Machine Reasoning for Determining Radiation Sensitivity of Semiconductor Devices

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***Abstract*—A machine reasoning system has been built in order to extract from device-level radiation test data a positive correlation between general device parameters and radiation sensitivity. The prototype machine reasoning engine was developed and tested on a dataset of 170 A/D and D/A converters to assess the contribution of device parametric attributes on the overall device latch-up sensitivity to radiation. The machine reasoning is developed with entropy-minimum based classification for decision rule generation and with the maximum entropy principle for determining the probability and margin of error of the generated rules. A preliminary testing of the machine reasoning system revealed that the semiconductor manufacturing process (including feature size and die area) is very important in radiation immunity of a device along with manufacturing year and conversion time (or settling time).**

***Index Terms*— Machine reasoning, inductive reasoning, information entropy, radiation impact, semiconductor device.**

I. Introduction

RADIATION effects in deeply scaled, complex semiconductor devices such as processors, memories or analog to digital (A/D) converters are strongly influenced by manufacturing process parameters, design margins, component architecture and specific radiation mitigation steps, just to name a few contributing factors. Each of these devices and process parameters may have their unique expression to the radiation environment. They may amplify or very often cancel each other to some degree.

We know this quite well from detailed studies of specially designed test structures where it is possible to isolate the influence of a single device parameter, transistor feature or design variation on the overall response to a specific radiation environment. For practical reasons, most of the radiation testing and all flight heritage data provide Single Event Effects (SEE) or Total Ionization Dose (TID) data for the entire device. Rarely does the end user have access to the detailed device design files or process parameters. In most cases, such information is deemed highly proprietary.

It is the norm for very complex devices that 10's if not 100's of subtle device features may be able to contribute to the overall device's radiation response, making it almost impossible to know which specific features contribute to the observed device response. This means that, in most practical situations, past test results of, for example, a microprocessor would poorly predict the radiation response of a similar processor even if manufactured by the same manufacturer.

This is not to say that prior radiation experiments or heritage data for like devices are without value. JPL has captured general lessons learned in a number of selection guidelines [1] from the long history of radiation research that lend one to some useful recommendations without the need of a detailed design and construction analysis. It is well known, for example, that the scaling trends have positive effects on TID susceptibility below the 65-90 nm node. Similarly, the charge particle induced bipolar latch-up loop in a parasitic PNP + NPN structure is unsustainable if feature scaling leads to a supply voltage collapse during the latch-up event [2]. As pointed out earlier, however, general rules that reduce the expected device radiation response to just a few factors are a great simplification and at best suitable to identify the most likely, average radiation response. Inherent to all such guidelines is the difficulty to identify from the wealth of part level test data positive and statistically significant correlations between device parameters and resulting radiation responses.

The purpose of this article is to report the development of a machine reasoning system which can be trained to comb through the existing radiation dataset and extract radiation guidelines. A prototype machine reasoning engine was built to identify common device parametric attributes and characteristics in A/D and D/A converters that are indicative of Single Event Latch-Up (SEL) sensitivity. SEL is caused by the so-called Bipolar Latch-Up loop inside a semiconductor device by the particle-triggered PNP + NPN parasitic bipolar structure, which provides a low impedance path in power rail leading to shorting of power supply line and the ground and thus to undesired functional property or damage [2].

The article is organized as follows. Chapter II introduces the framework of machine reasoning for (a) dominant attribute discovery and (b) guidelne rule extraction using the discovered attributes. In Chapter III, we discuss the A/D and D/A converter training dataset, device parametric attributes considered, and the resulting machine reasoning predictions for SEL sensitivity in A/D and D/A converters. Chapter IV concludes the article.

II. Machine Reasoning Framework

The main theory behind dominant attribute discovery and

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guideline rule extraction using training datasets is inductive reasoning with information entropy minimum principle [3]. In information theory, "information measure" compares the outcome one observes to a prior state of expectation. Therefore, information can be related to a prior estimate of probability, and thus the quantity of information (I_Q) is defined as proportional to the negative of the logarithm of probability (p), with k a constant [4]: $I_Q = -k \ln p$. Information entropy (S) is defined as the expected value of information, and thus is defined as: $S = -kp \ln p$.

In our context, information entropy is interpreted as a measure of uncertainty in correlating an outcome, True or False, to a certain device parameter. In the ideal entropy minimum state, all of the information has been extracted, which leads to a guideline rule for affirming or negating an outcome with the highest certainty for the given radiation test data. Further, since new test data can be easily added to the framework, any additional radiation test data would promptly update the dominant attributes, the initial guideline rule, and the certainty of the rule, making it a learning machine-reasoning system.

A. Dominant Attribute Discovery

Extracting guideline rules from binary data is simple. A typical example one may encounter is the following statement: If the ADC was manufactured on the SOI process, latch-up will not occur. Therefore, the first step in determining the dominant attribute is to convert all analog-valued sample data to binary valued data. The first step for the "binarization" is performed by threshold calculation with conditional entropy minimization, in which the threshold value of an attribute in binarizining the analog sample values is the one which minimizes its conditional entropy. Referring Figure 1, the conditional entropy $S(x)$, which, for a chosen value x, is defined with conditional probabilities of two outcomes, True (T) and False (F), under 2 conditions (one for a sample value lower than a certain threshold value and the other greater than that) as,

$$S(x) = -p(x_-)[p(T \mid x_-)\ln p(T \mid x_-) + p(F \mid x_-)\ln p(F \mid x_-)] \\ - p(x_+)[p(T \mid x_+)\ln p(T \mid x_+) + p(T \mid x_+)\ln p(T \mid x_+)],$$

where, $p(x\text{-})$ is the ratio of the number of samples below x and the total number of samples, and $p(x\text{+})$ is the ratio of the number of samples above x and the total number of samples. $p(T|x\_)$ and $p(T|x_+)$ are probabilities of outcome T given that the sample value is below and above x, respectively.

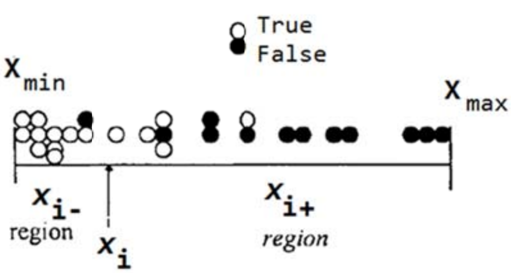

Fig.1. Illustration of a threshold determination for an attribute.

A binarized sample data is obtained after converting the analog data, via corresponding thresholds, into binary values, 1 for sample values above the threshold, -1 for below the threshold, and 0 for no data sample.

The same conditional entropy concept and its use with threshold value determination can also be applied on binarized attribute values to successively determine dominant attributes in correlating an attribute to the outcomes. Consider a binarized data which has N number of samples, each of which is consists of m attributes and one outcome, T or F. Then, we can form a conditional entropy equation for the ith attribute as follows:

$$S_i = -p_i(-1)[p_i(T \mid -1)\ln p_i(T \mid -1) + p_i(F \mid -1)\ln p_i(F \mid -1)] \\ - p_i(1)[p_i(T \mid 1)\ln p_i(T \mid 1) + p_i(F \mid 1)\ln p_i(F \mid 1)],$$

where, $p_i(-1)$ is the ratio of the number of samples of '-1' in attribute i and the total number of samples (which is N in this case), and $p_i(1)$ is the ratio of the number of samples of '1' and the total number N. $p(F|1)$ and $p(F|-1)$ are probabilities of outcome F given that the sample value is 1 and -1, respectively.

After applying the conditional entropy to all m attributes, a certain attribute A_k which produces the minimum conditional entropy will be the best attribute in correlating the sample data to the outcomes.

B. Decision Rule Derivation with Dominant Attributes

Then the guideline rule, R_k for the attribute k, can be drawn from the best (highest) conditional probability from the set of four: $p_k(T|-1)$, $p_k(F|-1)$, $p_k(T|1)$, and $p_k(F|-1)$. Specifically, the guideline rule of an outcome (T or F) is formed by the just one of the outcome-condition set whose probability is highest:

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R: IF (Attribute Condition), THEN (Outcome).
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If, for example, $p_k(T|1)$ is the highest from the set, then the guideline rule is formed as follows:

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Rk: IF (Ak = 1), THEN (T).
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In this step, the probability (or certainty) of this guideline rule itself is generated from the maximum entropy based Bayes estimate by [4]

$$< p_k(O) >= \frac{x_k + 1}{n_k + 2},$$

where, x_k is the total number of samples satisfying the condition A_k = (1 or -1) and O_k = (T or F), and n_k is the total number of samples satisfying the attribute condition A_k = (1 or -1). Also, the margin of error of the drawn probability is obtained by

$$e_k(O) = z \cdot \sqrt{\frac{<p_k(O)>\cdot\{1-<p_k(O)>\}}{n_k+2}},$$

where z is the z-score for a confidence interval, 1.65 for 90%, 1.96 for 95%, and 2.57 for 99%, for instance.

Usually, not all samples can be directly linked to a single guideline rule. If that were the case, the sample data would be very easy to classify without any help of algorithm or inference. Therefore, we apply step-wise approximation [5] by which, after the first attribute and its corresponding guideline rule are found, we remove all the samples which match the guideline from the binarized dataset and we repeat the conditional entropy minimum process for the remaining data samples. This "step" for attribute-guideline generation continues until there is no sample left in the binarized dataset, at which point we can say the set of guidelines generated in the process would most accurately represent the sample dataset in correlating their attributes and the outcomes. One will have created a complete SEL guideline decision tree once the entire dataset has been arranged and the attributes have been sorted by dominance.

Referring Figure 2, the conditional entropy minimum framework for dominant attribute discovery and corresponding rule from sample dataset is summarized in the following computational processes:

1) First, from a sample dataset with attributes and outcomes, each sample values of attributes are binarized by the threshold determined by the conditional entropy minimum principle.
2) Second, from the binarized dataset, conditional entropies for separating the outcomes by each attribute are calculated and, then, the attribute whose conditional entropy is the lowest is selected as the best attribute.
3) Third, using the best attribute, a prediction rule for outcome occurrence is made using the highest conditional probability for the 4 outcome-condition pairs, which in general is in the pattern of R_1: $A_1 = 0 \rightarrow$ T or $A_1 = 1 \rightarrow$ F, where A_1 is the value of the first order (most dominant) attribute. In this step, the unbiased probability (or certainty) of the prediction rule and the margin of error are calculated.
4) Fourth, from the binarized dataset, remove all the samples which satisfied the first rule pattern for the first order attribute.
5) Fifth, go to the Second step and repeat to obtain for R_2: $A_2 = 0 \rightarrow$ T or $A_2 = 1 \rightarrow$ F, where A_2 is the value of the second order (second dominant) attribute, and so on, until the dataset is empty.

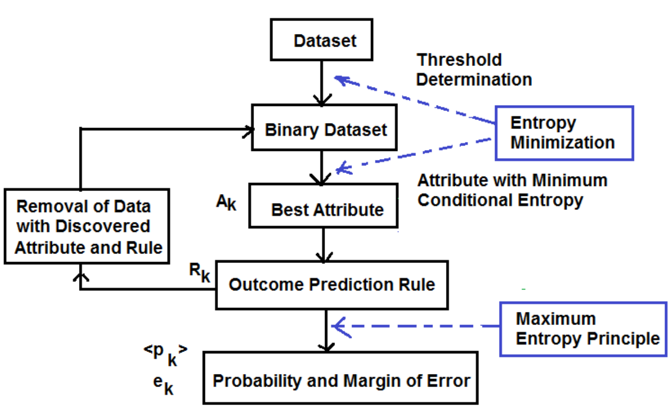

Fig.2. Machine Reasoning Process

After the dataset is empty and all the steps of rule are found. Then a decision tree structure is obtained as illustrated in Figure 3 using the dominant attributes.

When more data are added to the dataset, the process resumes from the first step to update the attributes and corresponding outcome prediction rules by the new evidence. Alternatively, validation result of the attributes and the rules using a test dataset can be added to the original (or training) dataset to further improve the attribute selection and outcome prediction.

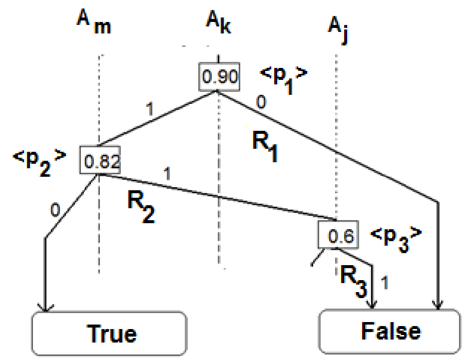

Fig.3. Decision tree structure example.

III. Machine Reasoning on Radiation Test Data

A. *Radiation Test Data*

The dataset used in the study is primarily composed of the following two sources: (a) NASA JPL RAD Central which lists the parts tested by JPL and their reports and (b) NASA GSFC Radiation Data Base which contains a list of parts tested by GSFC and JPL. Additionally, other published or internal documents such as selection guidelines and compendium reports [6] are used to select device attributes that may contribute to overall SEL sensitivity of ADC/DACs.

In the above two sources, some reports are 20 years old or older, and only 10% of them were reported in the year 2010 or later. The breakdown of the reporting years of the data is as follows: 1980s (12%), 1990s (49 %), 2000s (29 %), and 2010 and later (10%).

The collected dataset contains 170 radiation test data with SEL thresholds and SEL saturation cross sections. It is assumed that different device attributes can lead to a total suppression of latch-up (i.e., guard rings) while others merely raise the threshold. Based on this assumption, the breakdown of the data in terms of somewhat arbitrary threshold categories is indicated in Table I.

TABLE I
THE NUMBER OF TEST DATA IN 4 LET CATEGORIES

SEL Immune LET Level	< 5 MeV	5 - 37.5 MeV	37.5 - 75 MeV	> 75 MeV
Number of Test Data	27	65	18	60
Percentage of Data	16%	38%	11%	35%

B. *Device Parametric Attributes*

Relevant device attributes are selected by identifying device parameters commonly included in the test report. In addition, attributes are included based on the underlying physics of SEL sensitivity such as feature size, supply voltage, substrate material, etc. Unfortunately, many attributes which are known to be important are not readily available. For example, the feature size and die area information is not usually available from datasheets. Reliability reports and data books from manufacturers shed some light on these two attributes; however, more often than not, direct help from the manufacturers is essential. The parametric attributes adopted for the work with justification, if applicable, are:

1) Manufacturer: The companies which fabricated devices.
2) Converter type: ADC or DAC is an attribute. According to the JPL guideline, the failure rate of DAC is 1/25, which is much lower than ADC.
3) Resolution of Device: The number of bits is an attribute. The internal JPL guidelines states that the failure probability of an ADC with 12 –bit or higher resolution is 0.2.
4) Process Technology: Bipolar, CMOS, LCCMOS, BiCMOS, and SOI/SOS. The JPL guideline states that Bipolar technology is immune to SEL while it is sensitive to the total irradiation dose rate (TID). Also it states that more recent CMOS or BiCMOS technology is more tolerant to SEL effect. On the other hand, it has been know that the SEL sensitivity can be reduced by lightly doped epitaxial layers grown on heavily doped substrate and silicon on insulator (SOI (on Silicon Dioxide) or SOS(on Sapphire)). The insulating silicon dioxide reduces the parasitic device capacitance. While thin Oxides are susceptible to SEGR (Single Event Gate Rupture) due to radiation induced leakage current, however, thick oxides in which holes can be accumulated are more susceptible to the total irradiation dose (TID) effect of radiation.
5) Substrate Feature Size: The smallest spacing between repeated features in μm. It is hypothesized that smaller feature size would have many more nodes affected by a single particle thus increase the SEL sensitivity.
6) Die Area: Size of semiconductor die in mm^2.
7) Architecture/Algorithm of ADC/DAC: For ADC - (a) Successive Approximation which hardware components of comparators and switched capacitors, (b) Flash which is composed of comparators and characterized with big die size, high count of input capacitors, and high power dissipation, (c) Integrating ADC with analog integrators, comparators, and count pulses, and (d) Sigma-Delta Modulation which is a digital intensive architecture with composition of integrators, comparators, and digital filters, and for DAC - (a) Resistor architecture with weighted resistors or so-called R-2R ladder as Multiplying DAC, (b) Charge Redistribution which is composed mainly of switched capacitors, and (c) Current Steering architecture which is characterized by low voltage differential signaling with current switching cells..
8) Sampling Rate: For ADC in MHz
9) Conversion Rate: for ADC in μs and for DAC, settling time in μs.
10) Manufactured Year: Manufacture's data or lot code. More recent CMOS or BiCMOS technology is more tolerant to SEL effect, but the manufacture's data or lot code is not always provided in the test report.
11) Minimum DC voltage: Lowest bias voltage in V. It is known that, when the supply voltage is reduced, the cross-section of SEL increases. The lower bias voltage reduces the direct current in the devices and therefore the critical charge required to upset the circuit is also reduced.
12) Power Consumption in mW.
13) Radiation Hardened or not.

C. *Outcomes with Respect to LET Level*

Electronic Stopping Power is the amount of energy lost by the incident ion along its path in the absorber medium when colliding with atomic electronics in the unit of [MeV/cm]. Liner Energy Transfer (LET) is defined, from the electronic stopping power, divided by the mass density of the absorber medium, so it is equivalently mass electronic stopping power in unit if [MeV cm2/mg]. As mentioned previously, one can anticipate that some of the device characteristics have a strong influence on the SEL threshold. Therefore, the outcome or the result classification of test data is divided in to 3 SEL immunity categories (or hypotheses) with respect to LET levels:

- H1: Immune to LET higher than 5 MeV,
- H2: Immune to LET higher than 37.5 MeV, and
- H3: Immune to LET higher than 75 MeV.

D. *Dominant Attribute Extraction and Guideline Derivation*

In the H1 category for a device to be SEL immune for 5 MeV or higher LET, the most dominant attribute by the machine reasoning framework is the Manufactured Year of devices. The binarization threshold value calculated by the conditional entropy minimization is year 2005, and by this number, for any device, manufactured year is converted to 1 (later than 2005) or -1 (earlier than 2005) or 0 (when there is no year information). This finding is not too surprising as, over time, feature size and voltage scaling will lead to internal field gradients that are eventually too low to maintain a latch-up current. In 2005, the predominant CMOS feature size was approximately 350 nm, while the voltage was scaled to Vdd= 0.3 V [7]. The guideline rule by the (manufactured) Year is:

`R1: {Year = -1} → T` ("if Year<2005, immune to 5 MeV or higher").

The guideline certainty and the margin of errors are calculated as: $<p_1>= 0.92871$ and $<e_1>=0.095337$. The number of samples removed by this Year= -1 pattern is 26, and these 26 samples are removed for consideration in the 2nd round of attribute selection and rule derivation. The next 2 rules are as follows:

`R2:{Die Area = 1} →T` , $<p_2>=0.8335$, $<e_2>=0.1721$

`R3:{Settling Time=-1}→T` , $<p_3>=0.9414$, $<e_2>=0.0789$

The step continues until the dataset is empty. There are 11 steps of attribute selection and rule extraction for H1. In the order of importance, the attributes determined for H1 are: Year, Die Area, Settling Time, and Feature Size.

In H2 category for a device to be SEL immune for 37.5 MeV or higher LET, the most dominant attribute is determined to be Die Area. The binarization threshold value for Die Area is calculated as 15 mm^2 and, by this number, device die area is converted to 1 (larger than 15) or -1 (smaller than 15) or 0 (when there is no die area information). The rule according to Die Area is:

`R1:{Die Area = 1} → F` ("If Die Area > 15 mm^2, NOT immune to 37.5 MeV or higher").

And the certainty and the margin of errors are calculated as: $<p_1>= 0.7998$ and $<e_1>=0.35083$.

The number of samples removed by this Die Area pattern is only 3, and these 3 samples are removed for consideration in the next round of attribute selection and rule derivation. In the second step, the same Die Area is selected as the dominant attribute with a rule:

`R2:{Die Area= -1} →T` ("else if Die Area< 15 mm^2, immune to 37.5 MeV or higher") with $<p_2>=0.6665$ and $<e_2>=0.2177$.

This second step removes 19 samples. Despite its importance as attribute, the low certainty and high margin of error are due mainly to the lack of information on Die Area in most of the sample data - only 22 samples out of 170 have die area information. The next step of the rule is found as follows:

`R3:{Year= -1} →T` , $<p_3>=0.75$ and $<e_3>=0.3$.

The rule for H2 has eventually 11 steps. In the order of importance, the attributes determined for H2 are: Die Area, Year, Settling Time, and Feature Size. Compared with the top 4 attributes for H1, those for H2 are exactly the same except the switched order for the top and the second attributes.

In H3 category for a device to be SEL immune for 75 MeV or higher LET, the most dominant attribute is determined to be Die Area as in H2 category. The binarization threshold value for Die Area calculated by thee conditional entropy minimization is 15 mm^2 as in H2. The guideline rule according to Die Area is:

`R2: {Die Area = 1} → F` ("if Die Area > 15 mm^2, NOT immune to 75 MeV LET or higher") with $<p_1>= 0.7998$ and $<e_1>=0.35083$.

Again, despite its importance as attribute, the low certainty and high margin of error of Die Area is due mainly to the lack of information in most devices. The next 2 rules are as follows:

`R2:{Year = -1} →T` , $<p_2>=0.75$, $<e_2>=0.3$

`R3:{Settling Time= 1}→F` , $<p_3>=0.7998$, $<e_2>=0.1109$

The attribute section and rule extraction continue and the H3 has a total of 11th steps. In the order of importance, the attributes determined for H3 are: Die Area, Year, Settling Time, and Converter Type (ADC or DAC), and Feature Size. Compared with the top 4 attributes for H1 and H2, those for H3 are exactly the same except the added attribute of Converter Type.

The attributes and the corresponding guideline rules for 3 different categories of SEL immunity are nothing but *a priori* information based on the dataset and the dataset alone. Next, we test this machine reasoning system for a fictitious candidate device.

E. Testing the Machine Reasoning System

Now we run the machine reasoning code to check a fictitious A/D converter:

- Bit-Resolution: 12
- Process Technology: CMOS
- ADC Architecture: successive approximation
- Conversion Time: A/D converter with 0.2 μs
- Power Consumption: 75 mW,
- Power Supply: single supply of +5V
- Feature Size: 2 μm
- Die Area: 9.6 mm^2.
- Year: unknown

For H1, since the device lacks the Year information, the first 2 steps of the rule are skipped or missed, but the third step of the rule with Die Area matches and produces the output as sown in Figure 4, indicating that "The Die Area is bigger than 5.0 mm^2, therefore device is immune to 5 MeV or above LET level with certainty of 0.8335 and a margin of error at 0.1722."

```
This is for H { 1 } {  LETth > 5 MeV }
0 miss
1 miss
2 Attr No. 18 { DieArea[mm^2] } > 5.0 THEREFORE Hypothesis is TRUE
  with <p>= 0.8335 +/- 0.17212
```

Fig. 4. Decision output on H1 for a fictitious A/D converter.

For H2, the device misses the first step but matches with the second step of the rule (with Die Area threshold of 15 mm^2) with $<p>=0.667$ and $<e>=0.2177$, as shown in Figure 5, indicating that "The device is NOT immune to 37.5 MeV or above LET level with certainty of 0.6665 and a margin of error 0.2177 because its Die Area is smaller than 15.0 mm^2." Apparently the device's immunity against SEL in 37.5 MeV is much lower than that for 5 MeV, and the margin of error for the SEL immunity is too high to accept this device for H2 category.

```
This is for H { 2 } {  LETth > 37 MeV }
0 miss
1 Attr No. 18 { DieArea[mm^2] } < 15.0 THEREFORE Hypothesis is FALSE
  with <p>= 0.6665 +/- 0.21777
```

Fig. 5. Decision output on H2 for a fictitious A/D converter.

For H3, the device misses the first step but matches with the second step but with very low certainty as shown in Figure 6: $<p>=0.5$ and $<e1>=0.231$, indicating that "The device is NOT immune to 75 MeV or above LET level with certainty of 0.5 and a margin of error 0.23096 because its Die Area is smaller than 15.0 mm^2." Actually the guideline is more like a coin toss. Apparently the device's immunity against SEL in 75 MeV or above is too low to accept.

```
This is for H { 3 } { LETth > 75 MeV }
0 miss
1 Attr No. 18 { DieArea[mm^2] } < 15.0 THEREFORE Hypothesis is FALSE
  with <p>= 0.5 +/- 0.23096
```

Fig. 6. Decision output on H3 for a fictitious A/D converter.

IV. Conclusions

A prototype machine reasoning system was built in order to extract from a device-level radiation test dataset of 170 A/D and D/A converters a positive correlation between device parameters and SEL sensitivity. A preliminary testing of the machine reasoning system revealed that semiconductor manufacturing process (including feature size and die area) was very important in SEL immunity of a device along with manufacturing year and conversion time (or settling time). However, these important attributes, feature size and die area in particular, were usually proprietary and thus not readily available, which resulted in high margin of error even though the guideline rule certainty was rather high. An important limitation of the finding is that the result was made from the available dataset which was dominant in numbers with outdated or obsolete devices. More data with multiple testing of updated devices may change the dominant attributes and the guideline rules extracted in the present study.

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