function 0.757871 +(-10.335355 * V(1)) +(-0.801717 * V(2))
E22 22 0  function -15.304038 +(27.702725 * V(1)) +(0.794741 * V(2))
E23 23 0  function -20.766132 +(39.259432 * V(1)) +(2.821530 * V(2))
E24 24 0  function -7.039589 +(14.522268 * V(1)) +(1.009189 * V(2))
E51 51 0  function 1/(1 + exp(-V(21)))
E52 52 0  function 1/(1 + exp(-V(22)))
E53 53 0  function 1/(1 + exp(-V(23)))
E54 54 0  function 1/(1 + exp(-V(24)))
E81 81 0  function -17.333016 +(-8.673347 * (1/(1 + exp(-V(21)))))
+(10.524507 * (1/(1 + exp(-V(22))))) +(21.503769 *  (1/(1 + exp(-
V(23))))) +(-11.787620 * (1/(1 + exp(-V(24)))))
E94 94 0  function 1/(1 + exp(-V(81)))

.ends ann_diode
```

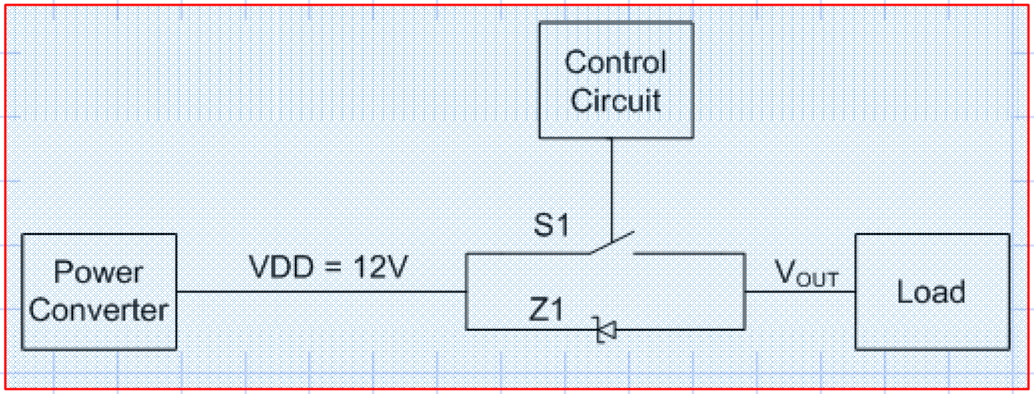
➢ *Can be exported into any SPICE simulator*

Case Studies

- A Multi-Layered Perceptron (MLP) using Backpropagation training method was used in all applications;
- The training data was prepared by a combination of real device measurements, datasheet information and calculations from Mission specific Worst Case Database, which considers the exact environmental conditions (temperature, radiation, duration) of a particular project;
- The following Flight devices were used as case studies:
  - 3.9V 1N6634 Zener;
  - 2.5 Regulator IS1009;
  - Bipolar transistor 2N2222;
  - Diode 1N6642;
  - Analog devices OpAmp AD8138;
  - Linear Technologies OpAmp LT1499;

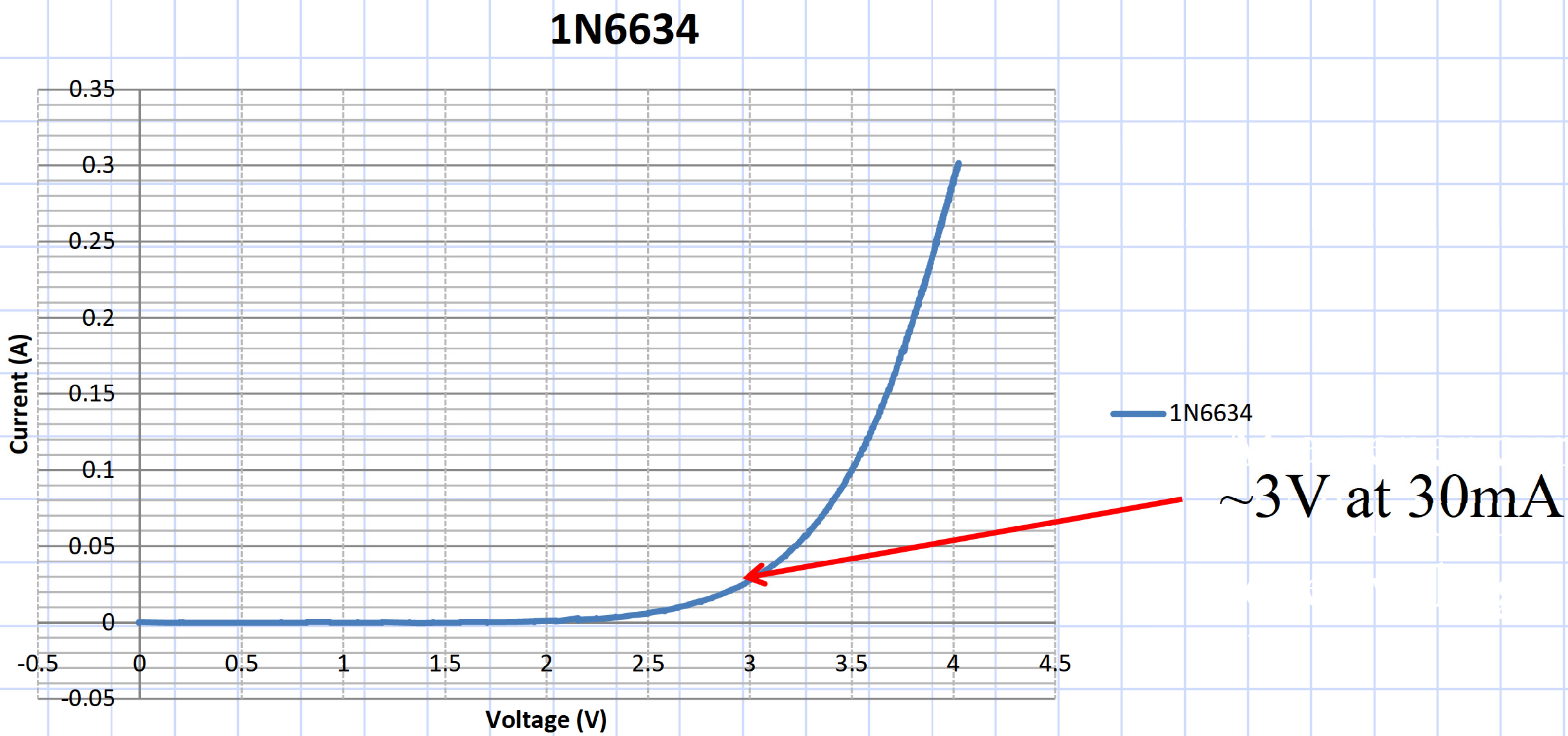
Zener 1N6634 (1)

- Discrepancy between Flight hardware behavior as measured in the laboratory and simulated behavior;
- Zener 1N6634 below, which should be clamped to 3.9V when the load is disabled, is only 3V for a load current of 30 mA;
- Due to low zener voltage when the load interface is disabled, the load is being powered to 9V.
  - At 9V some of the drivers chips are marginally on
- *The combined effect of these two issues results in erroneous state for the load interface.*

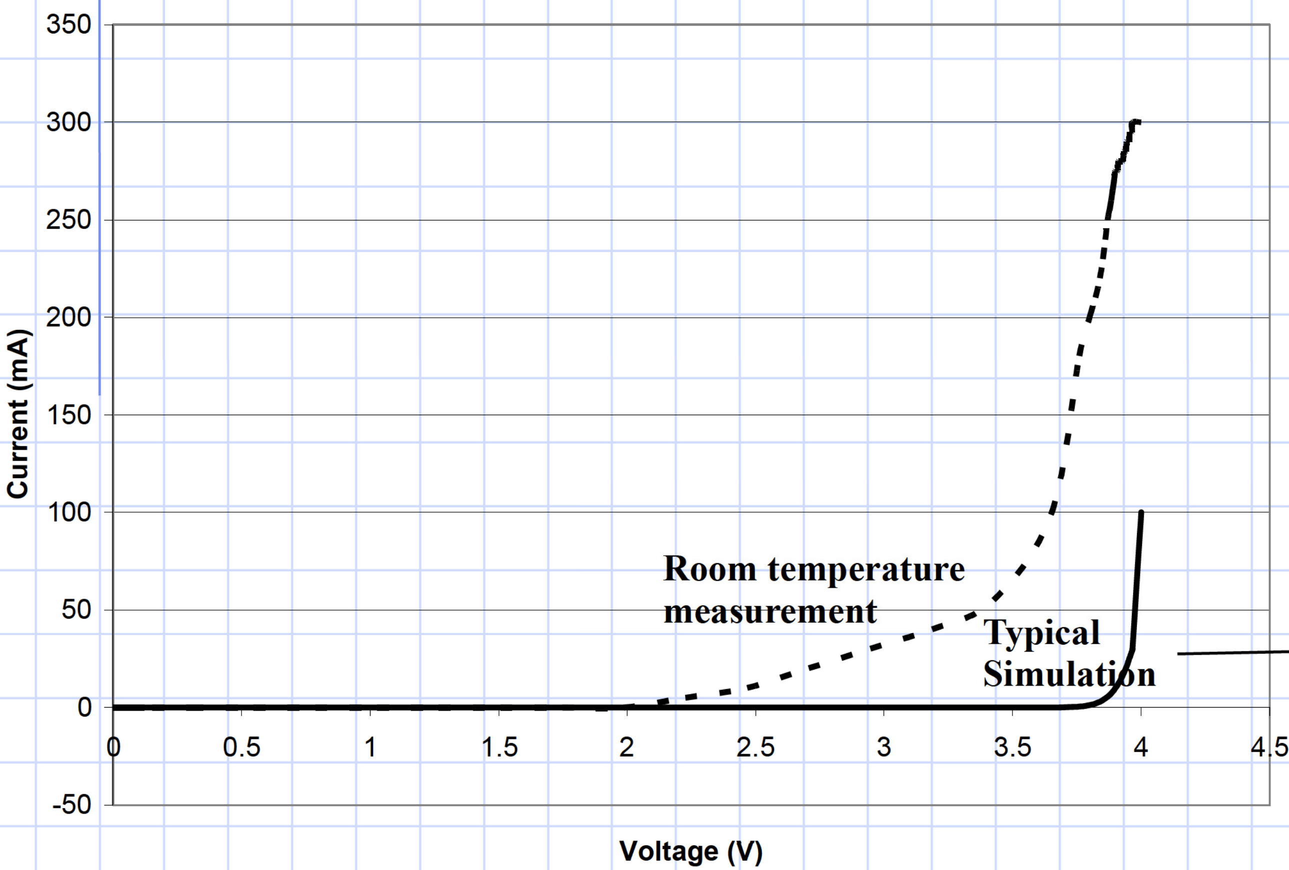


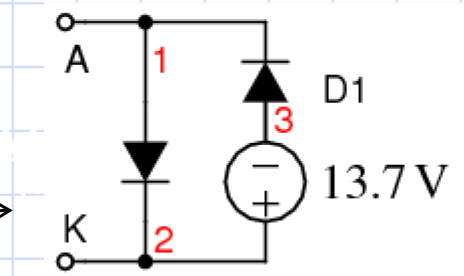
Zener 1N6634 (2): Measurements

- From below it can be seen that the 3.9V zener has a really soft knee and does not fully turn on until about 250mA.
- At 30mA, the current through Z1 when the load interface is disabled, the zener voltage is ~3V



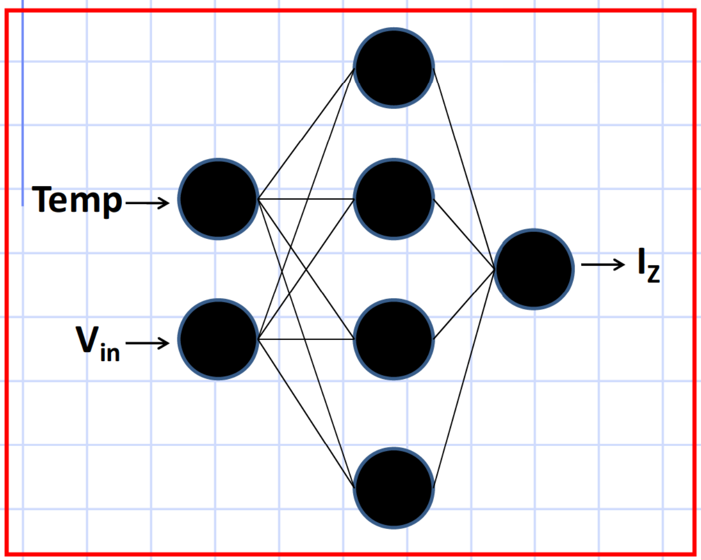
Zener 1N6634: Simulation x Actual Behavior





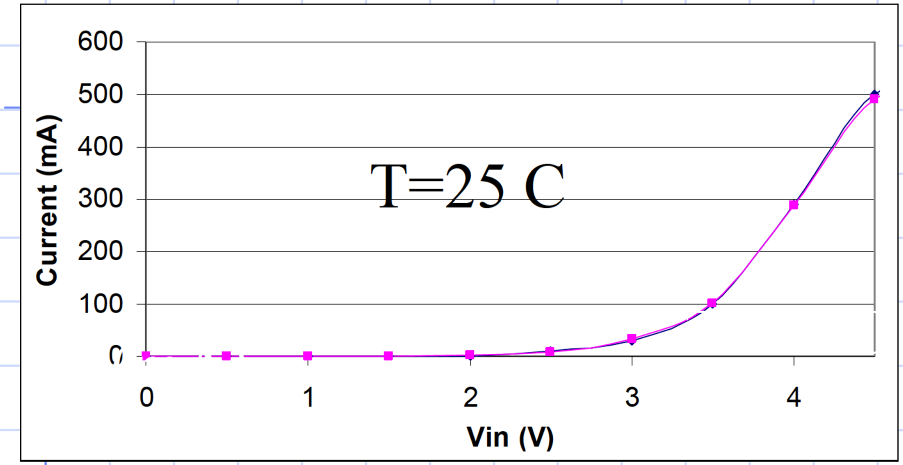
ANN Model for 1N6634

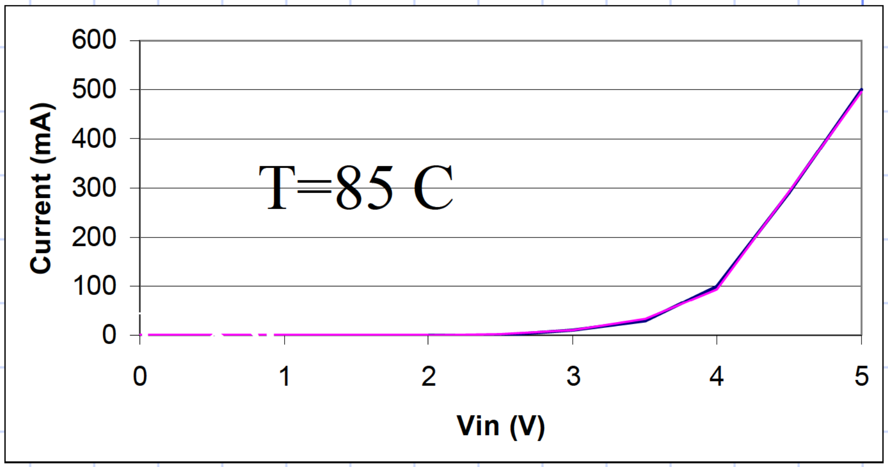
- 2 inputs: Input voltage and temperature;
- 4 neurons in the hidden layer;
- 1 output: Zener current;

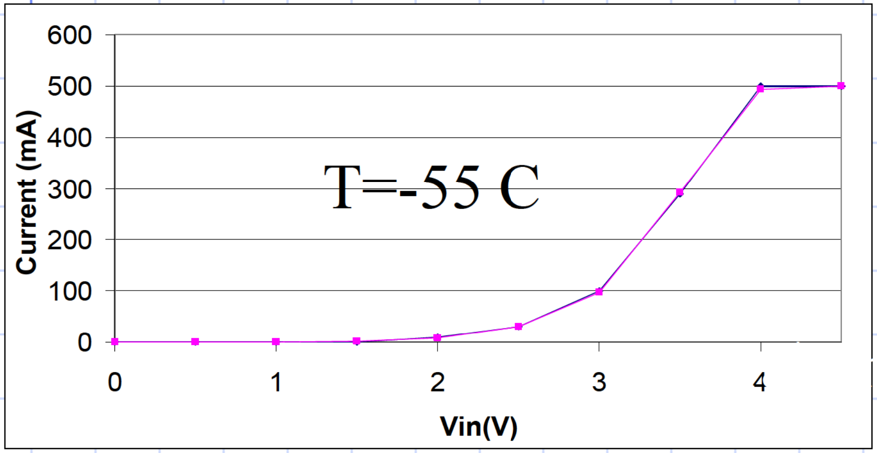


- *Training data collected both from previous measurements and by data from Worst Case Database, the latter being used to augment training set and model the diode temperature dependency.*
- *Total of 900,000 iterations, approximately 10 minutes for ANN convergence.*

1N6634: Training Result





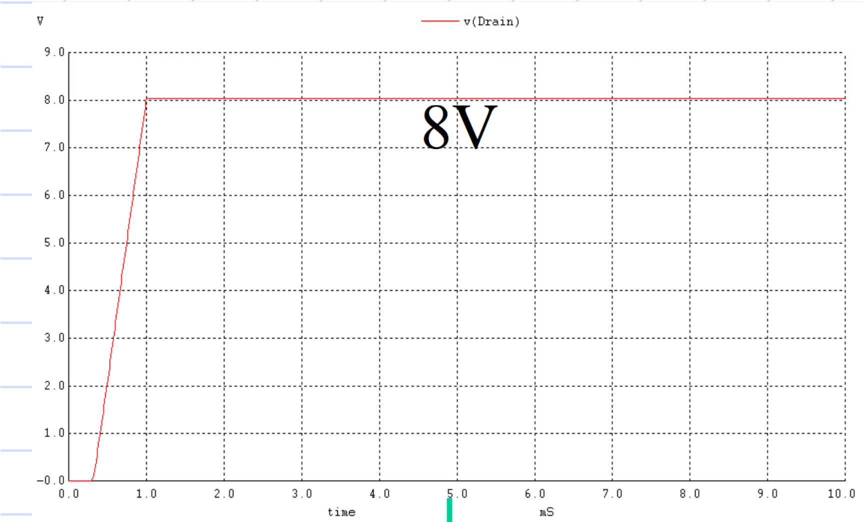


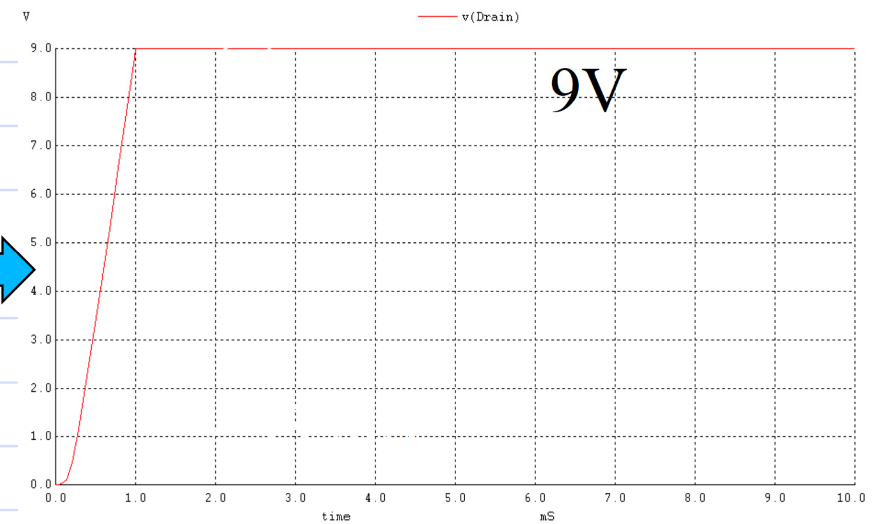
Training results (Vin x I) at three different temperatures

Target in blue, training in pink

- *Average error below 1 %;*

Simulation Comparison





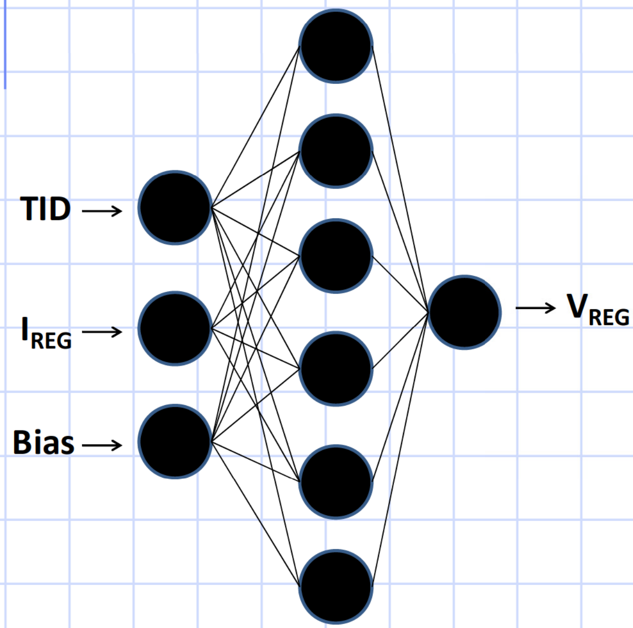
Using SPICE Model

Using ANN Model

- *ANN model correctly predicts a voltage of 9V for a load of ~ 30 mA;*
- *SPICE model predicts a voltage of 8V for a load of ~ 30 mA: simulation fails for the circuit*

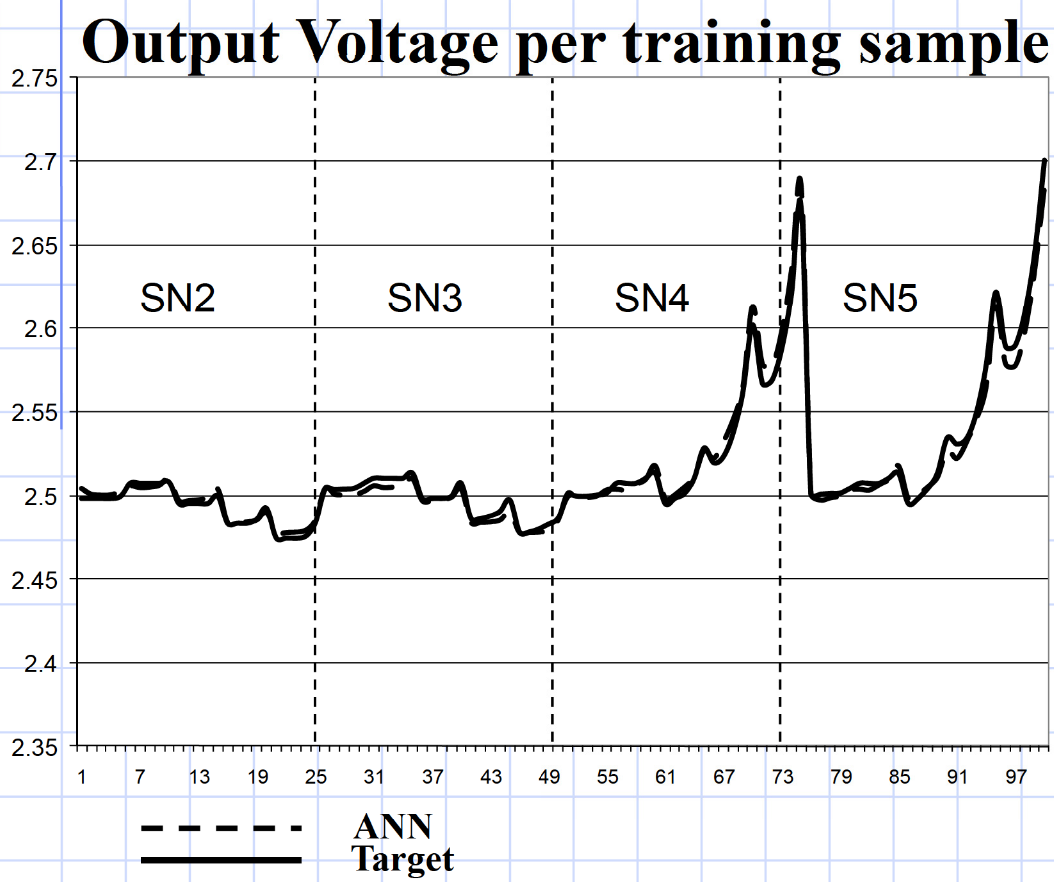
IS1009 2.5V Voltage Regulator (1)

- Topology: 3 x 6 x 1
- ANN trained using actual 514 measured data for this device for different *radiation levels* (up to 1Mrad of TID) at different regulator currents I_{REG} (from 200 uA to 10 mA). An extra binary input was also applied to the ANN, representing the state, powered or unpowered, of the device during irradiation.



➢ *After training, the maximum error between ANN output and each training sample was 0.58 %; and the average error was 0.15 %.*

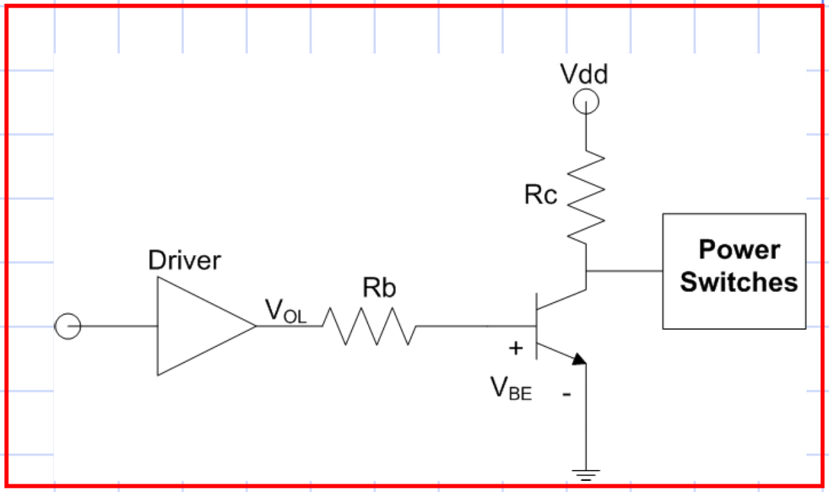
IS1009 2.5V Voltage Regulator (2)



- *Four devices were used for ANN training, serial numbers SN2, SN3, SN4 and SN5. SN1 and SN2 were unpowered during irradiation (Bias = 0); and SN4 and SN5 were powered (Bias = 1).*

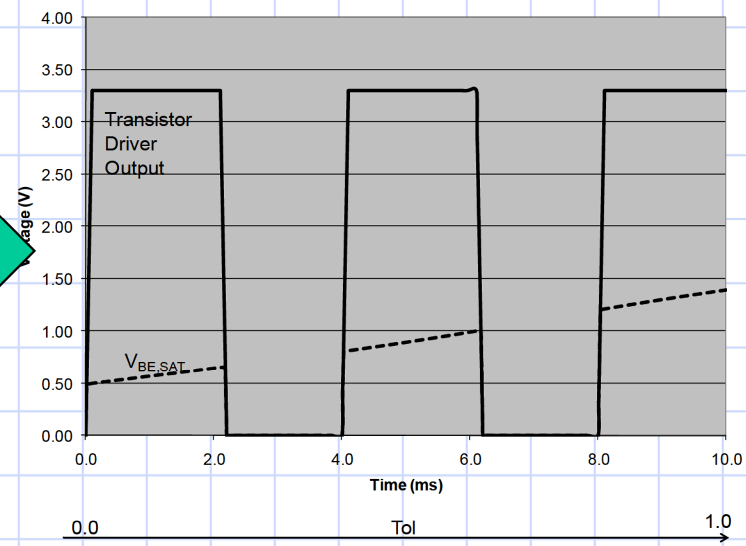
Bipolar Transistor 2N2222 (1)

- Model base-emitter junction voltage $V_{BE,sat}$;
- Critical when bipolar transistor is used as a switch: avoid unexpected transistor turn-on;
- Typical built-in simulation models produce a variation between 0.8V and 1.0V with temperature for $V_{BE,sat}$, whereas worst case variations can range from 0.47V and 1.4V ;



• Used compact ANN 2 x 4 x 1 to model this parameter;
• Two inputs, the input voltage applied at the junction, V_{BE}; and the initial tolerance *Tol*, which defines Worst Case Minimum, Nominal and Maximum values of $V_{BE,sat}$;

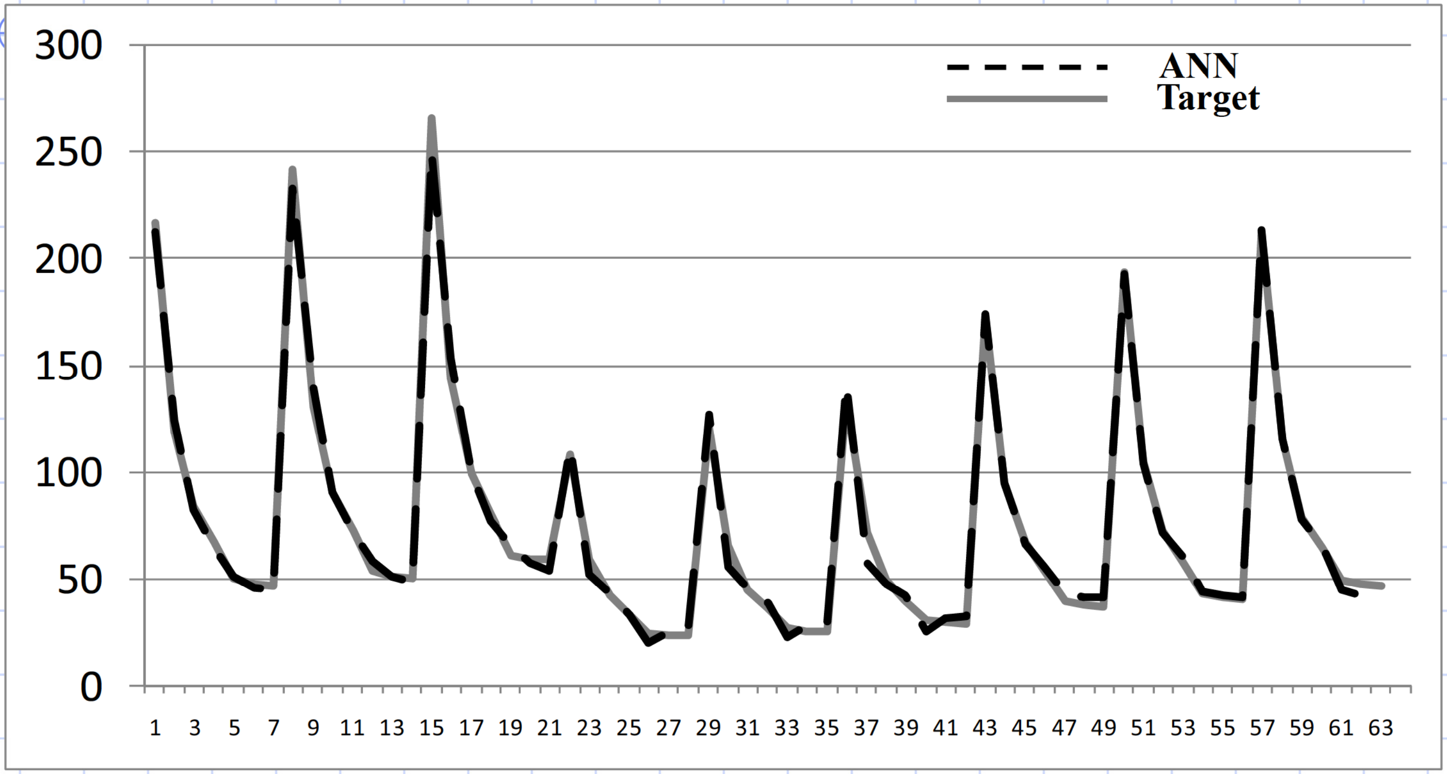
➢ *Produced ANN model, incorporated into SPICE netlist, reproduces more accurately data from WCDB;*



Bipolar Transistor 2N2222 (2)

- Model transistor gain β, which is a function of the temperature, Total Ionization Dose and transistor current;
- Three ANNs respectively generate Nominal, Minimum and Maximum values for the gain in order to capture large tolerance of the transistor gain;
- Used 3 x 6 x 1 topology:
  - Inputs are Total Ionization Dose (TID), transistor current (I_C) and temperature (Temp); and the output is the transistor gain β .
- Training data from actual radiation and temperature measurements from 514:
  - Data is further augmented into 3 sets (Minimum, Nominal and Maximum) using the Worst Case Database as a basis for extrapolating the measured data;

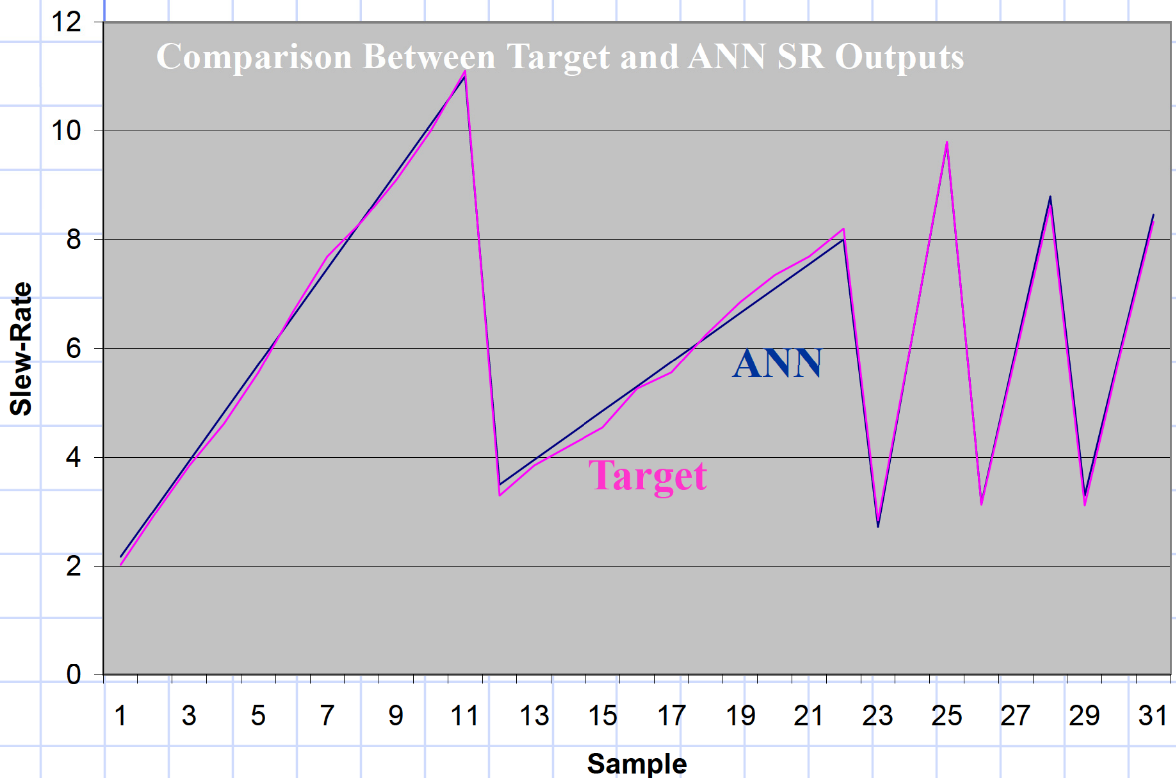
Bipolar Transistor 2N2222: Results



- *ANN able to map the training data relatively easily: the training time was less than 5 minutes and the average error was 5.7 %;*
- *Similar average error when testing ANN for data unseen during training, i.e., training for 10 and 50ºC,; testing for 30 ºC;*

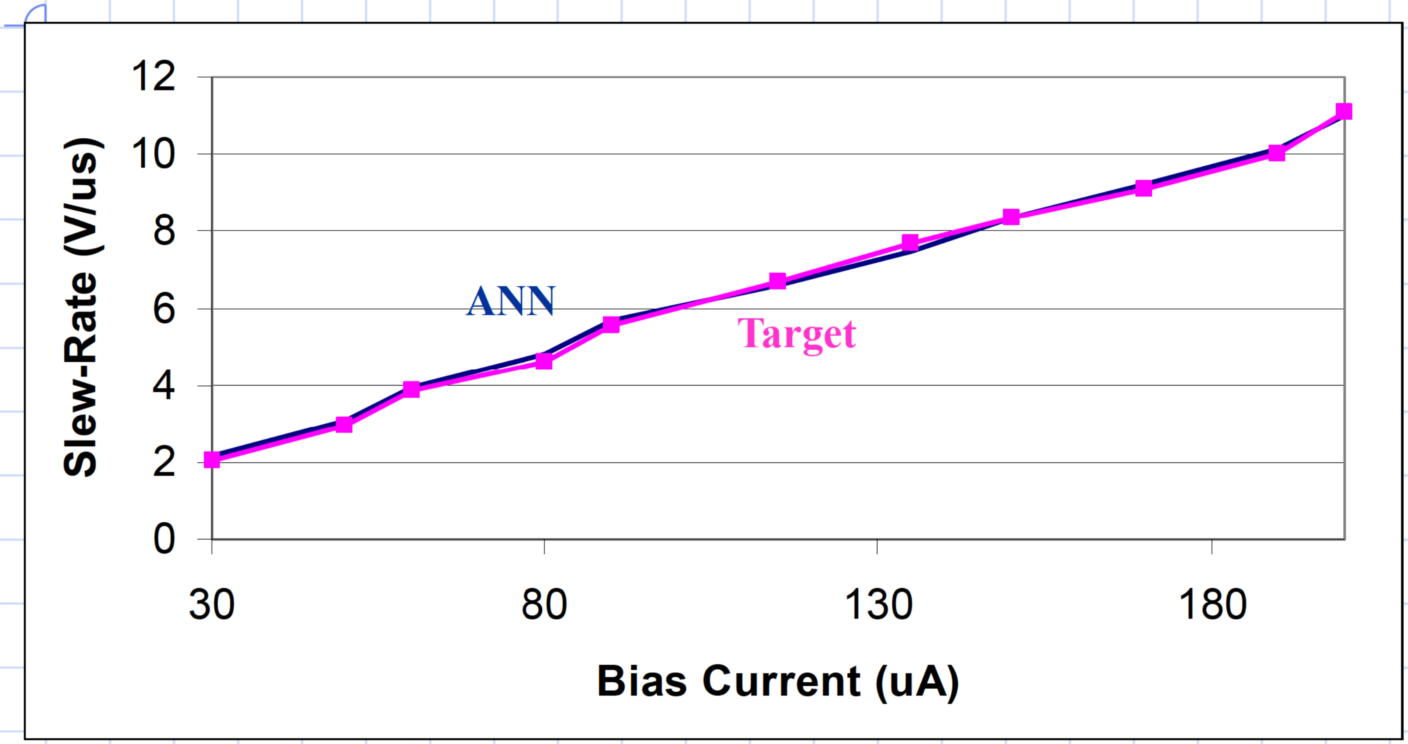
OpAmp LT1499

- Improve manufacturer provided model to characterize OpAmp slew-rate as defined per Mission Specific Worst Case Database;
- ANN Topology 4 x 8 x 1:
  - 4 inputs: temperature; radiation; end-of-life; and tolerance;
  - 1 output neuron: internal current source parameter used to calibrate the slew rate.



- *Average training error of 2.5%;*
- *Produced hybrid behavioral (ANN) + physical (manufacturer) model;*
- *Each sample encompasses a different combination of temperature; radiation; end-of-life; and tolerance;*

OpAmp LT1499: ANN Training Results



- OpAmp slew-rate can be adjusted by changing OpAmp Bias current in the manufacturer provided model;
- ANN follows closely target output defined by Mission Worst Case Database;

OpAmp LT1499 SPICE Model

Manufacturer Model (available in LT webpage)

```
.SUBCKT LT1498 3 2 7 4 6   ;(+IN -IN V+ V-
        OUT)
Q4 17 11 18  P1 1.006
Q3 16 10 15  P1 1
Q5 33 32 14   P1 1
QIC2 10 10 11   P1 1
QIC1 11 11 10   P1 1
Q4C 16 11 11   P1 1.5
 RINN 11 2 200
R1 12 7 2K
RCMP 14 7 12MEG
R4 4 17 2K
R2 13 7 2K
ROUT1 27 6 31.2
ROUT2 27 0 50K
C2 16 17 1PF
 VSENSE 33 4 0
FSENSE 19 4 VSENSE 1
VLS 7 32 1.4
GN1 7 22 13 12 290U
GP1 22 4 17 16 340U
GOUT 0 27 0 24 22E-3
*Changed on 03/17/11
*I1 7 14 200U
G1 7 14 VALUE = {(V(95)/1000000)}
xann 95 ANN_SR
```

ANN Behavioral (Not complete)

```
Subckt ANN_SR
*Temperature
V1 1 0 0V
*Radiation
V2 2 0 0V
*EOL
V3 3 0 0V
*Tolerance
V4 4 0 1V

E21 21 0  VALUE= {(0.196094 +(0.293057 * V(1)) +(0.535405 * V(2)) +(0.575036 * V(3))
+(1.189812 * V(4)) )}
E22 22 0  VALUE= {(0.129322 +(-0.700737 * V(1)) +(1.153544 * V(2)) +(-0.003692 * V(3)) +(-
0.070175 * V(4))  )}
E23 23 0  VALUE= {(-10.804480 +(2.797277 * V(1)) +(0.392758 * V(2)) +(0.341766 * V(3))
+(6.330332 * V(4)) )}
E24 24 0  VALUE= {(0.204462 +(1.394164 * V(1)) +(0.131962 * V(2)) +(-0.485072 * V(3))
+(2.315568 * V(4)) )}
E25 25 0  VALUE= {(-4.503322 +(1.555124 * V(1)) +(0.558309 * V(2)) +(0.874029 * V(3)) +(-
7.056897 * V(4)) )}
…
…

E51 51 0  VALUE= {(1/(1 + exp(-V(21))))}
E52 52 0  VALUE= {(1/(1 + exp(-V(22))))}
E53 53 0  VALUE= {(1/(1 + exp(-V(23))))}
E54 54 0  VALUE= {(1/(1 + exp(-V(24))))}
…
…

E58 58 0  VALUE= {(1/(1 + exp(-V(28))))}
E81 81 0  VALUE= {(-0.334930 +(-0.465463 * V(51)) +(1.351430 * V(52)) +(8.567907 * V(53))
+(-1.958266 * V(54)) +(-4.545431 * V(55)) +(1.971483 * V(56)) +(2.238303 * V(57)) +(-1.634766
* V(58))  )}
E94 94 0  VALUE= {(1/(1 + exp(-V(81))))}
E95 95 0  VALUE= {(V(94)* 210)}

.ends ANN_SR
```

Convergence Issues

- Neural Networks could easily be trained to capture the transfer function of the devices:
  - However SPICE would present convergence problems for large networks;

- *Need to keep right balance: very compact ANN may fail to map device curves; very large ANNs may produce convergence problems;*

- Other strategies to avoid convergence problems: re-group ANN equations, ramping up V_{DD}, increasing number of iterations, etc

Conclusions & Future Work

- The ANN tool produced a more accurate model of many devices;
- Demonstrated integration of ANN models into SPICE netlist for actual flight circuits;
- SPICE models include "knobs" to adjust for:
  - Temperature;
  - Radiation (TID);
  - Initial tolerance;
  - End-of-life effects;
- *How to make ANN models readily available to designers ?*
- *How to integrate ANN SPICE modeling into WCA process ?*
  - *Keeping and maintaining models database across Missions;*
  - *Two complementary methods: simulations to validate equations.*
- *Other solutions:*
  - *Automatic features of simulation tools (e.g., Silvaco, PSPICE) ? Understand tool limitations, availability;*

Acknowledgements

This research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration and funded through the internal Research and Technology Development program.