41st European Solid-State Circuits Conference
45th European Solid-State Device Research Conference

WORKSHOP

Variation-Aware Design for RF Engineers

Workshop Chair:
Stephan Weber
Cadence Design Systems

Workshop Venue:
Graz University of Technology
Inffeldgasse 25 D
September 18, 2015

Conference Organization:
JOANNEUM RESEARCH Forschungsgesellschaft mbH
Graz, Austria

Technical Co-Sponsorship
Variation-Aware Design for RF Engineers
Organizer: Stephan Weber, Cadence Design Systems

Creating an RF design is always a challenge, but producing it with acceptable yield is even more difficult. We start with discussing Monte-Carlo and PVT corner analysis, and their measures and problems like confidence intervals, uncertainties from non-normal distributions, etc. Then moving over to advanced techniques for yield prediction and optimization. A demo will be given using Cadence Virtuoso ADE GXL for design of RF key blocks.

Agenda:

08:45  **Important Statistical Techniques for Circuit Design**  Page 3
   Demonstration: Normal & Non-Normal Data Analysis, Confidence Intervals,
   Yield Estimation Methods, etc.
   Stephan Weber, Cadence Design Systems

11:00  **Coffee Break**

11:30  **Advanced Methods and Over-All Flow**  Page 27
   Demonstration: Variation-Aware Design in Cadence Flow
   Ioannis Syranidis, Cadence Design Systems

12:30  **End of Workshop**
VARIATION-AWARE DESIGN FOR RF ENGINEERS

Not only RF...
Not only Monte-Carlo...
Not only Cadence...

Conference Sponsors:

OUTLINE

1. Session 2h
   • Basics: Corners & Monte-Carlo
   • Normal & non-normal data

2. Session 1h
   • Advanced methods & tools
   • Variation-Aware Design in Cadence Flow
OUTLINE: SESSION #1

1. Short Introduction
2. Corners vs Monte-Carlo
3. Monte-Carlo: How much can you trust?
4. Quantify the uncertainty
5. Advanced Monte-Carlo + Demo
6. Summary & Conclusions

INTRODUCTION

IC design is difficult
- Simulations, layout, DRC, LVS, ...

RF design is difficult
- Package, wiring parasitics, model accuracy limited, phase-noise,hb analysis, ...

So people tend to say
- „Only Si tells the truth...“
- „We need no high yield...“
INTRODUCTION

So why bother with „Variation-Aware Design“?

- You need to be prepared for many variations: T, Vdd, process, mismatch, VSWR, ???, etc. => robust design needed!
- We are engineers and need to find practical and economical solutions! => in reality the blue ribband for max. toggle frequency does not matter much
- A design may work in simulation with big margins at typ corner & conditions. And you even might be happy with 20% yield e.g. for a high-performance military system! BUT still tolerances may degrade yield to almost zero 😞!
  => yield prediction needed!

Example #1

- 3-stage balanced DC-coupled VGA: each stage has gain = 0...20dB
  => max. total gain = 60dB
  => corner simulations show good performance & no offset voltage
  => BUT reality: even a small input offset can already overdrive last stage! Yield almost zero!
  (Reference: Cadence knows...)
INTRODUCTION

Example #2

- $g_m C$ filter designed to be tunable for $\pm 50\%$ to compensate RC tolerances
- => corner run was fine, having even some margin
- => BUT reality: measured filter has even $\pm 90\%$ tolerance!
- => Customer switched foundry, but without improvement!
- => PDK had a Monte-Carlo setup, but due to a small bug the customer never applied it!!
  (Reference: Cadence knows...)

BEST QUESTION TO CADENCE EVER?

- How much do we need to **overdesign** in Cadence that it works in reality??
  - It depends....
  - E.g. a sweep on T may give you the margin on temperature
  - Full PVT + MC corner analysis may give you over-all margin
  - Of course do not forget e.g. wiring parasitics, substrate impacts, be aware of model limitations (breakdown, lumped models, special noise effects...)
  - How much margin for Monte-Carlo???
1ST CONCLUSION

- What can go wrong tend to go wrong
- Designers should run both corner analysis and Monte-Carlo!

Corners vs Monte-Carlo
- How much can you trust?
- Does it fit together?

OUTLINE: SESSION #1

1. Short Introduction
2. Corners vs Monte-Carlo
3. Monte-Carlo: How much can you trust?
4. Quantify the uncertainty
5. Advanced Monte-Carlo + Demo
6. Summary & Conclusions
CORNER ANALYSIS

- Stresses the design at extreme process points
  - Good for quickly finding problems
  - Maybe too extreme?
  - Usually 4-20 process corners, usually combined with temperature, voltage, VSWR
    => can end up in huge number of combinations!

- Gives unfortunately no real yield prediction & does not treat mismatch

MONTE-CARLO

- Mimics the production environment 😊
  - Requires statistical models
  - Needs usually 50 to 200 runs to get stable mean & sigma (if Gaussian)
  - Can detect failure regions not found by corners
  - Can treat mismatch!
  - Get correlations, histograms, yield and C_{PK}

- MC needs many points for verification of higher yields, like 2500-8000 for 3σ (0.17% loss single-sided)
**Problem:**
Standard (digital) corners (like SS, SF, FS, FF) may not fit to MC!!

**Reason:**
Those corners created by foundry based only on CMOS speed

---

**ONE SOLUTION: WORST-CASE DISTANCES**

Let your tools create correct “Analog” worst-case distance corners

=> Get worst-case e.g. on IP3, noise, etc.
=> User decides on σ-level he needs!

Note: Such WCD can also include mismatch!
=> more in Session #2!
**MC: HOW MUCH CAN YOU TRUST?**

Doing a MC analysis is a simple but also very **general** method to check statistical behavior and to get the yield

- Sometimes the **only** method you have...
- Almost always more **universal** than more complex methods!
- Pro MC
  - Has **no** restrictions on linearity, number of statistical variables, number of specs, etc.!!!
- Con MC
  - Quite slow convergence, usual rate $1/\sqrt{N}$
  - The **higher** the desired yield, the **more** points needed!
  - **All MC results depend on chance!!!**
MC: HOW MUCH CAN YOU TRUST?

Ask yourself

- Histogram looks like this:

  Is it correct to assume it is Gaussian? What are the problems if we do so?

- E.g. N=128 & sample standard deviation is 0.92dB. But what is the true $\sigma$? Can we give at least an interval?

WHAT IS MONTE-CARLO??

- Practically
  - We mimic our real-world system in a computer and use statistical models to include e.g. production variations
  - Even if models are not accurate MC is useful because we can check our design on robustness
  - Yield is one important measure, but also others
  - Also huge number of other applications

- For mathematicians
  - „Monte-Carlo integration works amazingly well“, e.g. independent on shape & number of dimensions
MC: QUESTIONS & CONCLUSIONS

- MC itself only assumes a stable process & i.i.d. samples
- MC also guarantees convergence of sample yield $Y = \frac{N_{\text{pass}}}{N}$!
- So can we always trust MC results? NO!
- Does MC converge even if a process has infinite number of statistical variables?
  - Yes/No?
  - Yes, at least for pure random MC
- Can we make correct estimations even if the distribution is not Gaussian?
  - Yes/No?
  - Yes, e.g. you may assume another distribution or use more general (distribution-free) theorems like Chebycev theorem!

MONTE-CARLO: QUESTIONS

- CLT: If we add the samples from many many different statistical variables we will approach the normal distribution?
  - Yes/No?
  - No, CLT comes with further restrictions like need for finite sigmas!
- If we extend the number of MC points, we can always improve accuracy?
  - Yes/No?
  - No, may not be true e.g. for the mean on a Pareto distribution
OUTLINE: SESSION #1

1. Short Introduction
2. Corners vs Monte-Carlo
3. Monte-Carlo: How much can you trust?
4. Quantify the uncertainty
5. Advanced Monte-Carlo
6. Summary & Conclusions

UNCERTAINTY: OF WHAT?

- Example: Assume a Gaussian PDF=N(μ,σ)
  - μ,σ: True & fix distribution parameters – usually unknown
  - MC run, e.g. N=128 points:
    - Gives certain sample mean m & standard deviation s
- Note: m & s depend on chance!
- Q: Can we „calculate“ a range in which e.g. the true parameters are (with certain confidence)??
CONFIDENCE INTERVALS

Standard approach:
Calculate confidence intervals!
For a Gaussian distribution it leads to the use of
Student-t (for $\mu$) and chi² distributions (for $\sigma$)!
In this case actually CI can be calculated directly from
data and they get tighter with $1/\sqrt{N}$!

Note: The CI width increases with confidence level
Usual choice: e.g. 95%

CONFIDENCE INTERVALS FOR YIELD

After a 128-point MC run I got 128 data samples
From this I can calculate (sample) yield
e.g. $y=1$ (no fails) => Note: Depend on chance!
EDA tools or math software often also have output
for yield CI
e.g. CI($y$)=[0.96,1.00]
Note: Depend on chance, N and conf level
=> This interval is very wide for moderate N!
=> For proving 99.7% yield you need e.g. N>2000!
CONFIDENCE INTERVALS: MEAN & SIGMA

- After a 128-point MC run I got 128 data samples.
- From this I can calculate (sample) mean and sigma! 
  e.g. $m=2\text{mV}$ and $s=10\text{mV}$
  Note: Depend on chance!
  Only correct for normal data!
- EDA tools or math software often also have output for CI 
  e.g. CI($m$)=$[0,4\text{mV}]$ and CI($s$)=$[8\text{mV},12\text{mV}]$
  Note: Depend on chance, normality, $N$ and conf level.

CONFIDENCE INTERVALS: QUESTION

- After a 128-point MC run I got e.g. a CI of $[0\text{mV}, 4\text{mV}]$ on the mean.
  Does it give me a guarantee that the true value is in that range (with desired confidence level like 95%)?
  - Yes/No?
  - No!
CONFIDENCE INTERVALS: PROBLEMS

- The MC data is the only thing we have. This depends on chance, so also CI depends on chance!
- Using the Student-t formula assumes a Gaussian distribution. How can I be sure if this is correct?
- What can we do?
  Do MC again & again => get many different CIs
  Just in average they should indeed give the correct range with desired coverage!

NORMAL GAUSSIAN DISTRIBUTION

- PDF of standard-normal distribution:
  \[ N(0,1) = \frac{1}{\sqrt{2\pi}} e^{-x^2} \]
- With \[ Y' = \mu + \sigma Y \]
  you can scale it to any normal PDF
- CDF is related to the error function
WHY THE NORMAL PDF IS SO IMPORTANT?

- CLT: If you add many small many arbitrary non-normal distributions, there is a „natural tendency“ to let the overall statistical distribution become normal Gaussian.

- Most parameters are just modeled assuming a Gaussian distribution!

- In many cases you get indeed almost normal distributions, e.g. for offset voltages.

If we assume a normal distribution, we can estimate the yield also by $C_{PK}$!

- E.g. single-sided spec: $C_{PK}=(\text{spec}-\mu)/3\sigma$
- As we do not know true $\mu$ & $\sigma$, we have to use sample mean and stddev! But this is still statistically much more stable than the sample yield!!
- Once you have $C_{PK}$ get yield $Y=\frac{1}{2}+\frac{1}{2}\text{erf}(3C_{PK}/\sqrt{2})$
- This works even if there is e.g. no fail sample in the MC run!
TOO GOOD TO BE TRUE?

**Pro $C_{PK}$**
- You can make design decisions based on much less MC point (or with same N we get tighter CI!!)
- Sample yield is „stupid“: Works like a one-bit ADC, i.e. is ignoring how much we are over the limit!

**Con $C_{PK}$**
- $C_{PK}$ is misleading if distribution is non-normal! Even for large N the $C_{PK}$ can have a large bias error!
- Even small deviations in shape can lead to large yield errors (esp. for large $C_{PK}$ values)

OUTLINE: SESSION #1

1. Short Introduction
2. Corners vs Monte-Carlo
3. Monte-Carlo: How much can you trust?
4. Quantify the uncertainty
5. **Advanced Monte-Carlo**
6. Summary & Conclusions
ADVANCED MONTE-CARLO

Up to know we have two yield estimation options, run MC then

1. Calculate sample yield
   => Too optimistic if no fails
   => Large variance, low bias (systematic error)!

2. Calculate $C_{PK}$ and the $Y$ from it
   => Low variance, large bias for non-normal data!
   => $C_{PK}$ preferable if data is Gaussian

REASONS FOR NON-NORMAL DISTRIBUTIONS

Discrete elements may have uniform PDF
$R_{\text{sheet}}$ or doping rate have log-normal PDF
Your circuit acts nonlinear (multiplier, divider, poles, overshoot,...)
Your result evaluation is nonlinear (dB, S-parameters, maximum, $|x|,...$)

=> It is very likely that you have to deal with non-normal data!!!
NOW WAY OUT?

- If you know well e.g. your data is log-normal, then you can fit a log-norm PDF (instead of a normal PDF – as for C_PK!)
- If no „guess“ is available, you can use distribution-free yield estimators
  - E.g. by sample yield or via Chebycev theorem
    => CI much wider than for C_PK fit!!
    => Design decision inaccurate due to statistical variance!

NOW WAY OUT?

- You can try to fit a kind of „more universal“ core function to data, e.g. using 3 instead of 2 parameters
  - This way we can reduce the systematical error a lot
  - The statistical variance would increase a bit
    => Better over-all compromise! Called generalized C_PK
NEW GENERALIZED CPK

Non-normal modeling easier if we focus on spec-sided part + We replace mean $\mu$ by the mode + inclusion of a tail parameter $t$

Blue is a Gaussian fit, which is obviously bad

=> DEMO!!

NEW GENERALIZED CPK

Non-normal data
- RF bandpass filter
- Looking to filter ripple (in a certain band)
- Gives an asymmetric histogram! Why?
LC BPF EXAMPLE: PASSBAND RIPPLE

8th order

Nom. design for Butterworth
=> tolerances cause BW change
=> in-band ripple, etc.
=> e.g. 1dB BW hardly becomes better
but might be much worse
=> asymmetric histogram!

FLASH ADC: DIFFERENTIAL NONLINEARITY

DNL caused by offsets (Gaussian),
but DNL is related to worst-case offset
on all comparators
=> asymmetric histogram!
CMOS GATE: DELAY $t_{PD}$

- Delay related to CMOS ON-resistance
  - Is proportional to $1/(V_{GS}-V_{TO})$
  - $V_{TO}$ has normal distribution, but reciprocal function distorts the histogram
  - => asymmetric histogram!

ADVANCED MC – MORE SPEED METHODS

- $C_{PK}$ and $C_{GPK}$ give speed-up even without changing MC points or simulator setup
  - But doing that can further speed-up!

- #1 Avoid too many MC points with „autostop“
  - Stop if CI indicates „yield target reached or missed“

- #2 Reduce variance in estimates by advanced sampling schemes
  - Replace random e.g. by LHS or LDS
ADVANCED SAMPLING: LDS
LOW-DISCREPANCY SAMPLING

Faster convergence than random sampling and LHS

Accurate statistics (mean, standard deviation, skew etc) with fewer samples, due to better coverage in statistical space


OUTLINE: SESSION #1

1. Short Introduction
2. Corners vs Monte-Carlo
3. Monte-Carlo: How much can you trust?
4. Quantify the uncertainty
5. Advanced Monte-Carlo + Demo
6. Summary & Conclusions
SUMMARY & CONCLUSIONS

Some knowledge on statistics can really help a lot in result interpretation!

- The stronger assumptions you can apply the more stable your estimations become!
- But: The wrong assumptions lead to systematic errors! And often to wrong design decisions!

2nd Session:
How to speed-up statistical analysis even more?
Over-all step-by-step flow for variation-aware design
Tool state-of-the-art

APPENDIX: RULES OF THUMB FOR MC

Know what you want & know what you have

What is your yield? Examples:

- If Y<90% you can trust the sample yield using e.g. 100 points
  Because you can expect 10 fails, not bad for stable statistic!
- What if Y close to 100% and no fails?
  Then 95% yield CI is roughly given by adding 3 fails!
  („Rule of three“ (statistics) - Wikipedia)
  Example: N=1000, no fail => CI limit app. 0.3%
- Example: Y_{true}=99.73% (C_{pk}=1) => consider 3...8K points if data is non-normal or
  if data is normal use C_{pk} and app. 250 points 😊
- Sample yield convergence rate is always 1/√N 😊

Is your data normal distributed?

- Check this via QQ quantile plot! Giving a near-straight line?
- If (surely) normal you can trust mean, sigma & C_{pk} and convergence is 1/√N
APPENDIX: RULES OF THUMB FOR MC

Know the basic rules for near-normal case

- 95% confidence is usually sufficient and equivalent to $\pm 2\sigma/\sqrt{N}$
  
  => So to know variance on mean $\mu$ you need to know $\sigma$

- Also $\sigma$ has a variance: $\sim 1/\sqrt{2N}$, e.g.
  
  N=50 gives 10%, so if $\sigma\text{V}_{\text{offset}}=10\text{mV}$ it is typ. within 8..12mV
  
  with 95% confidence => not sooo bad
  
  N=200 gives 5% => often good enough

- Also $C_{\text{pk}}$ variance is dominated by $\sigma$ variations, so also $C_{\text{pk}}$ is often fine
  
  with 200 points!

- If data is non-normal also systematical errors might be present, and
  
  cannot be reduced by larger MC count!

- Other measures (such as correlations or the mode) may need more
  
  points (like 1000) 😏
VARIATION-AWARE DESIGN

Using Virtuoso ADE XL and GXL to determine worst case circuit conditions

Dr. Ioannis Syranidis, Cadence Design Systems

Conference Sponsors:

OUTLINE

- INTRODUCTION
- ADVANCED ANALYSES, METHODS & FLOWS
- INTERACTIVE SESSION: DEMO & QUESTIONS
OUTLINE

- INTRODUCTION
- ADVANCED ANALYSES, METHODS & FLOWS
- INTERACTIVE SESSION: DEMO & QUESTIONS

VARIATION ANALYSIS

THE PAST

- Until fairly recently, all you had to worry about was PVT (and that was complicated enough)
  - 6-12 process corners combined with temperature and voltage sweeps
  - Stress on the design at extreme process points
    - Maybe you’re overdesigning
  - SS/FF/SF/FS usually tuned for digital design
    - Maybe you’ll miss critical failure conditions for analog behavior
    - No local/mismatch effects are considered

- Sometimes you would also run Monte Carlo
  - But it was time consuming
  - After finding a problem, not always clear how to proceed
VARIATION AWARE DESIGN

THE PRESENT AND THE FUTURE

• Which simulations do you run?
  • You’ll need to combine statistical simulation (to capture process and mismatch variation) with corner conditions not considered in the statistical models, such as supply, temperature, load etc.

• Which design parameters do you tune?
  • To maximize efficiency, you’ll want to identify which device parameters have the most impact on each design spec, as well as which devices are most strongly affected by statistical mismatch variation.

VARIATION AWARE DESIGN

THE SOLUTION - ADE XL & GXL

• Advanced analyses work directly from existing ADE XL tests, measurements and specifications
OUTLINE

- INTRODUCTION
- ADVANCED ANALYSES, METHODS & FLOWS
- INTERACTIVE SESSION: DEMO & QUESTIONS

STATISTICAL CORNERS

BASIC METHODS – ADE XL FLOW

- A statistical corner is a combination of temperature, design variables and process parameters that define a scenario in which you want to measure the performance of your design.
  - Statistical corners can be created directly after a MC run for further analysis and design optimization.
STATISTICAL CORNERS

BASIC METHODS – ADE XL FLOW

- Create statistical corner
  - #1 from Worst Sample
  - #2 from Percentile
  - #3 from Selected Sample

STATISTICAL CORNERS

ADVANCED METHODS – ADE GXL FLOW

- Extraction of statistical corner for (up to) 3 sigma yield verification (applicable to each measurement)
  - Create K-Sigma corners
  - Create corners from Worst Samples

| K-Sigma corners | • Faster, less simulations needed  
|                 | • Recommended for larger circuits (stat. parameters>1000)  
|                 | • Statistical corner is derived from a model of the PDF of an output |

| Worst Samples corners | • More accurate, larger number of simulations needed  
|                       | • Statistical corner is a simulated MC sample |
STATISTICAL CORNERS
K-SIGMA CORNERS – ADE GXL FLOW

- Two convenient ADE GXL use models
  - Enable Auto Stop option during MC setup and select Target Sigma
  - Run on top of existing MC simulation results
- K-sigma corners based on an accurate statistical model of the output distribution
  - Auto Stop when model accuracy is ensured by the number of MC samples
  - Only 50-200 samples needed to achieve level of accuracy comparable to a 1500 sample brute force MC run
  - Minimum distance to nominal point is calculated in case of multiple solutions

STATISTICAL CORNERS
WORST SAMPLES CORNERS – ADE GXL FLOW

- ADE GXL use model
  - Enable Auto Stop option during MC setup and select Target Yield with corresponding probability
- Response Surface Modeling and Sample Reordering is used to accurately extract the worst sample of every spec using a small number of samples
OUTLINE

- INTRODUCTION
- ADVANCED ANALYSES, METHODS & FLOWS
- INTERACTIVE SESSION: DEMO & QUESTIONS

HIGH YIELD ESTIMATION

- Efficient (more than 3 sigma) Yield Estimation
  - Required in designs containing large number of replicated circuit units (SRAM, DFF etc)
  - Required in automotive applications where failure minimization is the major concern
  - 6 sigma is about 2 ppb failures (99.9999998%)
  - Brute force MC may require millions of simulations and is not a realistic option

- Accurate when the spec boundary is linear in the statistical parameter space
- Efficient for high dimensionality designs (large number of statistical parameter)
- Efficient in case of large number of specs
- Accurate even for cases of high non-linearity
HIGH YIELD ESTIMATION

WORST CASE DISTANCE

- Worst Case Distance finds the shortest distance from the nominal point to the specification boundary in the statistical parameter space
  - Worst Case Distance is a good indicator of circuit yield
  - Extension values of statistical parameters from the WCD point to the target sigma value
  - Typical requirement less than 100 simulations per specification
  - Statistical corner creation with specified sigma after WCD run

- WCD algorithm
  1. Run initial MC run
  2. Filter non-high yield spec (accurate MC results)
  3. Apply WCD to high yield specs
     i. Read process/mismatch parameters from MC run
     ii. Perform parameter space reduction
     iii. Run multiple sensitivity analysis iteration to find WCD

HIGH YIELD ESTIMATION

SCALED-SIGMA SAMPLING

- Scaled-sigma Sampling method generates a large number of samples in the failure region of a distorted (sigma scaled up) distribution
  - The failure rate is modeled as a function of the scaling factor
  - The model returns a yield estimate of the unscaled distribution
  - Uniform distribution is avoided as it cannot be related back to yield estimation for a large number of statistical parameters

OUTLINE

• INTRODUCTION
• ADVANCED ANALYSES, METHODS & FLOWS
• INTERACTIVE SESSION: DEMO & QUESTIONS

WORST CASE CORNERS

• Worst Case Corners run mode helps in reducing the project time devoted to simulation while still providing sufficient level of accuracy in examining the results
WORST CASE CORNERS

• WCC reduces the verification problem to a handful of meaningful conditions and avoids redundant simulations by intelligently selection of different sets of input values

• Easy setup based on existing ADE XL corners

• One WCC is created for each specification
  -- Two WCC for two-sided specs (range and tolerance)

• Different methods offered for WCC creation
  -- Best method (higher accuracy) depends on interrelation of swept variables and linearity range of circuit under the given conditions
  -- Automatic method combines Design of Experiments with local optimization to minimize the number of simulations
OUTLINE

• INTRODUCTION
• ADVANCED ANALYSES, METHODS & FLOWS
• INTERACTIVE SESSION: DEMO & QUESTIONS

MISMATCH CONTRIBUTION

• Mismatch contribution analysis identifies contributors to specification variance due to device mismatch
  – Designer aid in spotting devices limiting circuit performance

• Two convenient ADE GXL use models
  – Enable Auto Stop option during MC setup and select Sensitivity Accuracy
    • Automatically simulates the minimum required number of samples for accurate mismatch contribution calculations
  – Run on top of existing MC simulation results
MISMATCH CONTRIBUTION

- Hierarchical and flat views allow overview of contributions at different hierarchy levels
- Interactively highlight device location in schematic
- $R^2$ (also known as the coefficient of determination) represents the model goodness of fit for calculated data.

SUMMARY

THE SOLUTION - ADE XL & GXL

ADE XL and GXL provide an integrated flow to address the challenges of advanced node variation analysis
OUTLINE

- INTRODUCTION
- ADVANCED ANALYSES, METHODS & FLOWS
- INTERACTIVE SESSION: DEMO & QUESTIONS

INTERACTIVE SESSION
DEMO & QUESTIONS
VARIATION-AWARE DESIGN
Using Virtuoso ADE XL and GXL to determine worst case circuit conditions
Dr. Ioannis Syranidis, Cadence Design Systems