

Virtuoso Variation Options User Guide

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Introduction to Virtuoso Variation Option



Virtuoso[®] Variation Option extends the statistical variation capabilities of Virtuoso ADE Assembler and Virtuoso ADE Explorer to allow for more sophisticated statistical analyses to be performed on any design.

Following are the benefits of using Virtuoso Variation Option:

- Provides Fast Monte Carlo (FMC) method, which lets you extract useful statistical information without running the complete set of Monte Carlo samples, especially for high-sigma analysis. This reduces the simulation time.
- Provides mismatch contribution analysis and statistical sensitivity analysis to pinpoint most influential devices within a statistical simulation.
- Provides high-yield estimation capabilities for checking the outer boundaries of your design at the 4, 5, or 6-sigma level.
- Delivers advanced statistical sample reordering that improves the performance of the statistical simulation.
- Features easy, one-step creation of worst-case corners as derived by 3-sigma statistical sampling.
- Lets you integrate custom advanced optimization algorithm written in either C++ or Python into ADE Assembler.

Related Topics

License Requirements

Virtuoso Variation Option User Guide

Introduction to Virtuoso Variation Option

[Fast Monte Carlo Method](#)

[Mismatch Contribution Analysis](#)

[Yield Verification](#)

[The Confidence Interval - Autostop Method](#)

[Statistical Corner Creation](#)

[High Yield Estimation](#)

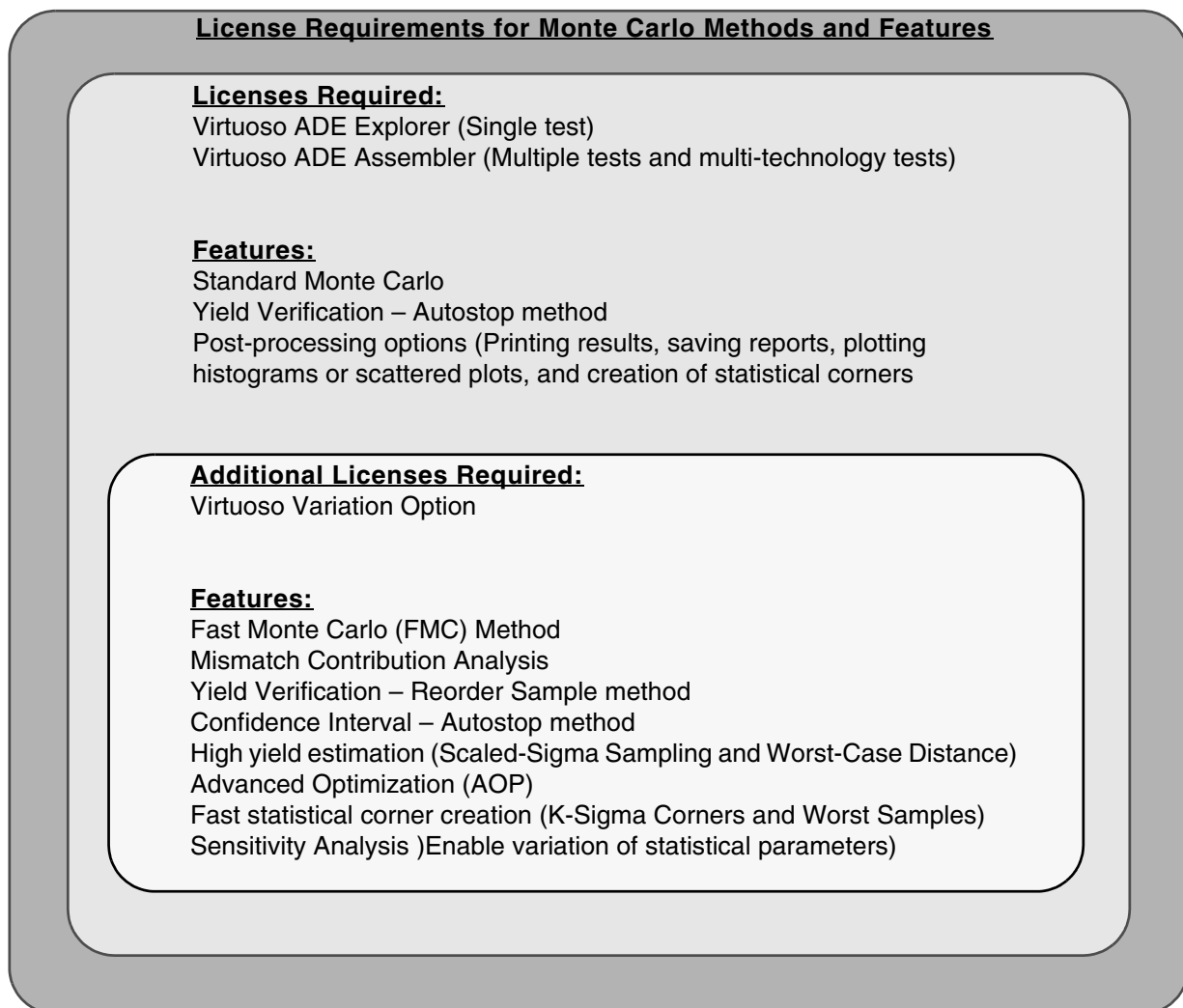
[Advanced Optimization](#)

[Yield Improvement](#)

License Requirements

Virtuoso Variation Option is available with the 95265, Virtuoso Variation Option license. In addition, it also requires the license for ADE Explorer or ADE Assembler depending on the tool it is used with.

The following figure shows the licenses required to run various Monte Carlo methods and features.



Virtuoso Variation Option User Guide

Introduction to Virtuoso Variation Option

Related Topics

[Introduction to Virtuoso Variation Option](#)

[Fast Monte Carlo Method](#)

[Mismatch Contribution Analysis](#)

[Yield Verification](#)

[The Confidence Interval - Autostop Method](#)

[Statistical Corner Creation](#)

[High Yield Estimation](#)

[Advanced Optimization](#)

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Statistical Sampling Methods

Spectre supports the following methods of sampling for Monte Carlo analysis:

- Random

The Random sampling method takes the Brute Force approach of sequentially calling a random number generator without considering the samples generated previously. There is no sample selection or rejection. Therefore, it allows all samples to have an equal chance of getting selected from the population.

The Random algorithm has a convergence accuracy of $1/\sqrt{N}$.

- Latin Hypercube

The Latin Hypercube method is a quasi-random sampling algorithm with sample selection and rejection. The sample space is evenly divided into probable subspaces. All sample points are then chosen simultaneously making sure that the total ensemble of sample points is a Latin Hypercube sample and that each subspace is sampled with the same density. This method requires fewer samples to get accurate results. This method is recommended when you know how many simulation points you need to run.

The Latin Hypercube algorithm has a convergence accuracy of $1/N^{2/3}$.

- Low-Discrepancy Sequence

The Low-Discrepancy Sequence (LDS) method uses a deterministic sequence to get a uniform coverage of the sampling space, which makes it better than the Random sampling method. In addition, LDS uses autostop features to generate samples, which is not supported by Latin Hypercube method. The convergence speed for LDS is faster than the Random sampling method and is comparable to the Latin Hypercube method. Therefore, overall, LDS method is better than both, Random and Latin Hypercube.

Related Topics

[Monte Carlo Form](#)

[Fast Monte Carlo Method](#)

[Mismatch Contribution Analysis](#)

[Yield Verification](#)

[The Confidence Interval - Autostop Method](#)

[Statistical Corner Creation](#)

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Introduction to Virtuoso Variation Option

High Yield Estimation

Yield Improvement

Mismatch Contribution Analysis

Mismatch Contribution Analysis is a Monte Carlo post-processing feature that helps in identifying the important contributors to mismatch variation. You can then modify the identified devices in the schematic and make the design less sensitive to mismatch variation. You can apply this method to existing standard Monte Carlo results or use the Sensitivity Accuracy method to automatically run the minimum required number of points.

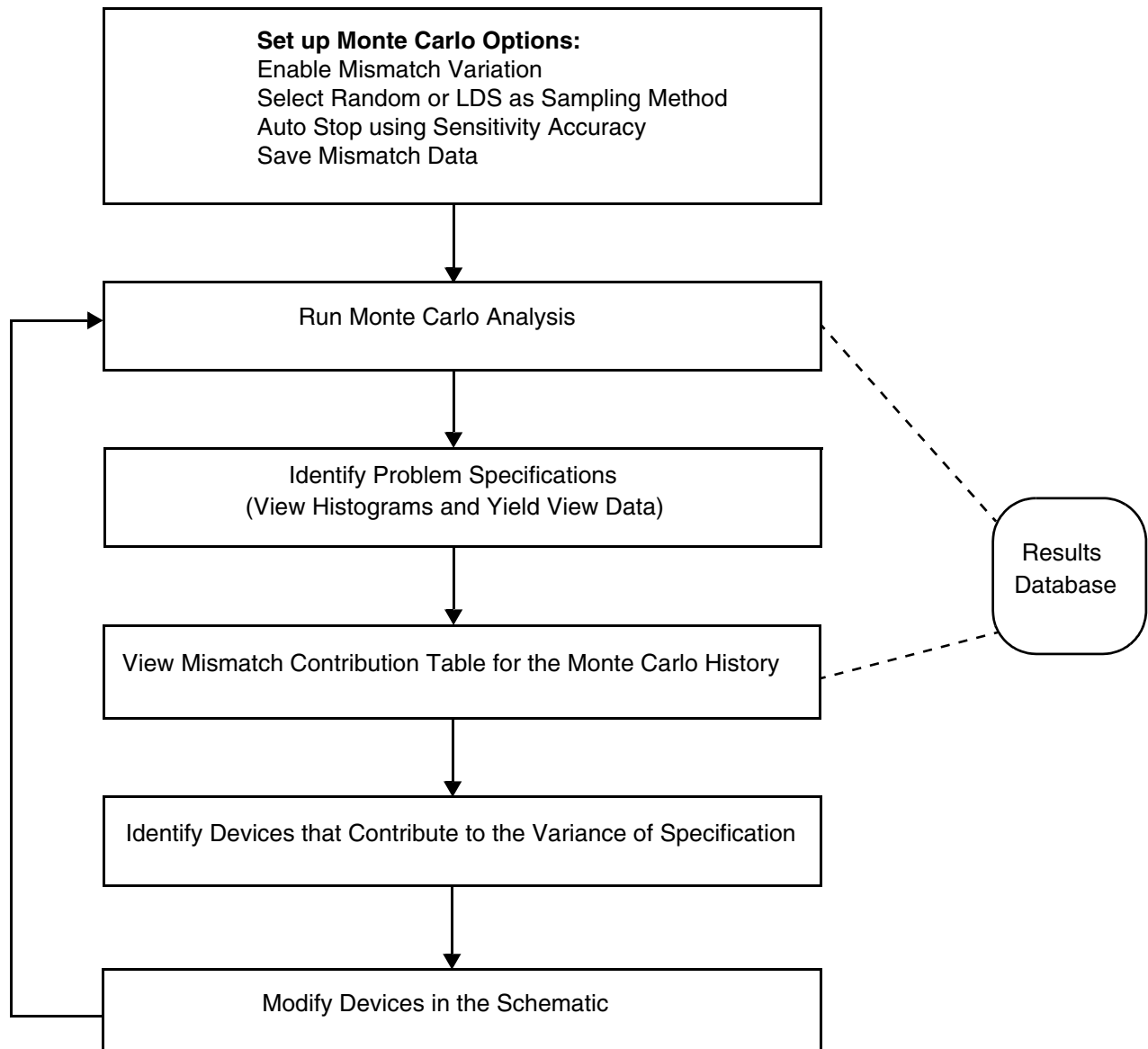
The Sensitivity Accuracy method is used to post-process Monte Carlo results and view the Mismatch Contribution table when you are not sure about the number of samples required to view the mismatch contribution results. This method helps in automatically determining the number of samples required to be run to meet the target accuracy level so that post-processing for Mismatch Contribution analysis can be done. The number of samples depends on the design and the number of statistical parameters defined by the model files.

When you select this method, the Monte Carlo run is stopped as soon as a model for variation contribution can be built for every output.

Virtuoso Variation Option User Guide

Mismatch Contribution Analysis

The following workflow shows how you can save and analyze the mismatch contribution data to improve your design.



Related Topics

[Running Mismatch Contribution Analysis](#)

[Viewing Results of Mismatch Contribution Analysis](#)

[Running What-If Analysis](#)

Running Mismatch Contribution Analysis

To run mismatch contribution analysis:

1. Open your design in ADE Assembler or ADE Explorer.
2. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
3. Click the *Simulation Options* command.

The Monte Carlo form opens.

Monte Carlo

Method: Sensitivity Accuracy

Variation: Mismatch

Max Points: auto

Points per Job: Group automatically, Max (10)

Save Waveforms (Simulation Data)

Sampling Method: Low-Discrepancy Sequence

Seed: 12345

First Point: 1

Netlist Options:

Specify Instances/Devices (Not Specified)

Specify Mismatch ID (Not Specified)

Specify Design Variables (Not Specified)

OK Cancel Defaults Help

4. From the *Method* drop-down list, select *Sensitivity Accuracy*.

Virtuoso Variation Option User Guide

Mismatch Contribution Analysis

5. From the *Variation* drop-down list, select *Mismatch*.
6. Select the *Save Waveform (Simulation Data)* check box to save the waveform data so that it can be used later for post-processing.

The modeling of variation in the outputs due to statistical variation can be done by using the post-processing option to view and analyze the mismatch contribution results. Therefore, for mismatch contribution analysis, it is required that you select this check box to save the data for Monte Carlo analysis so that it can be later used for post-processing.

7. From the *Sampling Method* drop-down list, select *Low-Discrepancy Sequence*.
8. Click *OK* to close the Monte Carlo form.
9. Click *Run Simulation* to run the mismatch contribution analysis.

Virtuoso Variation Option User Guide

Mismatch Contribution Analysis

After the Monte Carlo run is complete, the Sensitivity Analysis-MonteCarlo.M form opens, displaying the results of mismatch contribution analysis in the *Mismatch Contribution* tab.

	Max	Current Nominal Yield = 98.00% R ² = 0.99999	Voffset Nominal Yield = 100.00% R ² = 0.99999
Top	100%	100%	100%
/IO/AmpOut/M6	92%	92%	0%
/IO/AmpIn/NM0	41%	0%	41%
/IO/AmpIn/M1	40%	0%	40%
/IO/AmpIn/M4	10%	0%	10%
/IO/AmpIn/M3	9%	0%	9%
/IO/AmpOut/M8	4%	4%	0%
/IO/AmpIn/M10	1%	1%	0%
/IO/AmpIn/M9	1%	1%	0%
/IO/AmpOut/M7	1%	1%	0%

Related Topics

[Monte Carlo Form](#)

Virtuoso Variation Option User Guide

Mismatch Contribution Analysis


[Mismatch Contribution Analysis](#)

[Viewing Results of Mismatch Contribution Analysis](#)

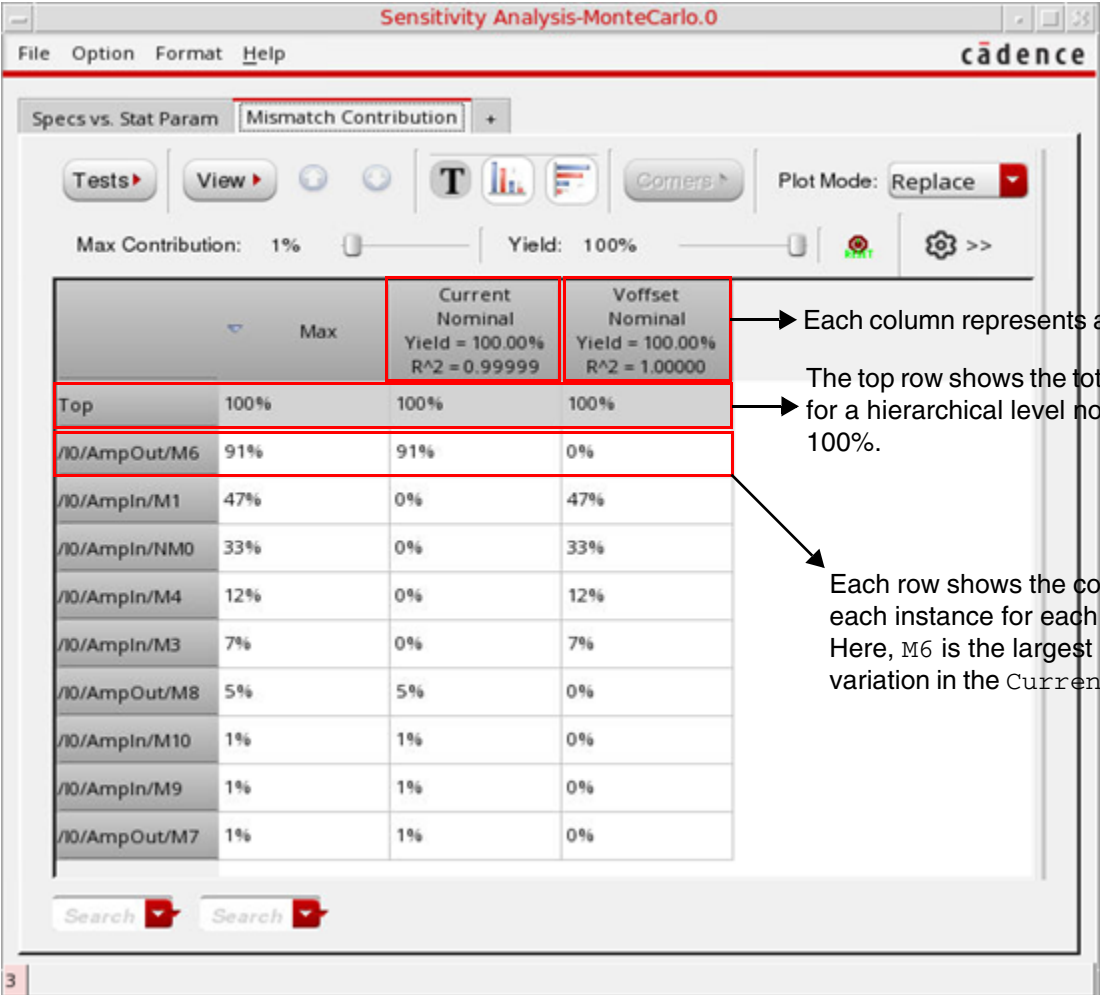
[Running What-If Analysis](#)

Viewing Results of Mismatch Contribution Analysis

To view the results of mismatch contribution analysis, do one of the following:

- Click *Mismatch Contribution* () on the toolbar of the *Results* tab in ADE Assembler.
- In the *History* tab on the Data View assistant, right-click a history name and then choose *Mismatch Contribution*.

The Sensitivity Analysis-MonteCarlo.N form appears, displaying the results in the *Mismatch Contribution* tab.



Each column represents a specification.

The top row shows the total contributions for a hierarchical level normalized to 100%.

Each row shows the contribution from each instance for each specification. Here, M6 is the largest contributor to variation in the Current specification.

	Max	Current Nominal Yield = 100.00% R^2 = 0.99999	Voffset Nominal Yield = 100.00% R^2 = 1.00000
Top	100%	100%	100%
/IO/AmpOut/M6	91%	91%	0%
/IO/AmpIn/M1	47%	0%	47%
/IO/AmpIn/NM0	33%	0%	33%
/IO/AmpIn/M4	12%	0%	12%
/IO/AmpIn/M3	7%	0%	7%
/IO/AmpOut/M8	5%	5%	0%
/IO/AmpIn/M10	1%	1%	0%
/IO/AmpIn/M9	1%	1%	0%
/IO/AmpOut/M7	1%	1%	0%

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Mismatch Contribution Analysis

Related Topics

[Mismatch Contribution Analysis](#)

[Running Mismatch Contribution Analysis](#)

[The Mismatch Contribution Table](#)

[Running What-If Analysis](#)

The Mismatch Contribution Table

The results of mismatch contribution analysis are displayed in a table on the *Mismatch Contribution* tab of the Sensitivity Analysis-MonteCarlo.N form.

In this table:

- Each row represents an instance of the design. For example, */I0/AmpOut/M6*.
- Each column represents an output specification. For example, *Current* and *Voffset*.
- Each cell shows the contribution (in percentage) of an instance towards the variance of the corresponding specification. All the contributions are normalized to 100%.

By default, the tool computes the proportions of a Monte Carlo sample variation by using a linear model. This is indicated by the R^2 (R squared) value in the column headers. The tooltip for column headers also shows how these proportions are calculated.

	Max	Current Nominal Yield = 100.00% R ² = 0.99999	Voffset Nominal Yield = 100.00% R ² = 1.00000
Top	100%	100%	Proportion of Monte Carlo sample variance explained by multivariate linear model = 99.999%

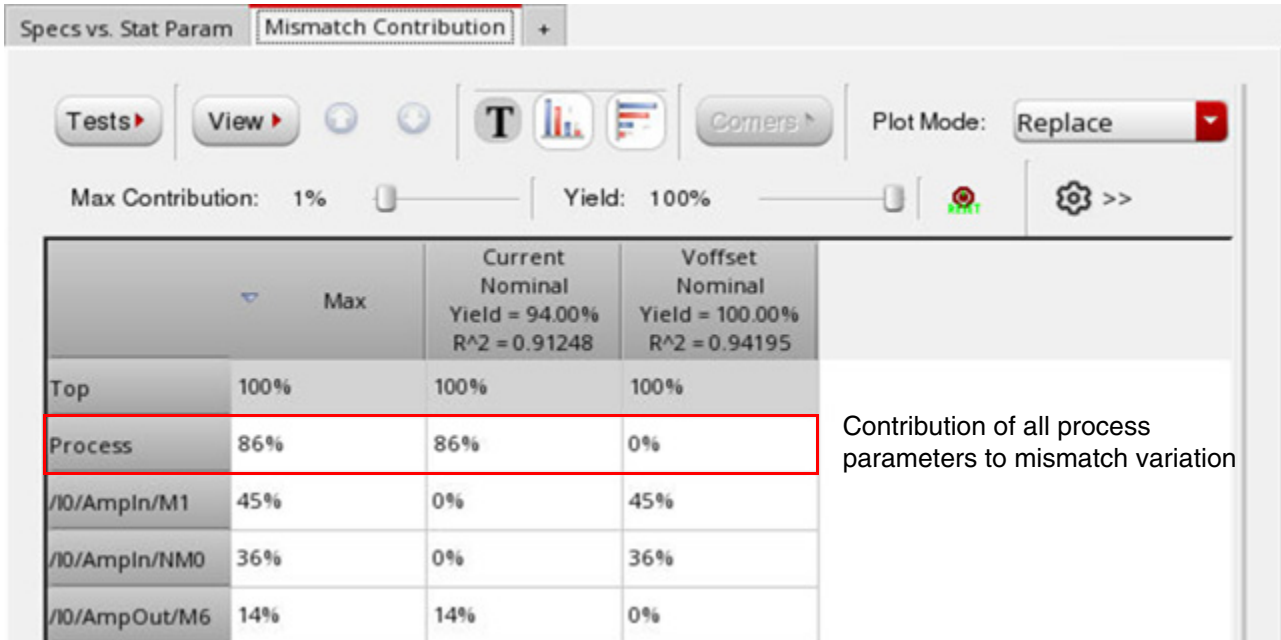
R^2 (Goodness of Fit) reports how much of the total variance is explained by the model. If the R^2 value is lower than the threshold value of 90%, the results of the linear model might not be useful. Therefore, in such cases, the tool automatically switches to the quadratic model to calculate variance data for a particular specification more accurately. The column header is also updated to indicate this change.

If you run the mismatch contribution analysis by selecting *All* as *Variation* on the Monte Carlo form, an additional *Process* row is displayed in the mismatch contribution results, as

Virtuoso Variation Option User Guide

Mismatch Contribution Analysis

shown in the following figure. This row shows the contributions of all the process parameters to mismatch variation.



Related Topics





[Mismatch Contribution Analysis](#)

[Viewing Results of Mismatch Contribution Analysis](#)

[Toolbar of the Mismatch Contribution Tab](#)





Toolbar of the Mismatch Contribution Tab

The toolbar of the *Mismatch Contribution* tab of the Sensitivity Analysis-MonteCarlo.N form contains the following commands.

Icon	Command Name	Description
N/A	<i>Tests</i>	<p>Selects the test for which you want to view the mismatch contribution results.</p> <p>The mismatch contribution table can display data for only one test at a time. By default, it shows the data for the first test in the setup.</p>
N/A	<i>View</i>	<p>Selects one of the following views:</p> <ul style="list-style-type: none"> ■ <i>Hierarchical</i>: Shows mismatch contribution results per instance. ■ <i>Flat</i>: Shows mismatch contribution results per parameter. This is the default view. ■ <i>Flat - Show Parameters</i>: Shows each statistical parameter in the <i>instance_name:parameter_name</i> format. As there can be multiple parameters for a device, each parameter is shown in a separate row. ■ <i>Variance</i>: Shows the variance values for each instance or parameter. ■ <i>Percentage</i>: Shows the contribution of each instance or parameter to variance in percentage.
	<i>Ascend parameter hierarchy</i>	Ascends the design hierarchy one level.
	<i>Descend parameter hierarchy</i>	Descends the design hierarchy one level.
	<i>Display numerical values</i>	Displays the mismatch contribution results in numerical values.
	N/A	Displays vertical bar graphs to compare data in the rows.

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Mismatch Contribution Analysis

	N/A	Displays the horizontal bar graphs to compare data in the columns.
N/A	<i>Corners</i>	Selects the corner for which you want to view the mismatch contribution results.
N/A	<i>Plot Mode</i>	Selects one of the plotting modes to plot the mismatch contribution results: <ul style="list-style-type: none"> ■ <i>Replace</i>: Replaces the graph in the active window with a new graph. ■ <i>Append</i>: Appends the result in the active graph window or subwindow. ■ <i>New SubWin</i>: Plots the result in a new subwindow within the existing graph window. ■ <i>New Win</i>: Plots the result in a new graph window.
N/A	<i>Max Contribution</i>	Hides the rows for the instance or parameters whose contribution to the variance is greater than or equal to the value specified by the <i>Max Contribution</i> filter. Use this filter to focus on the devices that have high contribution to the variance of the circuit.
N/A	<i>Yield</i>	Hides the columns for the specifications whose yield exceeds the value specified by the <i>Yield</i> filter. Use this filter when you need to focus on the outputs that are not achieving the required specification yield.
	<i>Reset</i>	Resets the <i>Max Contribution</i> and <i>Yield</i> filters to initial values.
	<i>Open the Mismatch Tuner</i>	Opens the Mismatch Tuner, which you can use to see how a change in the size of any device instance impacts the variation of circuit output.
	<i>Close the Mismatch Tuner</i>	Closes the Mismatch Tuner.

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Mismatch Contribution Analysis

Related Topics

[Mismatch Contribution Analysis](#)

[Running Mismatch Contribution Analysis](#)

[Viewing Results of Mismatch Contribution Analysis](#)

[Running What-If Analysis](#)

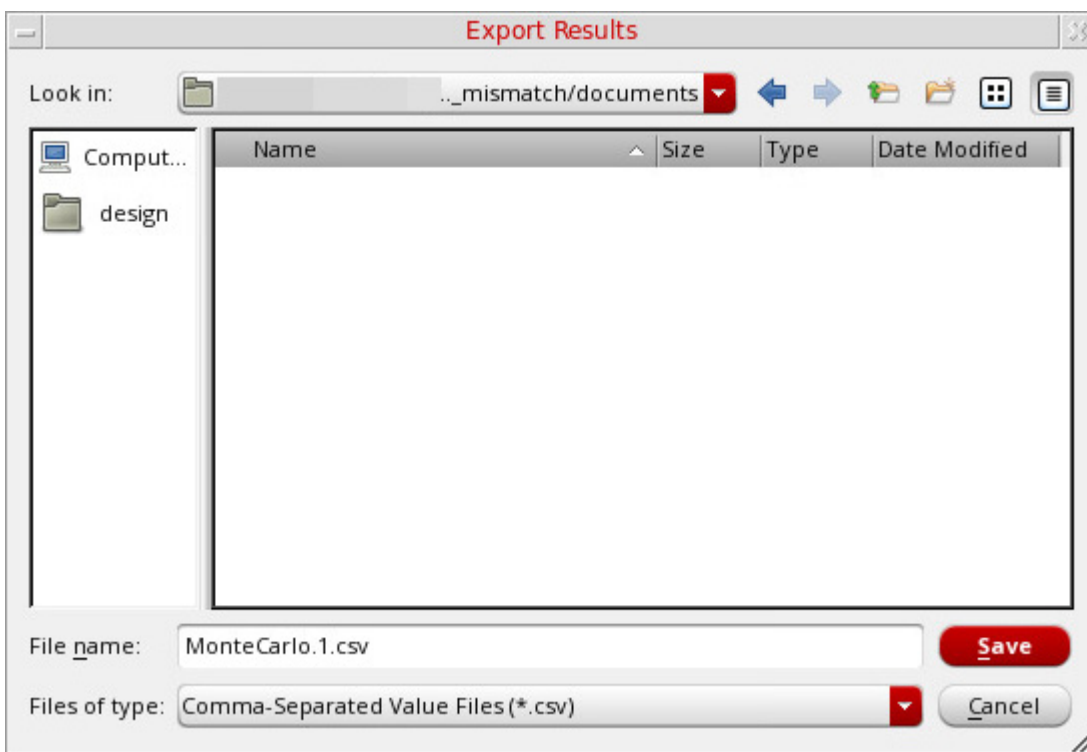
Exporting Mismatch Contribution Results

You can export the results of mismatch contribution analysis to a CSV file for post-processing.

To export the results of mismatch contribution analysis to a CSV file:

1. On the *Mismatch Contribution* tab of the Sensitivity Analysis-MonteCarlo.N form, choose *File – Export Result to CSV – Current Tab*.

The Export Results form opens.



2. In the *File Name* field, specify the name of the CSV file to which you want to export the results of mismatch contribution analysis.
3. Click *Save*.

For mismatch contribution results, data in the CSV file after exporting results is displayed exactly the same way as it is displayed in the Mismatch Contribution table.

For example, on the Mismatch Contribution table, if you have:

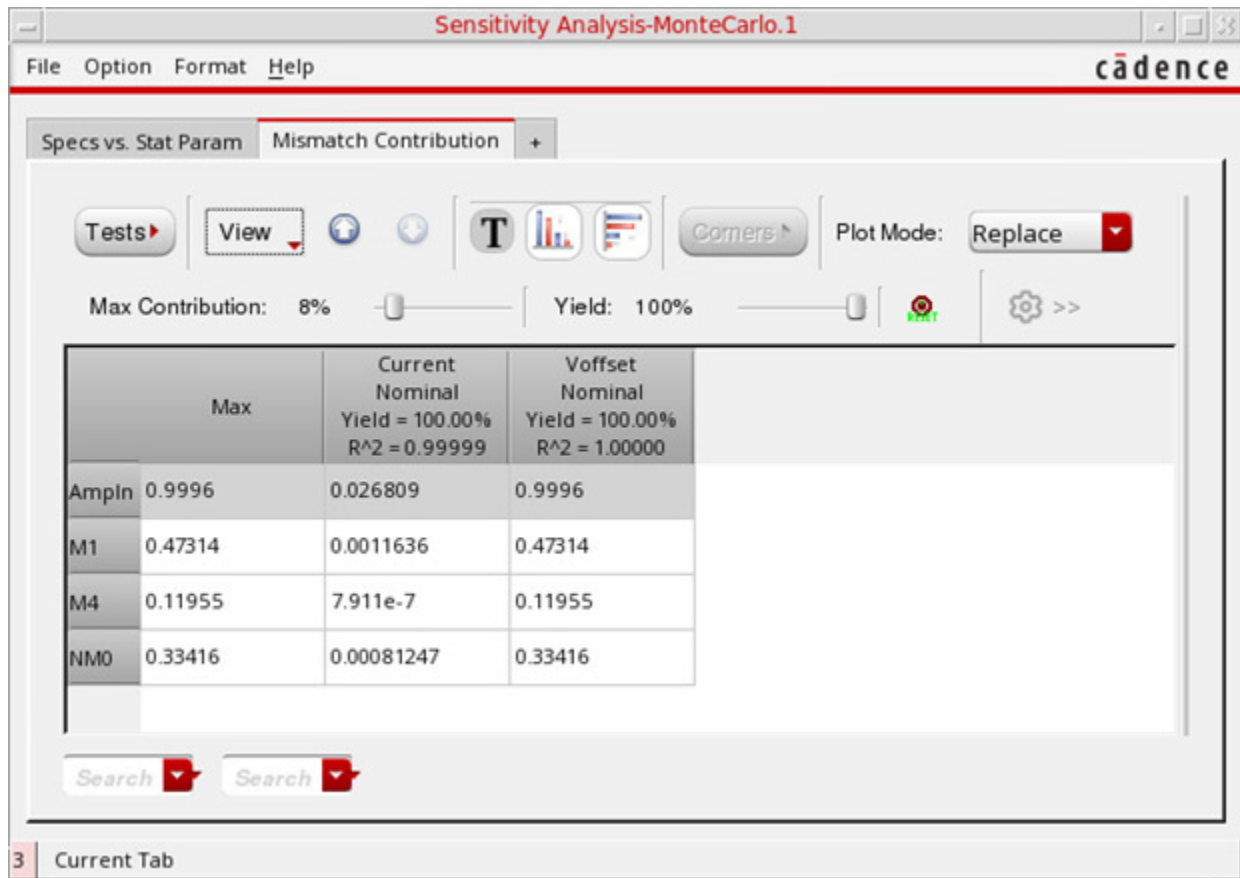
- selected instances to display hierarchically and descended to the level, AmpIn.

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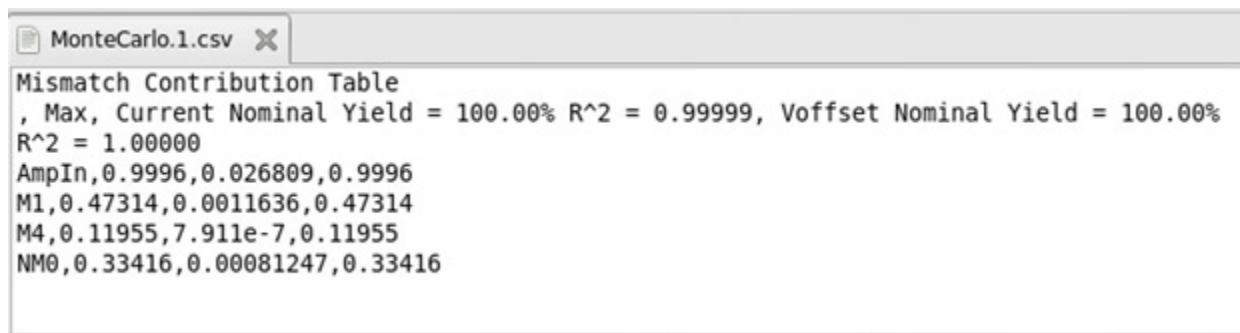
Mismatch Contribution Analysis

- filtered data to display only the instances that have a contribution value equal to or greater than 8%.
- selected data to display as variance.

Data in the mismatch contribution table is displayed as follows:



The following figure shows an example of the contents of the CSV file, when the results are exported to the CSV file.



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Mismatch Contribution Analysis

You can observe that the CSV file contains data exactly as you see it in the mismatch contribution table.

Related Topics

[Mismatch Contribution Analysis](#)

[Running Mismatch Contribution Analysis](#)

[Viewing Results of Mismatch Contribution Analysis](#)

Running What-If Analysis

You can use Mismatch Tuner on the *Mismatch Contribution* tab to perform what-if analysis on how a change in the size of any device instance impacts the variation of the circuit output. The mismatch tuner helps you tune the contribution of an instance by changing its area multiplier.

Note: The *Open the Mismatch Tuner* command is disabled if the instances are displayed in the *Hierarchical* view. You need to change the view to the *Flat* view by using the *View* command in the toolbar of the *Mismatch Contribution* tab.

To identify the impact of a change in the size of a device on the variation of the circuit output:

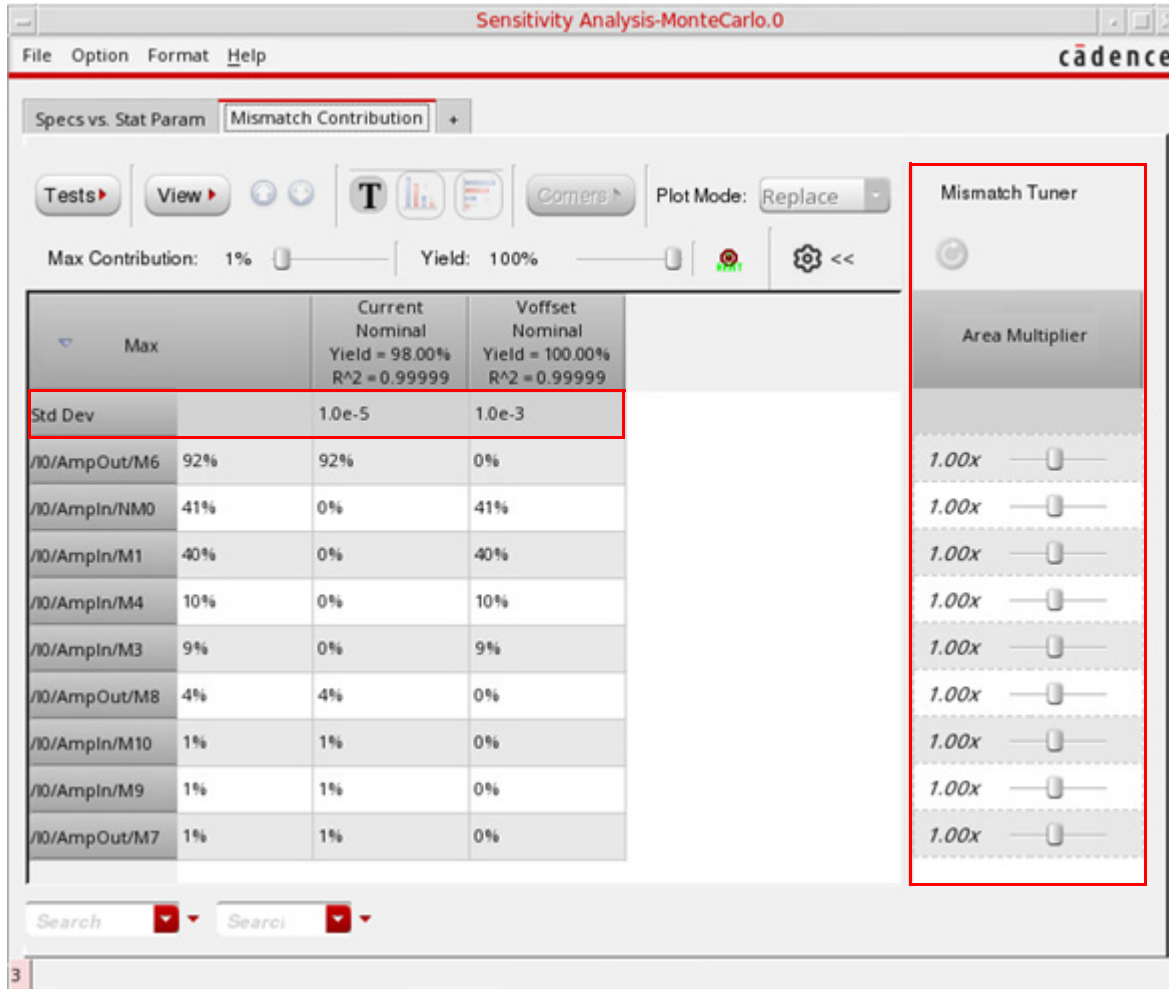
1. On the *Mismatch Contribution* tab, click the *Open the Mismatch Tuner* command.

For each instance, a row is added to the *Mismatch Tuner* pane. Each row has a slider to change the area multiplier of the corresponding instance. In addition, the *Std Dev* row

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Mismatch Contribution Analysis

is displayed as the first row in the *Mismatch Contribution* table. This row displays the standard deviation for each output.



2. Drag the slider on the *Mismatch Tuner* to the left or to the right to decrease or increase the size of the corresponding instance. You can also change the size by typing a value in the range of 0.1–10 in the text field to the left of the slider.

The predicted standard deviation values due to the change in the instance size are shown in the *Std Dev* row. In addition, the value in parenthesis shows the percent change in value. If there is any change in the standard deviation of any specification, its

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Mismatch Contribution Analysis

value is displayed in red or blue to indicate a negative or positive impact on the variation of that specification.

	Max	Current Nominal Yield = 98.00% R^2 = 0.99999	Voffset Nominal Yield = 100.00% R^2 = 0.99999
Std Dev		1.6e-5 (+48.88%)	9.3e-4 (-6.95%)
/I0/AmpOut/M6	96%	96%	0%
/I0/AmpIn/NM0	32%	0%	32%
/I0/AmpIn/M1	46%	0%	46%
/I0/AmpIn/M4	12%	0%	12%
/I0/AmpIn/M3	10%	0%	10%
/I0/AmpOut/M8	2%	2%	0%
/I0/AmpIn/M10	1%	1%	0%
/I0/AmpIn/M9	1%	1%	0%
/I0/AmpOut/M7	1%	1%	0%

The variance contribution value for that instance is also updated in the corresponding row. The updated values are displayed in blue or red.

- Continue to change the area multiplier for different devices until the desired changes in the standard deviation for the specifications is achieved. You can later reflect these changes in the design by modifying the instance parameters in the Variables and Parameters assistant or by modifying the schematic.

The transistor area can be increased by maintaining the width-to-length ratio (w/l) and simultaneously increasing both the width (w) and length (l) of the transistor by a certain factor. For example, to increase the transistor area by $2\times$ while maintaining the w/l ratio, you can increase both w and l by the square root of 2.

Note the following:

- You can clear all the multipliers by using the *Reset table to original contribution values* command on top-left corner of the *Mismatch Tuner*.

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Mismatch Contribution Analysis

- When the *Mismatch Tuner* is open, the variance contribution values are displayed only in the numerical format. If data is displayed in vertical or horizontal bar graphs, the data its format automatically changes to numerical when you open the *Mismatch Tuner*.
- The mismatch contribution and yield filters are hidden when the *Mismatch Tuner* is in progress.
- You cannot descend or ascend through the design hierarchy while the *Mismatch Tuner* is open.

Related Topics

[Mismatch Contribution Analysis](#)

[Viewing Results of Mismatch Contribution Analysis](#)

[The Mismatch Contribution Table](#)

[Toolbar of the Mismatch Contribution Tab](#)

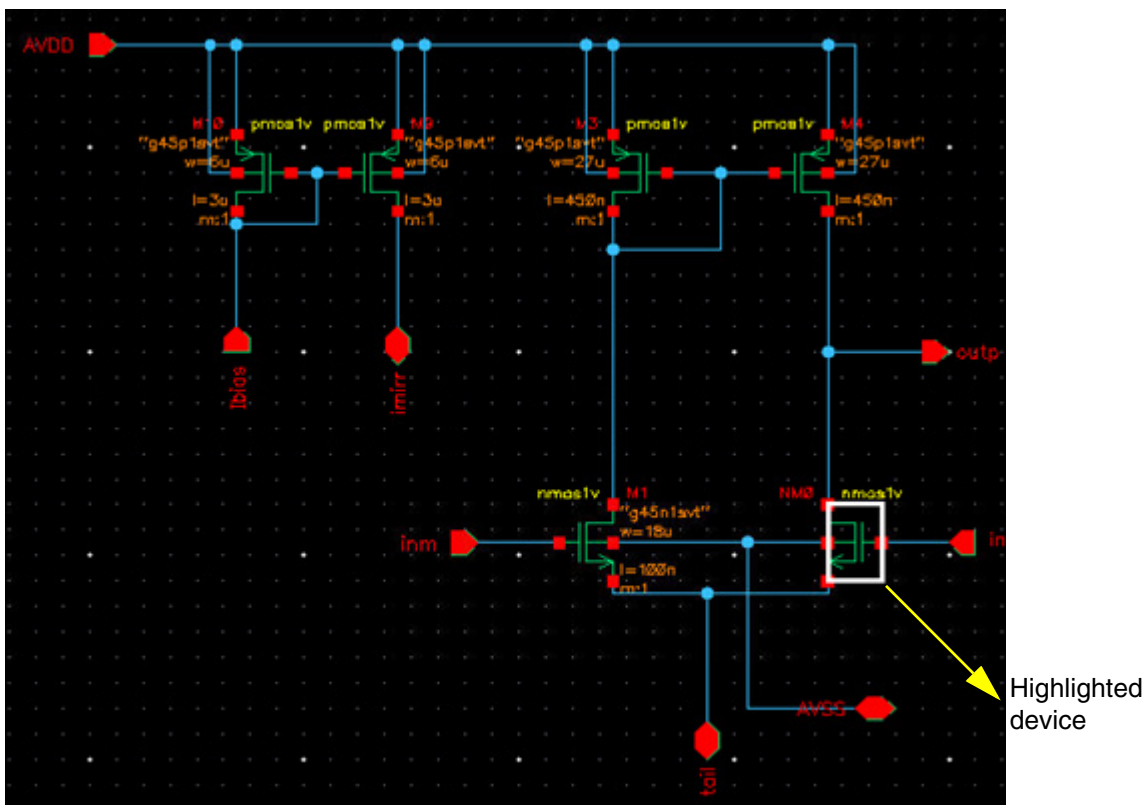
Highlighting a Device on Schematic

While analyzing data in the mismatch contribution table, you can highlight a device on the schematic to view its exact location. This can help in identifying and modifying a device in the schematic to improve the variance data, if required.

To highlight a device on the schematic:

- ➔ Right-click a row and choose *Highlight on Schematic*.

Alternatively, you can press *H* on the keyboard.



Related Topics

[Mismatch Contribution Analysis](#)

[Running Mismatch Contribution Analysis](#)

[Viewing Results of Mismatch Contribution Analysis](#)

[Running What-If Analysis](#)

Virtuoso Variation Option User Guide

Mismatch Contribution Analysis

Fast Monte Carlo Method

The Fast Monte Carlo (FMC) engine is implemented in the Spectre simulator. The FMC method lets you extract useful statistical information without running the complete set of Monte Carlo samples, especially for high-sigma analysis. This reduces the simulation time.

The FMC method identifies the tail samples out of total N Monte Carlo points without simulating all N points for the specified circuit measurement specification or set of measures. The number of sample points that is actually simulated is circuit dependent.

In FMC method, you must specify any two of the following parameters:

- *Total Samples* (`numruns`)
- *Target Yield* (`fmcsigma`)
- *Tail Samples* (`fmcnumtailsamples`)

For example, the following settings are equivalent, which indicates that for 1M samples, the sample at 4.2 Sigma is the 14th worst sample:

- *Total Samples* = 1M and *Target Yield* = 4.2
- *Target Yield* = 4.2 and *Tail Samples* = 14
- *Total Samples* = 1M and *Tail Samples* = 14

The following table lists the relation between the fields, *Max Points*, *Target Yield*, and *Tail Samples* for FMC method.

Total Samples	Target Yield	Reported Samples	Sigma Range
20K	3	28	(2.99, 4.06)
100K	4	4	(3.98, 4.42)
1M	4.2	14	(4.2, 4.89)
100M	5.4	4	(5.39, 5.73)
500M	5.8	3	(5.73, 6)

Virtuoso Variation Option User Guide

Fast Monte Carlo Method

1B	5.8	4	(5.79, 6.11)
----	-----	---	--------------

Outputs and Target Specifications

To reduce the run time, it is recommended that you enable only the minimum set of specifications of interest. If both min and max for the goal are not needed for a high-sigma analysis, you can use either of them based on what is the actual criterion for a failure of the specific measurement.

Related Topics

[Workflow of Fast Monte Carlo Method](#)

[Running the Fast Monte Carlo Method](#)

[Spectre FMC Analysis](#)

Workflow of Fast Monte Carlo Method

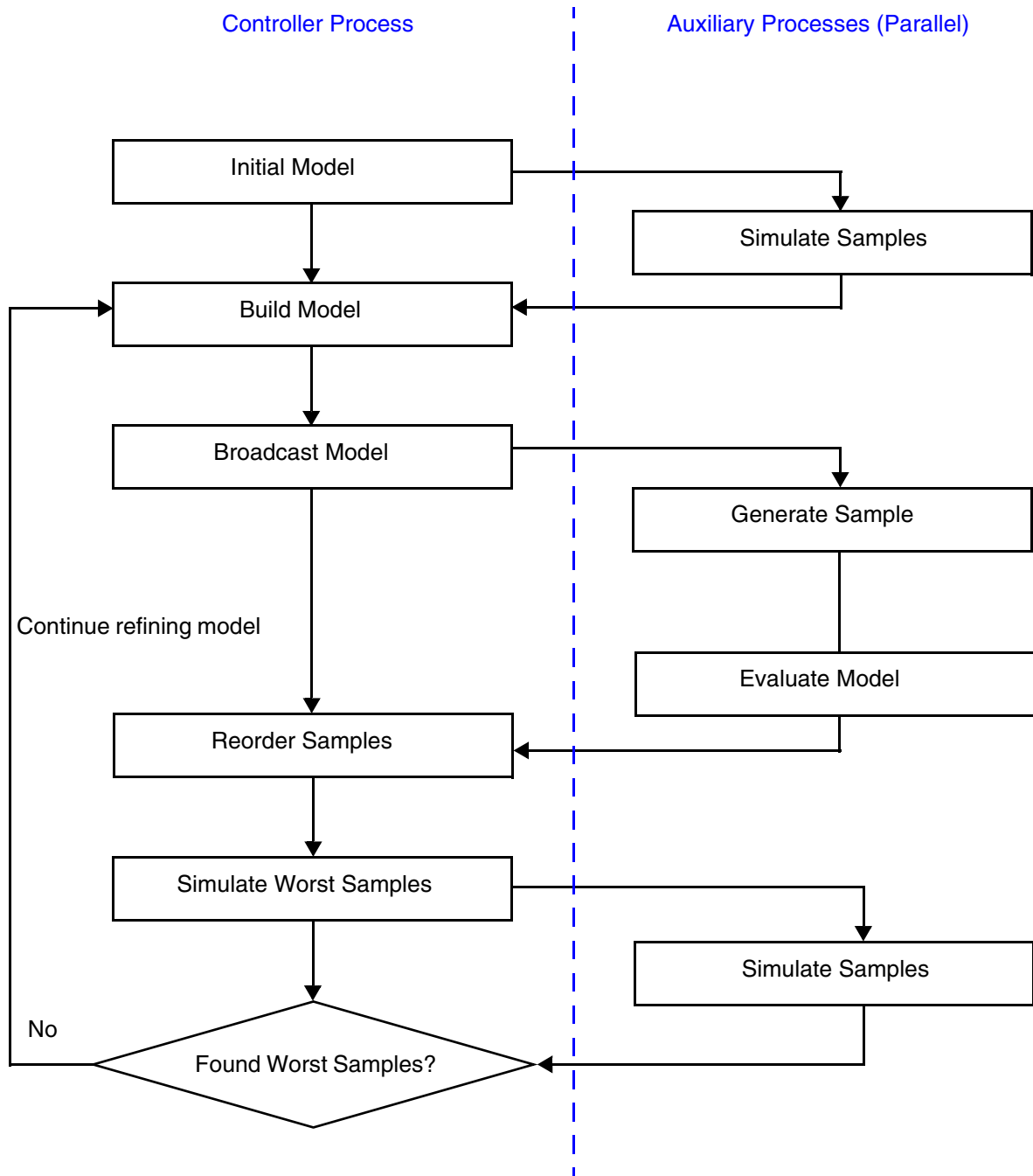
The Fast Monte Carlo (FMC) method first runs a group of samples and obtains measurements, then the algorithm builds a model and predicts the worst sample based on the user-specified results and specifications. It may take a few group iterations from model building, worst-sampling prediction, and verification to find out the tail of distribution. The FMC method thus improves performance and reduces memory cost when compared with the normal Monte Carlo method.

The FMC method also supports multi-process distribution to further improve the performance. The sample generation, model evaluation, and simulation are processed by worker processes running in parallel.

Virtuoso Variation Option User Guide

Fast Monte Carlo Method

The following figure shows the workflow of the FMC method.



Virtuoso Variation Option User Guide

Fast Monte Carlo Method

Related Topics

[Fast Monte Carlo Method](#)

[Running the Fast Monte Carlo Method](#)

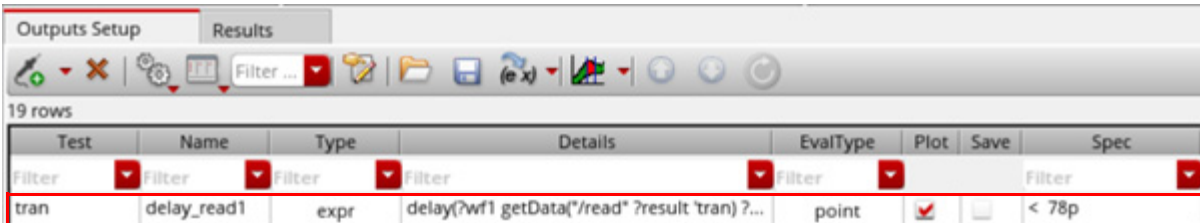
[Spectre FMC Analysis](#)

Running the Fast Monte Carlo Method

To run the FMC method:

1. Open your design in ADE Assembler.
2. In the *Outputs Setup* tab of ADE Assembler, define at least one specification.

In the following example, the output `delay_read1` has a specification.



Test	Name	Type	Details	EvalType	Plot	Save	Spec
Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter
tran	delay_read1	expr	delay(?wf1_getData(*?read* ?result 'tran') ?...	point	<input checked="" type="checkbox"/>	<input type="checkbox"/>	< 78p

3. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
4. Click the *Simulation Options* command.
The Monte Carlo form opens.
5. From the *Method* drop-down list, select *FMC Worst Samples*.
6. Specify any two of the following fields:
 - a. In the *Total Samples* field, specify the maximum number of points to be simulated.
The default value is 400.
 - b. In the *Target Yield* field, specify the yield value that you want to achieve for your design. For example, 3 Sigma.
 - c. In the *Tail Samples* field, specify the number of tail samples. For example, 10.
7. In the *Budget* field, specify the number of simulations to be run for FMC method. For example, if you set this field to 500, no more than 500 points are simulated for FMC Worst Sample method. This is an optional field.
8. In the *Initial Points* field, specify the number of initial points based on which metrics, such as mean and standard deviations, are calculated and annotated in histograms. Specifying a higher number of initial points improves the accuracy of mean and standard deviation measurements.

In FMC Worst Sample method, an initial model is built after the initial sampling group finishes. The initial model can be built with additional data points by increasing the number of initial points.

Virtuoso Variation Option User Guide

Fast Monte Carlo Method

9. Select the *Save Waveform (Simulation Data)* check box to save the waveform data so that it can be used later for post-processing.
10. Click *OK* to close the Monte Carlo form.
11. In the *Run* toolbar of ADE Assembler, click *Run Simulation* to run the FMC method.

The results are displayed in the *Results* tab, as shown in the following figure.

The screenshot shows the 'Results' tab in ADE Assembler. The 'Yield' section is expanded, showing a table of test results. The table has columns for Test, Name, Yield, Min, Target, Max, and Errors. The results show that all 150 points passed for all tests, with a confidence level of <not set> and a filter of <not set>. The tests include delay_read1, read0, read1, write0, write0n, write1, and write1n, each with a summary row and a detailed row. The yield for all tests is 100% (150/150).

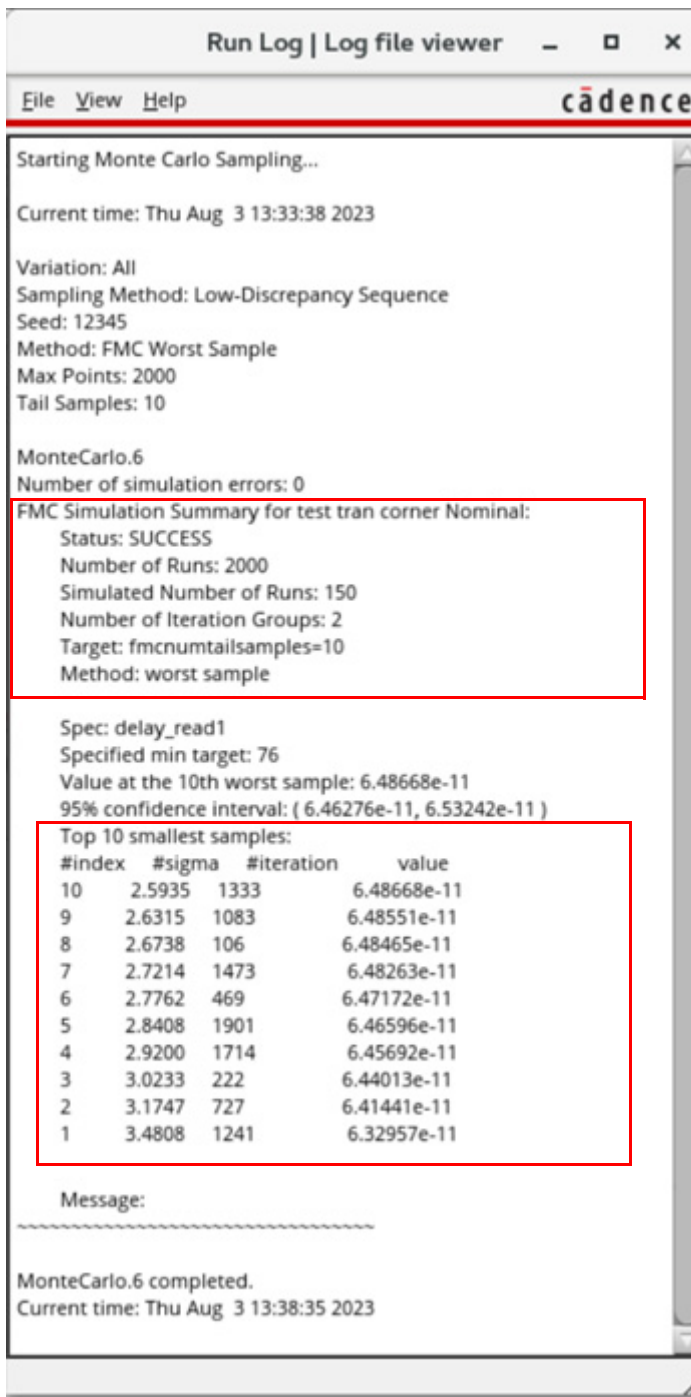
Test	Name	Yield	Min	Target	Max	Errors
150 passed/150 pts Confidence Level: <not set> Filter: <not set>						
-	tran					
-	delay_read1(summary)	100% (150/150)	66.03p	< 78p	75.41p	0
	delay_read1	100% (150/150)	66.03p	< 78p	75.41p	0
-	read0(summary)	100% (150/150)	133.7u	info	545.7u	0
	read0	100% (150/150)	133.7u	info	545.7u	0
-	read1(summary)	100% (150/150)	1.786	info	1.792	0
	read1	100% (150/150)	1.786	info	1.792	0
-	write0(summary)	100% (150/150)	7.767m	info	13.57m	0
	write0	100% (150/150)	7.767m	info	13.57m	0
-	write0n(summary)	100% (150/150)	1.789	info	1.797	0
	write0n	100% (150/150)	1.789	info	1.797	0
-	write1(summary)	100% (150/150)	1.789	info	1.797	0
	write1	100% (150/150)	1.789	info	1.797	0
-	write1n(summary)	100% (150/150)	7.582m	info	13.6m	0
	write1n	100% (150/150)	7.582m	info	13.6m	0

The number of passed points and total number of points are reported. Note that the yield estimate is not reported in the results. Metrics, such as *Mean*, *Std Dev*, that are normally reported for a standard Monte Carlo run are also omitted from the *Yield* results view.

Virtuoso Variation Option User Guide

Fast Monte Carlo Method

12. From the toolbar of the *Results* tab, click *Open Run Log* to open the run log.



Top 10 smallest samples

This FMC run identified the top worst samples out of 2000 total points, but only 150 sample points were actually simulated.

Virtuoso Variation Option User Guide

Fast Monte Carlo Method

13. In the *Results* tab, from the *Select the results view* drop-down list, select the *Detail –Transpose* view.
14. In the toolbar of the *Results* tab, click *Configure what is shown in the table* and deselect *Signals*.

The results are displayed in the *Detail – Transpose* view as follows.

Point	mc_iteration	Pass/Fail	write0	write0n	read0	write1	write1n	read1	delay_read1
1	1	pass	12.41m	1.794	216.6u	1.793	10.93m	1.791	69.1p
2	2	pass	10.55m	1.795	293.1u	1.793	11.08m	1.79	69.6p
3	3	pass	11.72m	1.789	175.9u	1.79	11.85m	1.786	67.72p
4	4	pass	11.91m	1.795	227.3u	1.79	12.69m	1.79	73.39p
5	5	pass	10.83m	1.792	226.4u	1.793	10.31m	1.789	68.43p
6	6	pass	10.8m	1.792	232.7u	1.795	10.48m	1.789	71.21p
7	7	pass	12.53m	1.793	177.3u	1.792	11.46m	1.79	66.03p
8	8	pass	9.879m	1.794	308.7u	1.793	7.582m	1.79	73.1p
9	9	pass	11.48m	1.795	212.6u	1.793	11.7m	1.791	67.57p
10	10	pass	13.57m	1.793	168.9u	1.794	12.37m	1.789	67.02p
11	11	pass	9.746m	1.791	272.8u	1.792	10.49m	1.789	70.25p
12	12	pass	10.95m	1.794	216.3u	1.794	10.18m	1.791	68.72p
13	13	pass	10.53m	1.793	203u	1.795	12.12m	1.79	70.72p
14	14	pass	12.42m	1.79	228.4u	1.793	12.33m	1.788	66.31p

15. Click the header of the output specification column to sort the values in the ascending order.

The values in the column are sorted,

delay_read1
66.03p
66.19p
66.26p
66.31p
67.01p
67.02p
67.11p
67.13p

Related Topics

[Fast Monte Carlo Method](#)

[Workflow of Fast Monte Carlo Method](#)

[Spectre FMC Analysis](#)

[Monte Carlo Form](#)

Features Not Supported in the Fast Monte Carlo

The following features are not supported when you run the Fast Monte Carlo (FMC) method:

- ADE calibration features including pre-run scripts or `calcVal` expressions
- Reliability analysis
- Result reevaluation and rerun unfinished points
- History merging and reference history
- MATLAB output expressions
- The *Job Control Mode* field `ICRP`

Note: The ADE job policy cannot be changed in the middle of an FMC run because the *Max Jobs* field is set at the start of the run.

Related Topics

[Fast Monte Carlo Method](#)

[Workflow of Fast Monte Carlo Method](#)

[Running the Fast Monte Carlo Method](#)

Virtuoso Variation Option User Guide

Fast Monte Carlo Method

Yield Verification

The accuracy of the yield estimate from a Monte Carlo run increases by simulating a large number of samples. However, running a large number of simulations can consume a lot of time and resources for large designs. You can perform one of the following yield verification methods to estimate the yield during the Monte Carlo analysis. These methods can be run when the target yield less than 4 sigma.

- Yield Verification - Autostop

This method is used to automatically identify the appropriate number of samples for Monte Carlo analysis to simulate based on a target yield estimate. The Monte Carlo run will stop automatically without running additional simulations as soon as it can be determined that the yield is above or below the target.

For more information about the Yield Verification - Autostop method, see [Performing Yield Verification](#) in *Virtuoso ADE Explorer User Guide*.

- Yield Verification - Reorder Samples

This method is available only when you have the Virtuoso Variation Option (VVO) license. To verify the yield, you require a large number of samples when the yield is above or slightly below the target. For example, when verifying a 3-sigma target with confidence value 90 percent, the run can be stopped if the first 1800 samples (approximately) pass the specification. The sample reordering method helps you verify the yield without simulating such a large number of samples.

These yield estimation methods are used only when the sigma value is equal to 3. For higher sigma values, you can use either the Scaled-Sigma Sampling (SSS) method or the Worst-Case Distance (WCD) method.

Related Topics

[Workflow of the Yield Verification - Reorder Samples Method](#)

[Running the Yield Verification - Reorder Sample Method](#)

[The Scaled-Sigma Sampling Method](#)

Virtuoso Variation Option User Guide

Yield Verification

The Worst-Case Distance Method

Workflow of the Yield Verification - Reorder Samples Method

In the Yield Verification - Reorder Samples method, the Monte Carlo samples are ordered from worst to best based on failure probability modeling. First, a small number of samples are simulated to fit into the model of performance and statistical variation. Then, the remaining Monte Carlo samples are generated, but not simulated. The samples are then reordered based on the performance model. After that, simulation begins with the samples that have the highest probability to fail.

The detailed steps are as follows:

1. The run begins with an initial Monte Carlo sampling, in which a small number of samples are simulated in the normal order (a minimum of 50 samples). The Sensitivity Accuracy method is applied that stops simulating new Monte Carlo samples after enough data is available for accurate modeling.
2. After the initial sampling and modeling is complete, the remaining samples are generated but not simulated. The total number of samples required for the run is determined automatically from the target yield and the probability requirements specified in the Monte Carlo form. For each of the remaining samples, the statistical parameter values are generated, and the samples are ordered using failure probability modeling.
3. Now, the Monte Carlo samples are simulated in the highest probability to fail order. The Monte Carlo run stops automatically in both cases—target yield is met or not met.
 - When the yield is low, the failed samples are simulated first.
 - When the yield is high, the run stops early when the specifications pass for the samples with high probability to fail. The remaining samples have very low probability to fail.

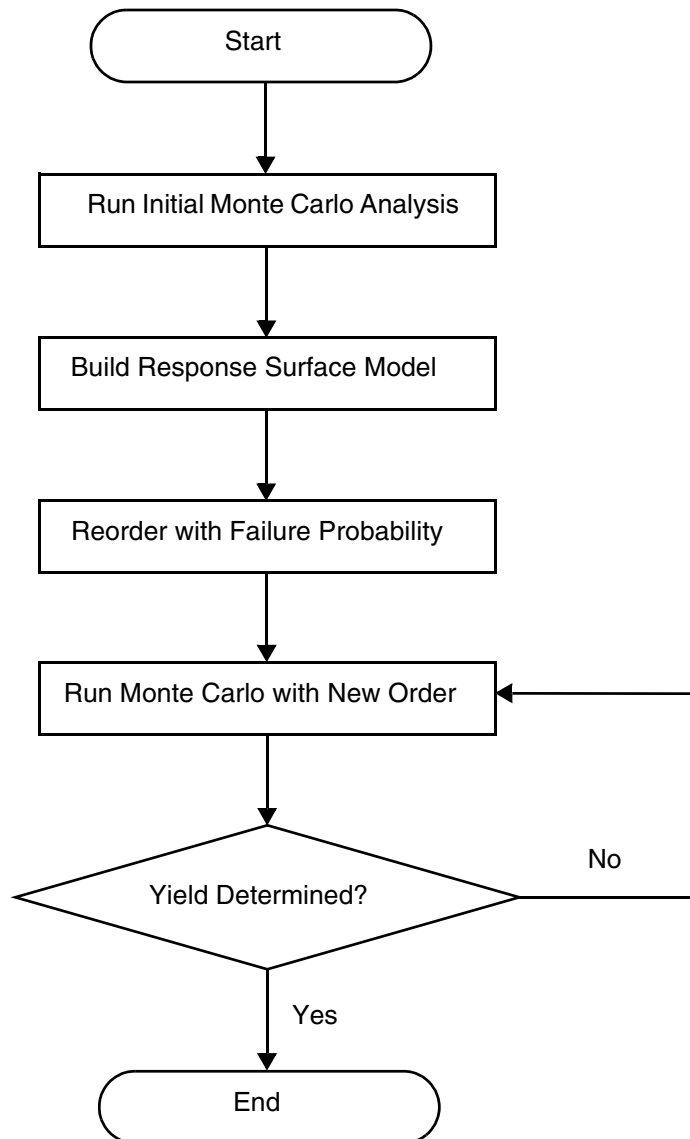
If the design has low yield, the failed samples are identified early, and the simulation run is stopped. On the other hand, if the design has high yield, it can be determined earlier that the yield target is met if the most probable to fail samples pass the specification. If these worst samples pass the specifications, the run stops early.

In both the cases, the run stops earlier than the traditional significance test method using a normal random sequence of samples. Significant time saving is observed in high yield cases, since the worst-case samples are simulated much earlier in the run.

Virtuoso Variation Option User Guide

Yield Verification

The following figure shows the workflow of this method.



Related Topics

[Yield Verification](#)

[Running the Yield Verification - Reorder Sample Method](#)

Running the Yield Verification - Reorder Sample Method

Before you run the *Yield Verification -Reorder Sample* method, ensure that the following environment variable is set to `t`:

```
envSetVal("maestro.monte" "showMethodYieldVerificationReorderSamples" 'boolean t)
```

To verify yield using the Yield Verification - Reorder Sample method:

1. Open your design in ADE Assembler or ADE Explorer.
2. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
3. Click the *Simulation Options* command.

Virtuoso Variation Option User Guide

Yield Verification

The Monte Carlo form opens.

The screenshot shows the 'Monte Carlo' dialog box with the following settings:

- Method: Yield Verification - Reorder Samples
- Variation: All
- Max Points: 2289
- Target Yield: 3 (sigma)
- Probability: 95 %
- Points per Job: Group automatically (selected), Max (10)
- Save Waveforms (Simulation Data): checked
- Sampling Method: Low-Discrepancy Sequence
- Seed: 12345
- First Point: 1
- Netlist Options: (empty)

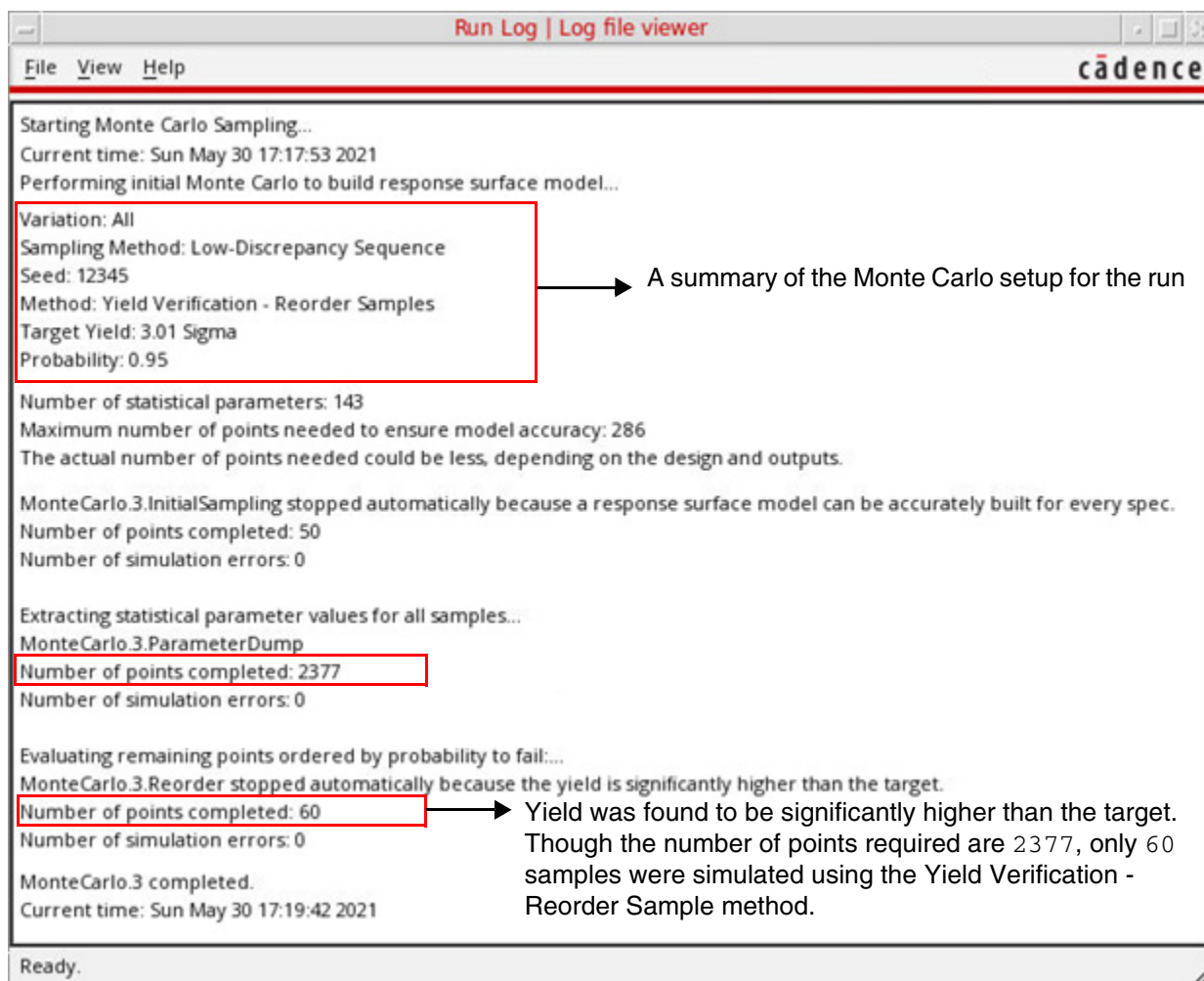
4. From the Method drop-down list, select *Yield Verification - Reorder Sample*.
5. From the *Variation* drop-down list, select *Process, Mismatch, or All*.
6. The *Max Points* field shows the maximum number of points that will be run.
This value depends on both the *Target Yield* and *Probability*. The number of simulations required is typically much smaller.
7. In the *Target Yield* field, specify the yield value that you want to achieve for your design. The target yield can be specified in either sigma or percentage
8. In the *Probability* field, select a probability percentage value.

Virtuoso Variation Option User Guide

Yield Verification

9. Probability values closer to 100% will require more simulations before the yield estimate can be determined to be lower or higher than the target. Smaller probability values require less simulations before autostop is triggered. The default value is 95%.
10. Select the *Save Waveform (Simulation Data)* check box to save the waveform data so that it can be used later for post-processing.
11. From the *Sampling Method* drop-down list, select *Random* or *Low-Discrepancy Sequence*.
12. Click *OK* to close the Monte Carlo form.
13. Click *Run Simulation* to run the *Yield Verification - Reorder Sample* method.

The Run Log reports the following information.



Virtuoso Variation Option User Guide

Yield Verification

The *Yield* view of the *Results* tab displays the results of the Monte Carlo run for the Yield Verification - Reorder Sample method.

The screenshot shows the 'Results' tab in the 'Yield' view. The table below is a representation of the data shown in the screenshot. A red box highlights the summary row and the 'Yield' column for the 'tran' test group.

Test	Name	Yield	Min	Target	Max	Mean	Std Dev	Cpk	Errors
		60 passed/60 pts	Yield > 99.87%		Confidence Level: 95%		Filter: <not set>		
-	tran								
	write0	100% (60/60)	7.767m	< 50m	13.57m	11.42m	1.099m	9.74	0
	write0n	100% (60/60)	1.789	> 1.75	1.797	1.793	1.632m	8.26	0
	read0	100% (60/60)	133.7u	< 50m	484.7u	235.1u	63.8u	191	0
	write1	100% (60/60)	1.789	> 1.75	1.796	1.793	1.615m	8.84	0
	write1n	100% (60/60)	7.582m	< 50m	13.6m	11.29m	1.164m	10.7	0
	read1	100% (60/60)	1.786	> 1.75	1.792	1.79	1.003m	13.9	0
	delay_read1	100% (60/60)	66.03p	< 78p	75.41p	69.24p	1.904p	1.04	0

Resulting yield for each specification and the number of points passed/number of points completed

Related Topics

[Monte Carlo Form](#)

[Statistical Sampling Methods](#)

[Yield Verification](#)

[Workflow of the Yield Verification - Reorder Samples Method](#)

[showMethodYieldVerificationReorderSamples](#)

Statistical Corner Creation

After running Monte Carlo simulations, you can analyze the yield and identify the specifications for which the results need improvement. You can then create statistical corners to use them in further analysis and design optimization. Statistical corners contain the simulation settings needed to recreate the statistical variable values for a specific condition. Statistical corners apply to a particular measurement or specification.

Virtuoso Variation Option provides the following advanced methods to create statistical corners:

- **K-Sigma Corners**

A corner created by the K-Sigma Corners method is based on modeling and extrapolation from the Probability Density Function (PDF) of the output. This corner is not one of the samples generated by the simulator and this method is typically faster than the Worst Samples method.

The K-Sigma Corners method is strongly recommended over the Worst Samples method when the number of statistical parameters is large (> 1000).

- **Worst Samples**

A corner created by the Worst Samples method is from a sample generated by the simulator. It represents the condition that allows the yield verification sign-off to pass. If the design meets specifications at the corner from the Worst Samples method, yield verification is likely to pass with the same target yield and probability. The total number of samples considered by the Worst Samples method represent the sign-off condition for the given target yield and probability.

The Worst Samples method is recommended when high accuracy is needed and the number of statistical parameters is not large (< 1000).

Related Topics

[The K-Sigma Corners Method](#)

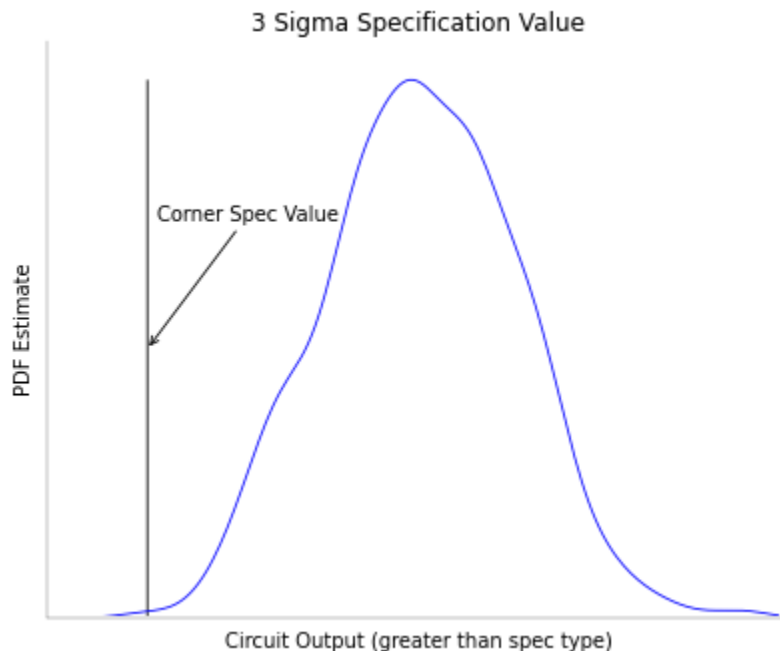
[The Worst Samples Method](#)

The K-Sigma Corners Method

This method creates the K-Sigma statistical corner that meets the specified target yield value and applies the stopping criteria according to which the Monte Carlo simulation is stopped when the K-Sigma statistical corner has been created for each specification.

It is possible that multiple corners meet the target specification criteria. Therefore, the K-Sigma method finds the most representative corner by calculating the minimum distance to the nominal point. This representative corner has a greater probability to occur. The statistical corner can then be used for further analysis of the design.

The fast K-Sigma corner algorithm estimates the Probability Density Function (PDF) of the performance distribution maintaining the accuracy of non-normal distributions. The specification target value is computed from the PDF estimate. Corners are generated based on the modeling and extrapolation from the PDF of the output.



This method is recommended if you prefer speed to accuracy.

Note: The K-Sigma Corners method is available only when the yield target is less than 4 sigma. By default, Monte Carlo uses single-sided sigma because the `useDoubleSidedSigma` variable is set to `nil`. Therefore, yield is represented as probability integration from $-\infty$ to $+K$ sigma in Gaussian distribution, and thus, 3 sigma is converted

to 99.865%. When this variable is set to τ , probability integration is done from $-K$ sigma to $+K$ sigma, and thus, 3 sigma is converted to 99.73%.

Related Topics

[Workflow of the K-Sigma Corners Method](#)

[Running the K-Sigma Corners Method](#)

Workflow of the K-Sigma Corners Method

The tool performs the following steps while running the K-Sigma Corners method:

1. Estimates the K-Sigma specification target. The specification target value is computed from the PDF estimate. The number of samples required to be run are based on the Monte Carlo sampling data. When the target sigma value is 3, a maximum of 200 samples are simulated.
2. Creates a representative statistical corner, which when simulated is close to the estimated value generated in step 1. This algorithm builds a model based on the statistical parameter data saved by the Monte Carlo run. At this point, a statistical corner can be generated without running any additional simulation.

To verify and improve the accuracy of this statistical corner, the Worst-Case Corners (WCC) simulations are run. The algorithm generates its best estimate of the K-Sigma statistical corner in addition to scaled corners with scale values equal to 0.5 to 2 (total of 11 scaled corners).

A WCC simulation begins by first simulating the statistical corner with $\text{scale}=1$. If the actual simulated result is very close to the predicted value, this means the model is accurate and there is no need to simulate another scaled corners. Then, the WCC simulation stops and a K-Sigma corner is created.

The WCC simulation can also stop because the spec target is set to the value computed from the PDF estimate. The tolerance value is automatically specified small enough, where if the spec is met, it is unlikely that one of the scaled corners that is not simulated finds a better result.

3. Creates a separate K-Sigma statistical corner for each specification.

Related Topics

[The K-Sigma Corners Method](#)

Virtuoso Variation Option User Guide

Statistical Corner Creation

Running the K-Sigma Corners Method

Running the K-Sigma Corners Method

Before you run the *K-Sigma Corners* method, ensure that the following environment variable is set to `t`:

```
envSetVal("maestro.monte" "showMethodKSigmaCorners" 'boolean t)
```

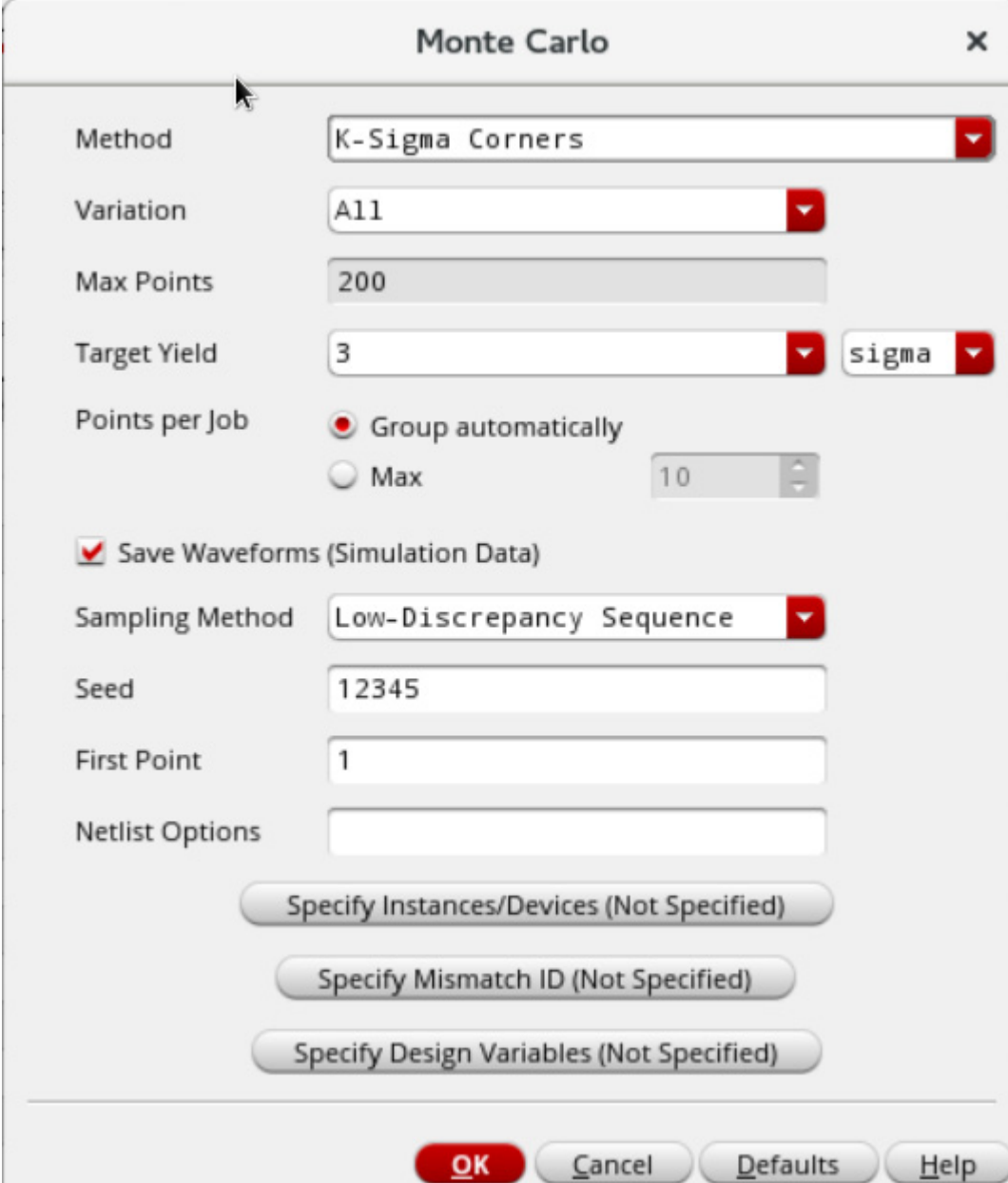
To create statistical corners using the K-Sigma Corners method:

1. Open your design in ADE Assembler or ADE Explorer.
2. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
3. Click the *Simulation Options* command.

Virtuoso Variation Option User Guide

Statistical Corner Creation

The Monte Carlo form opens.



The screenshot shows the 'Monte Carlo' dialog box with the following settings:

- Method: K-Sigma Corners
- Variation: All
- Max Points: 200
- Target Yield: 3
- Points per Job: Group automatically, Max (10)
- Save Waveforms (Simulation Data)
- Sampling Method: Low-Discrepancy Sequence
- Seed: 12345
- First Point: 1
- Netlist Options: (empty)

Buttons at the bottom: Specify Instances/Devices (Not Specified), Specify Mismatch ID (Not Specified), Specify Design Variables (Not Specified), OK, Cancel, Defaults, Help.

4. From the *Method* drop-down list, select *K-Sigma Corners*.
5. From the *Variation* drop-down list, select *Mismatch*, *Process*, or *All*.
6. The *Max Points* field shows the maximum number of points to be simulated.
This field is set to 200 points for the *K-Sigma Corners* method.

Virtuoso Variation Option User Guide

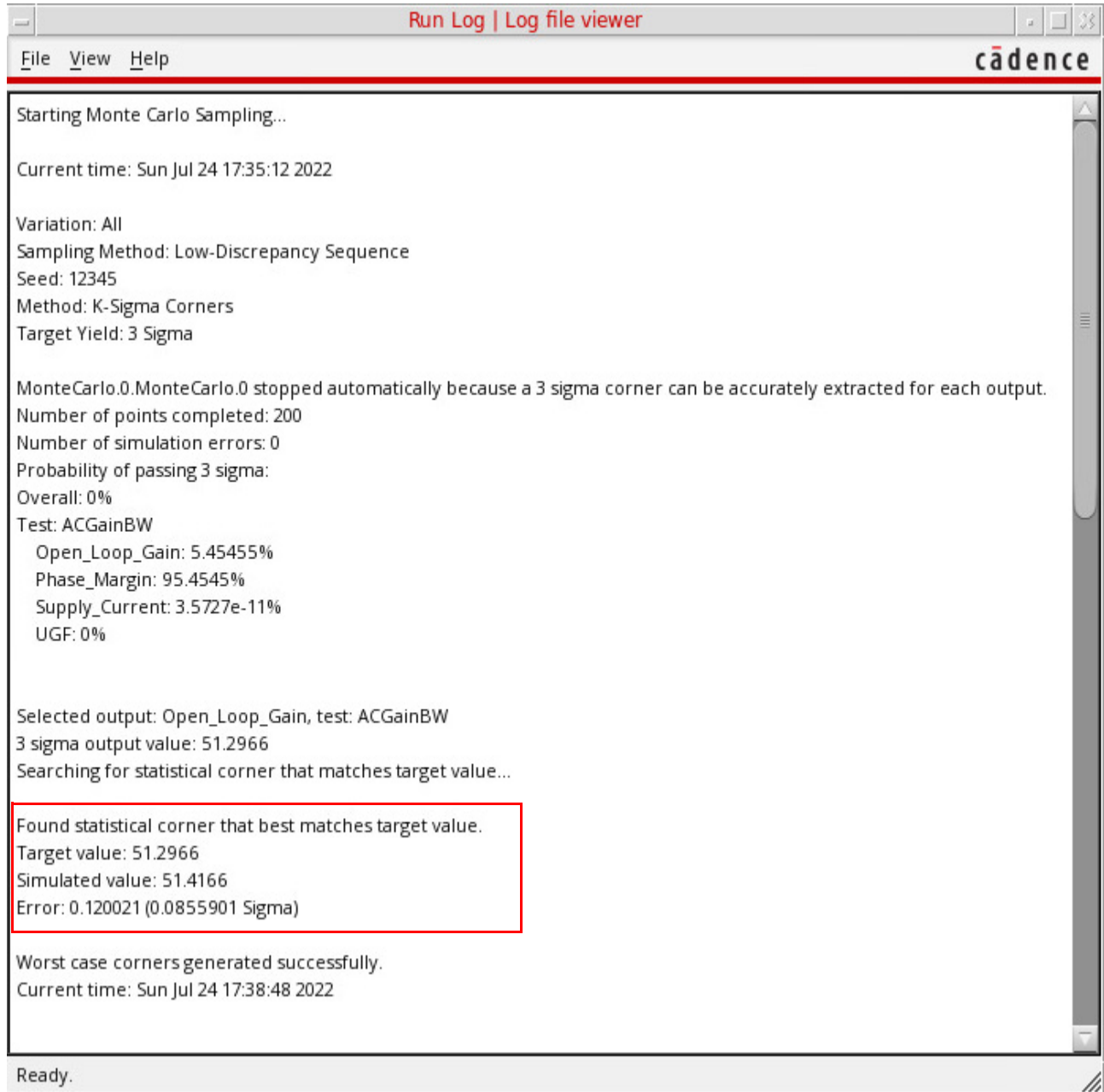
Statistical Corner Creation

7. Select the *Save Waveform (Simulation Data)* check box to save the waveform data so that it can be used later for post-processing.
8. From the *Sampling Method* drop-down list, select *Random* or *Low-Discrepancy Sequence*.
9. Click *OK* to close the Monte Carlo form.
10. Click *Run Simulation* to run the simulation.

Virtuoso Variation Option User Guide

Statistical Corner Creation

The Run Log reports both the estimated K-Sigma value of the specification (based on the PDF) and the simulated value of the corner.

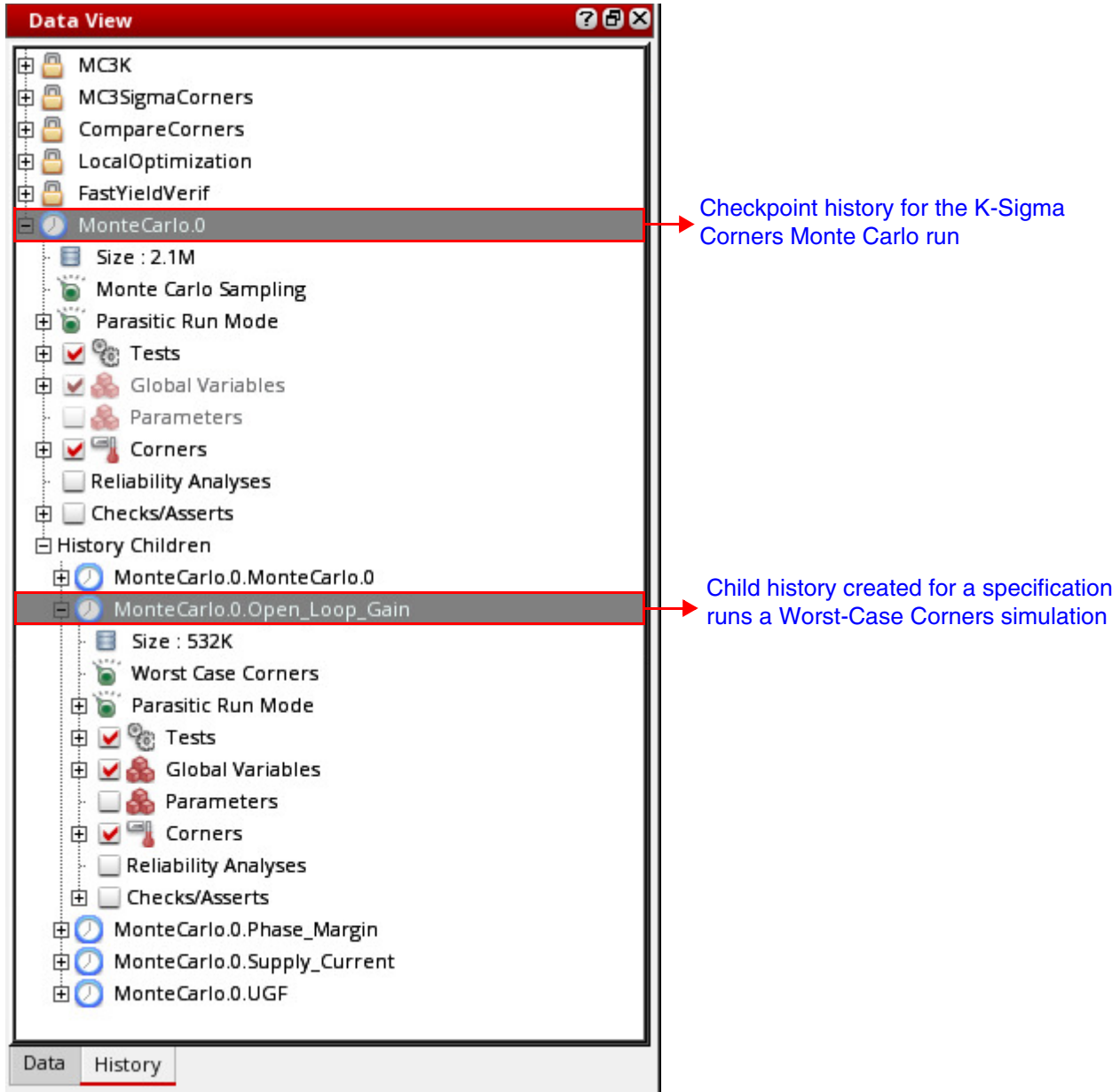


Virtuoso Variation Option User Guide

Statistical Corner Creation

Example

When you run the K-Sigma Corners method with target yield set to 3σ , the *MonteCarlo.N* and its child histories are created for each specification as shown below.

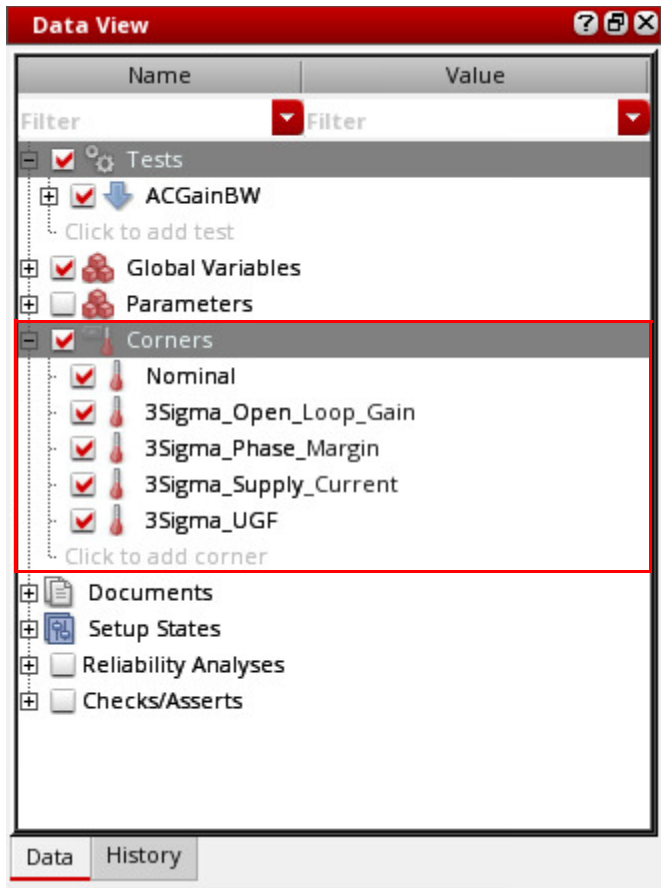


The *MonteCarlo.N* history is created first and shows the general simulation data set for the simulation. Next, the simulation run proceeds to extract the statistical corners and a child history is created for each spec with run mode set to Worst-Case Corners.

Virtuoso Variation Option User Guide

Statistical Corner Creation

After worst-case corners are created for all the specifications, the simulation creates 3-sigma statistical corners for each specification. These corners are displayed in the Data View assistant and the Corners Setup form:

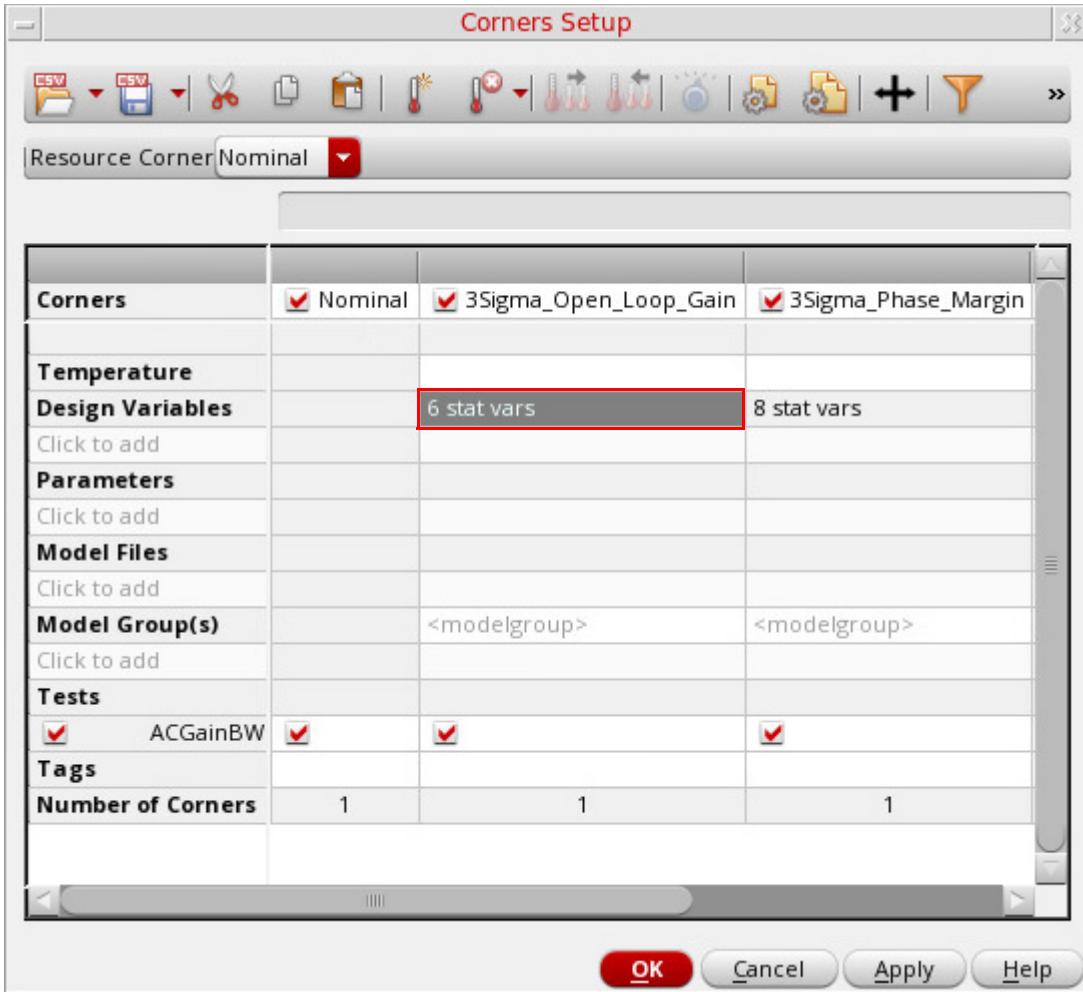


The K-Sigma statistical corners are named as $K\text{Sigma_specification_Name}$, where K is the specified sigma value. For example, the sigma value in this example is 3; therefore, the K-Sigma corner names are $3\text{Sigma_specification_name}$.

Virtuoso Variation Option User Guide

Statistical Corner Creation

You can view the details of statistical parameters that are used to create a K-Sigma corner by double-clicking the cell in the *Design Variables* row under the column for that corner in the Corners Setup form.



On the *Results* tab, two tabs are displayed at the bottom for this Monte Carlo simulation run—*MonteCarlo.N* and *MonteCarlo.N.specification_name*, where *MonteCarlo.N*

Virtuoso Variation Option User Guide

Statistical Corner Creation

is the history for the K-Sigma Corners run and *MonteCarlo.N.specification_name* is the child history for the Worst-Case Corners run for the last specification in the setup.

Test	Name	Yield	Min	Target	Max	Mean -3Sigma	Mean	Mean +3Sigma	Std Dev	Sigma to Target	Cpk
Yield Estimate: 87.5 % (175 passed/200 pts) Confidence Level: <not set> Filter: <not set>											
- ACGainBW											
	Supply_Current	95% (190/200)	102.8u	< 108u	108.8u	102.7u	106u	109.4u	1.131u	1.72462	0.575
	UGF	92.5% (185/200)	2.751M	> 2.78M	2.939M	2.723M	2.828M	2.934M	35.28K	1.37229	0.457
	Phase_Margin	100% (200/200)	87.21	> 70	87.59	87.22	87.43	87.63	68.69m	253.692	84.6
	Open_Loop_Gain	99.5% (199/200)	52.76	> 53	59.35	52.96	57.17	61.38	1.402	2.97361	0.991

MonteCarlo.0 MonteCarlo.0.UGF

Child Monte Carlo run history with Worst-Case Corners run mode
K-Sigma Corners run history

You can simulate the design over the generated statistical corner for further analysis or design tuning.

Related Topics

[Monte Carlo Form](#)

[Statistical Sampling Methods](#)

[The K-Sigma Corners Method](#)

[Workflow of the K-Sigma Corners Method](#)

[showMethodKSigmaCorners](#)

Creating K-Sigma Corners from a Standard Monte Carlo Run

If you have already run a standard Monte Carlo analysis, you can create a K-Sigma corner from the results as a post-processing step.

To create K-Sigma statistical corners from a standard Monte Carlo simulation:

1. On the *History* tab of the Data View assistant, right-click the history for the Monte Carlo run for which you want to create K-Sigma corners, and then click *View Results*.

The results of the Monte Carlo run are displayed in the *Yield* view of the *Results* tab.

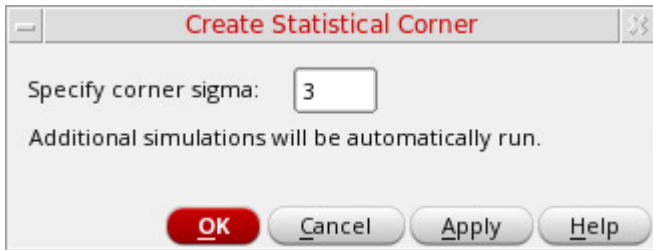
Test	Name	Yield	Min	Target	Max	Mean	Std Dev	Cpk	Errors
Yield Estimate: 88 % (44 passed/50 pts) Confidence Level: <not set> Filter: <not set>									
- AC									
- Op_Region(summary)	Op_Region	100% (50/50)	0	< 1	0	0	0	Inf	0
- Current(summary)	Current	100% (50/50)	1.1 mA	< 1.5m	1.15 mA	1.126 mA	10.79 uA	11.5	0
- UGF(summary)	UGF	98% (49/50)	531.7 MHz	> 533m	562.9 MHz	547.1 MHz	7.034 MHz	0.667	0
- Gain(summary)	Gain	100% (50/50)	46.64 dB	> 44	46.82 dB	46.74 dB	40.2 mdB	22.7	0
- Voffset(summary)	Voffset	100% (50/50)	2.392 mV	range...	3.726 mV	3.055 mV	299.5 uV	7.73	0
- TRAN									
- Swing(summary)	Swing	100% (50/50)	1.003	> 0.98	1.012	1.008	2.143m	4.32	0
- SettlingTime(summary)	SettlingTime	100% (50/50)	7.654 ns	< 8n	7.92 ns	7.765 ns	60.78 ps	1.29	0
- RelativeSwingPercent(...)	RelativeSwingPercent	100% (50/50)	77.19 %	> 75	77.88 %	77.52 %	164.8 m%	5.09	0
- PhaseMargin(summary)	PhaseMargin	90% (45/50)	19.57 degree	> 20	21.88 degree	20.64 degree	481.1 mdegree	0.443	0

2. Right-click a specification for which you want to create K-Sigma corners and then choose *Create Statistical Corner (Specify Yield in Sigma)*.

Virtuoso Variation Option User Guide

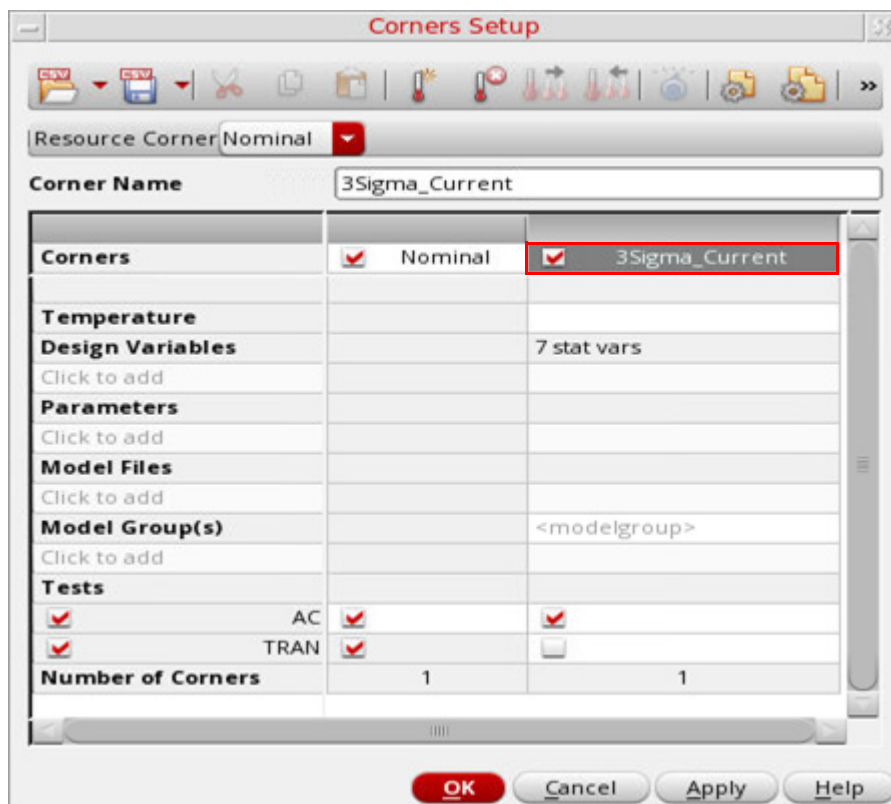
Statistical Corner Creation

The Create Statistical Corner form opens.



3. In the *Specify corner sigma* field, enter a sigma value less than four. The default is 3.
4. Click *OK* to close the form.

An additional simulation is run. After the simulation is complete, the K-Sigma corner created for the specification is displayed in the Corners Setup form.



Corners	Nominal	3Sigma_Current
Temperature		
Design Variables		7 stat vars
Parameters		
Model Files		
Model Group(s)		<modelgroup>
Tests		
AC	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
TRAN	<input checked="" type="checkbox"/>	<input type="checkbox"/>
Number of Corners	1	1

The K-Sigma corner is named as $N\text{Sigma_specification_name}$, where N is the sigma value that you specified in the Create Statistical Corner form. For the sigma value 3 and the specification `Current`, the name of the corner is `3Sigma_Current`.

Virtuoso Variation Option User Guide

Statistical Corner Creation

Related Topics

[The K-Sigma Corners Method](#)


[Workflow of the K-Sigma Corners Method](#)

[Running the K-Sigma Corners Method](#)

Displaying Mean K-Sigma and Median Columns in the Yield View

When you run a Monte Carlo simulation, the *Mean -3Sigma*, *Mean +3Sigma*, and *Median* columns are not displayed in the *Yield* view by default.

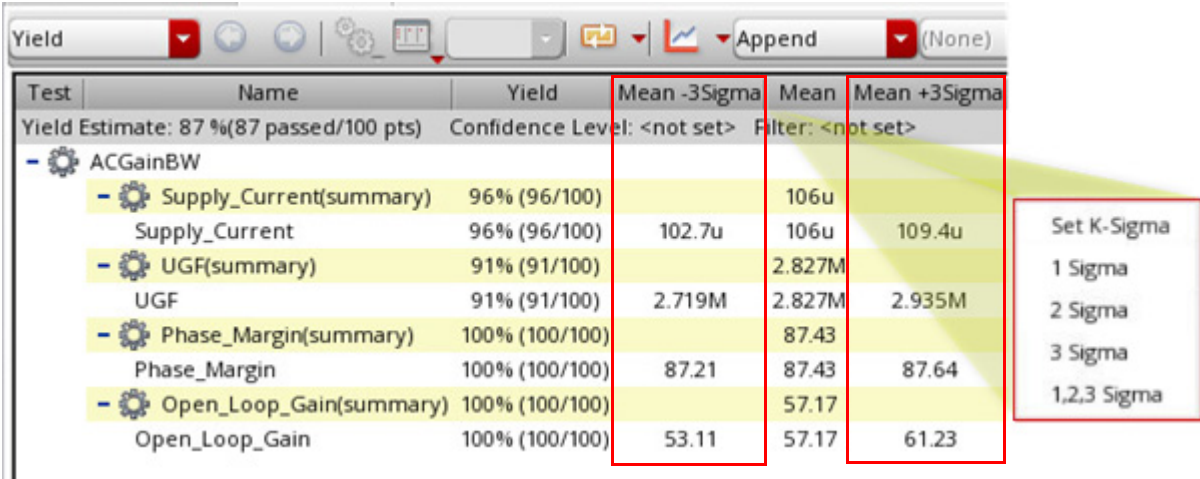
To display mean $\pm K$ -Sigma and *Median* columns in the *Yield* view:

1. In the *Yield* view of a Monte Carlo result, click *Configure what is shown in the table*  and choose *Mean +/- K-Sigma*, and *Median*.

Alternatively, you can also set the following environment variable to display mean $\pm K$ -Sigma columns.

```
envSetVal("adexl.gui" "yieldViewShowDefault" 'string "\"Min\" \"Target\" \"Max\" \"Mean\" \"Median\" \"Std Dev\" \"Cpk\" \"Errors\" \"User-Defined Columns\" \"Mean +/- K-Sigma\"")
```

The *Mean -3Sigma* and *Mean +3Sigma* columns are displayed to the left and to the right of the *Mean* column.



Test	Name	Yield	Mean -3Sigma	Mean	Mean +3Sigma
Yield Estimate: 87 % (87 passed/100 pts) Confidence Level: <not set> Filter: <not set>					
-	ACGainBW				
-	Supply_Current(summary)	96% (96/100)		106u	
	Supply_Current	96% (96/100)	102.7u	106u	109.4u
-	UGF(summary)	91% (91/100)		2.827M	
	UGF	91% (91/100)	2.719M	2.827M	2.935M
-	Phase_Margin(summary)	100% (100/100)		87.43	
	Phase_Margin	100% (100/100)	87.21	87.43	87.64
-	Open_Loop_Gain(summary)	100% (100/100)		57.17	
	Open_Loop_Gain	100% (100/100)	53.11	57.17	61.23

2. Right-click either the *Mean -3Sigma* or the *Mean +3Sigma* column and choose one of the following options:

- 1 Sigma*: Displays the *Mean -Sigma* and *Mean +Sigma* columns to the left and to the right of the *Mean* column.
- 2 Sigma*: Displays the *Mean -2Sigma* and *Mean +2Sigma* columns to the left and to the right of the *Mean* column.
- 3 Sigma*: Displays the *Mean -3Sigma* and *Mean +3Sigma* columns to the left and to the right of the *Mean* column.

Virtuoso Variation Option User Guide

Statistical Corner Creation

- ❑ *1,2,3 Sigma*: Displays the *Mean -3Sigma*, *Mean -2Sigma*, and *Mean -Sigma* columns to the left of the *Mean* column and *Mean +Sigma*, *Mean +2Sigma*, and *Mean +3Sigma* columns to the right of the *Mean* column.
- ❑ *Set K-Sigma*: Opens the Set K-Sigma form where you can specify the K-Sigma value or a list of K-Sigma values in the *K-Sigma* field.

For example, if you specify 4, 5 in this field, the *Mean -5Sigma* and *Mean -4Sigma* columns are displayed to the left of the *Mean* column and *Mean +4Sigma* and *Mean +5Sigma* columns are displayed to the right of the *Mean* column.

Test	Name	Yield	Mean -5Sigma	Mean -4Sigma	Mean	Mean +4Sigma	Mean +5Sigma
Yield Estimate: 87 % (87 passed/100 pts) Confidence Level: <not set> Filter: <not set>							
ACGainBW							
-	Supply_Current(summary)	96% (96/100)			106u		
	Supply_Current	96% (96/100)	100.5u	101.6u	106u	110.5u	111.6u
-	UGF(summary)	91% (91/100)			2.827M		
	UGF	91% (91/100)	2.647M	2.683M	2.827M	2.971M	3.007M
-	Phase_Margin(summary)	100% (100/100)			87.43		
	Phase_Margin	100% (100/100)	87.07	87.14	87.43	87.71	87.79
-	Open_Loop_Gain(summary)	100% (100/100)			57.17		
	Open_Loop_Gain	100% (100/100)	50.41	51.76	57.17	62.58	63.93

You can also set the environment variable `yieldViewKSigma` to specify various K-Sigma values that you want to display as columns in the *Yield* view.

Related Topics

[yieldViewKSigma](#)

The Worst Samples Method

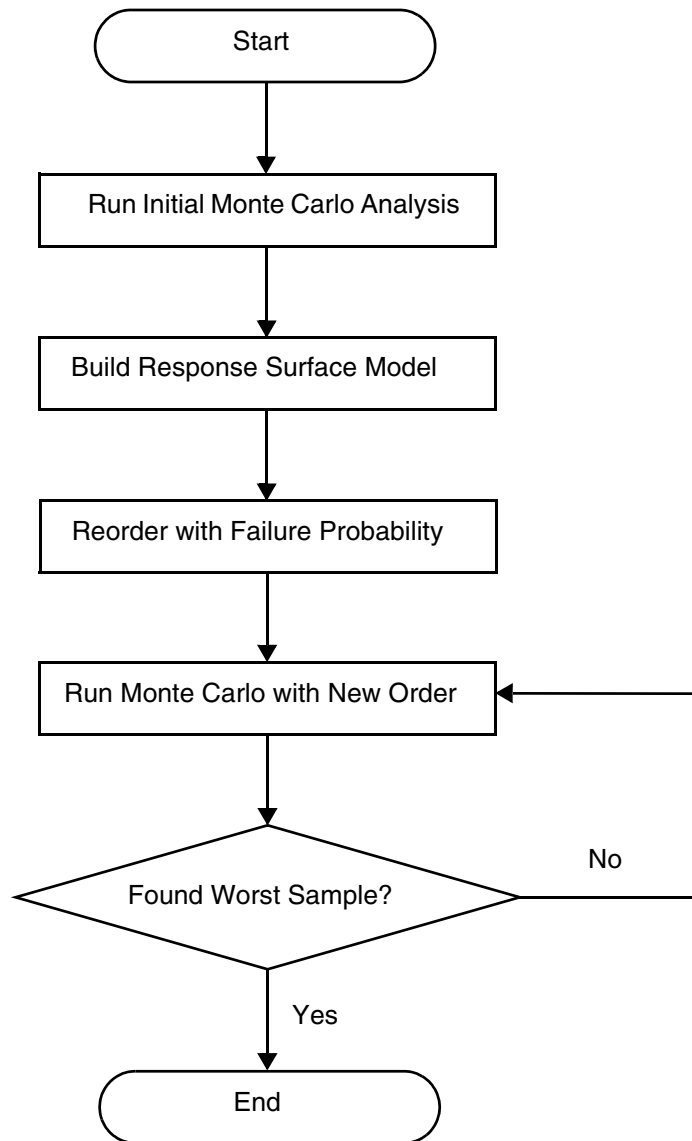
In the Worst Samples method, the points are reordered based on the response surface modeling and sampling is stopped when the worst sample is found for each specification. The statistical corners are automatically created from the worst samples.

As a first step, sample reordering is performed using the failure probability modeling. Since the samples are already reordered from worst to best, the worst samples method requires comparatively smaller number of simulations to run. However, considering that the failure probability modeling can have some uncertainties, a minimum of 10 samples per spec is simulated to confidently identify the worst sample. Some specifications may require running additional simulations before stopping. This method is recommended if you prefer accuracy to speed.

Virtuoso Variation Option User Guide

Statistical Corner Creation

The following figure shows the workflow of the Worst Samples Method.



Related Topics

[Running the Worst Sample Method](#)

Running the Worst Sample Method

Before you run the Worst Sample method, ensure that the following environment variable is set to `t`:

```
envSetVal("maestro.monte" "showMethodWorstSamples" 'boolean t)
```

To create statistical corners using the Worst Sample method:

1. Open your design in ADE Assembler or ADE Explorer.
2. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
3. Click the *Simulation Options* command.

Virtuoso Variation Option User Guide

Statistical Corner Creation

The Monte Carlo form opens.

The screenshot shows the 'Monte Carlo' dialog box with the following settings:

- Method: Worst Samples
- Variation: All
- Max Points: 2289
- Target Yield: 3
- Probability: 95 %
- Points per Job: Group automatically, Max (10)
- Save Waveforms (Simulation Data):
- Sampling Method: Low-Discrepancy Sequence
- Seed: 12345
- First Point: 1
- Netlist Options: (empty)

Buttons at the bottom: OK, Cancel, Defaults, Help.

4. From the *Method* drop-down list, select *Worst Samples*.
5. From the *Variation* drop-down list, select *Mismatch*, *Process*, or *All*.
6. The *Max Points* field shows the maximum number of points to be displayed.

Value for this field is automatically calculated based on the target yield or probability value. For example, it is set to 2289 when the probability is 95%. This value changes when you change the probability.

7. In the *Probability* field, specify the probability value (confidence level). The default probability is 95%.

Virtuoso Variation Option User Guide

Statistical Corner Creation

8. Select the *Save Waveform (Simulation Data)* check box to save the waveform data so that it can be used later for post-processing.
9. From the *Sampling Method* drop-down list, select *Random* or *Low-Discrepancy Sequence*.
10. Click *OK* to close the Monte Carlo form.
11. Click *Run Simulation* to run the simulation.

Virtuoso Variation Option User Guide

Statistical Corner Creation

The simulation run first performs initial Monte Carlo to reorder samples and then runs the worst sample algorithm to generate the worst sample for each specification. The following run log is generated for this simulation run.

The screenshot shows a 'Run Log | Log file viewer' window with a 'cadence' logo in the top right. The log content is as follows:

```
Starting Monte Carlo Sampling...
Current time: Tue May 25 15:07:23 2021
Performing initial Monte Carlo to build response surface model...
Runs initial Monte Carlo to build a response surface model for every spec. In this example, 75 samples were simulated.

Variation: All
Sampling Method: Low-Discrepancy Sequence
Seed: 12345
Method: Worst Samples
Target Yield: 3 Sigma
Probability: 0.95
For the same design, the number of completed points for a single job and the multiple jobs may vary because the initial surface model built by a single job and that built by multiple jobs may be different.

Number of statistical parameters: 124
Maximum number of points needed to ensure model accuracy: 248
The actual number of points needed could be less, depending on the design and outputs.

MonteCarlo.3.InitialSampling stopped automatically because a response surface model can be accurately built for every spec.
Number of points completed: 75
Number of simulation errors: 0

Extracting statistical parameter values for all samples...
MonteCarlo.3.ParameterDump
Number of points completed: 2289
Number of simulation errors: 0
The statistical parameters are extracted for 2289 points, which is the total number of Monte Carlo points based on the given target yield and probability

Current specs:UGF Gain Current Voffset_H Voffset_L
Evaluating remaining points ordered by probability to fail...
MonteCarlo.3.AC stopped automatically because the worst Monte Carlo sample has been found for the current output.
Number of points completed: 140
Number of simulation errors: 0
Spec:UGF, worst point number:108, point number in original Monte Carlo:437, value:5.23026e+08
Spec:Current, worst point number:131, point number in original Monte Carlo:1028, value:0.00116194
```

Annotations in the image:

- An arrow points from the text "Runs initial Monte Carlo to build a response surface model for every spec. In this example, 75 samples were simulated." to the log line "Number of points completed: 75".
- An arrow points from the text "For the same design, the number of completed points for a single job and the multiple jobs may vary because the initial surface model built by a single job and that built by multiple jobs may be different." to the log line "Number of points completed: 75".
- An arrow points from the text "The statistical parameters are extracted for 2289 points, which is the total number of Monte Carlo points based on the given target yield and probability" to the log line "Number of points completed: 2289".
- An arrow points from the text "Sample number of the sample identified as the worst sample for each spec" to the log line "Number of points completed: 140".
- An arrow points from the text "This value indicates that 65 additional points were simulated while identifying the worst samples for UGF and Current." to the log line "Number of points completed: 140".

Virtuoso Variation Option User Guide

Statistical Corner Creation

A comprehensive summary is added towards the end of the run log to show the worst samples for all the specifications together for each test.

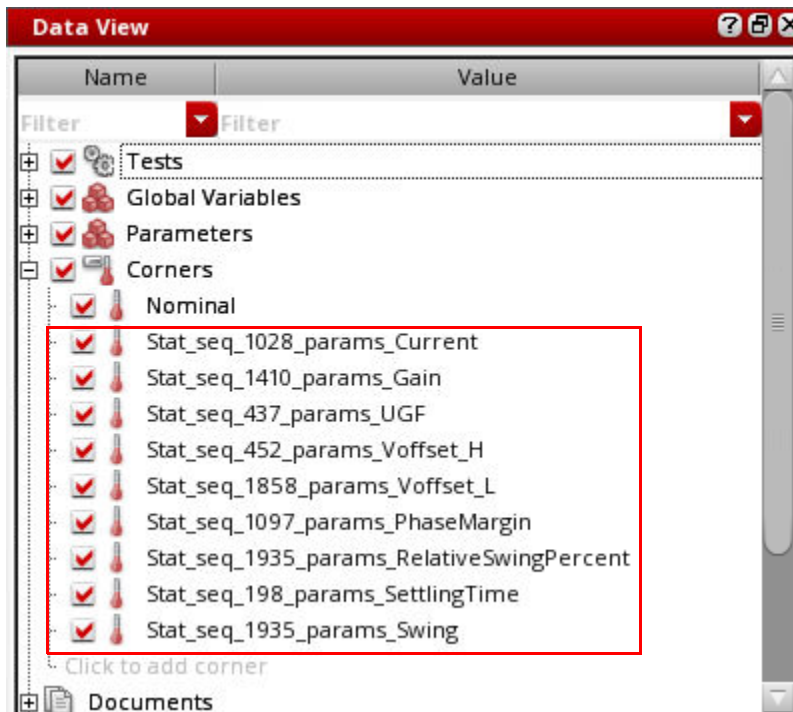
```
Summary:
Test:AC
Spec:Current, worst point number:131, point number in original Monte Carlo:1028, value:0.00116194
Spec:Gain, worst point number:140, point number in original Monte Carlo:1410, value:46.519
Spec:UGF, worst point number:108, point number in original Monte Carlo:437, value:5.23026e+08
Spec:Voffset_L, worst point number:149, point number in original Monte Carlo:1858, value:0.00212678
Spec:Voffset_H, worst point number:112, point number in original Monte Carlo:452, value:0.00391144

Test:TRAN
Spec:PhaseMargin, worst point number:231, point number in original Monte Carlo:1097, value:19.0762
Spec:RelativeSwingPercent, worst point number:246, point number in original Monte Carlo:1935, value:76.9706
Spec:SettlingTime, worst point number:209, point number in original Monte Carlo:198, value:8.06289e-09
Spec:Swing, worst point number:246, point number in original Monte Carlo:1935, value:1.00062

MonteCarlo.3 completed.
Current time: Tue May 25 15:17:09 2021
```

A statistical corner is generated for each specification in the setup. These corners can be viewed in the Data View assistant and the Corner Setup form. The naming convention for these corners is

Stat_seq_Worst_corner_number_params_Specification_name.



Virtuoso Variation Option User Guide

Statistical Corner Creation

Related Topics

[Monte Carlo Form](#)

[Statistical Sampling Methods](#)

[The Worst Samples Method](#)

[showMethodWorstSamples](#)

Virtuoso Variation Option User Guide

Statistical Corner Creation

The Confidence Interval - Autostop Method

The *Confidence Interval - Autostop* method automatically stops Monte Carlo analysis when the confidence interval for the output standard deviation divided by the output value range falls below the *Stop Percentage* value. The default *Stop Percentage* value is 5%.

In this method, you need not define number of sample points to run, target yield value, and specification targets because Monte Carlo run stops automatically when the stopping criteria is met, where stopping criteria is defined as follows:

$$\frac{(\sigma_{\text{upper bound}} - \sigma_{\text{lower bound}})}{(\text{output}_{\text{upper bound}} - \text{output}_{\text{lower bound}})} < \text{Stop Percentage}$$

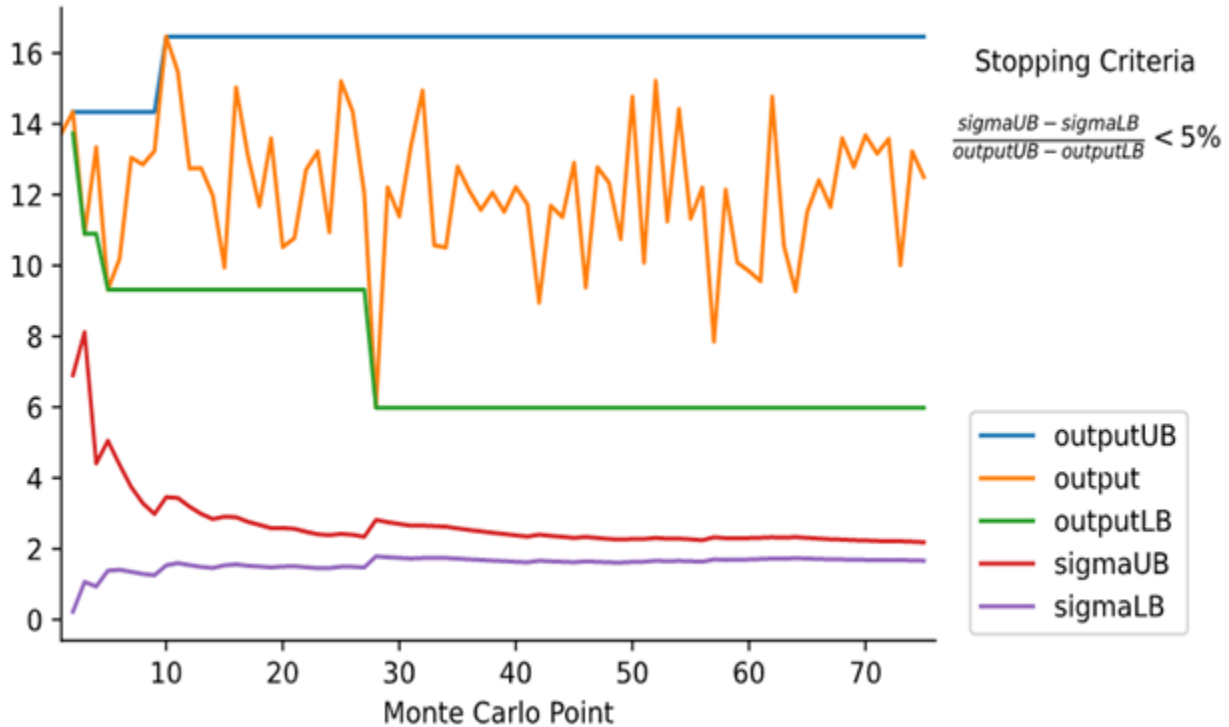
The Monte Carlo run stops automatically after simulating all outputs satisfy the stopping criteria or after simulating the number of sample points specified in the *Max Points* field on the Monte Carlo form.

Decreasing *Stop Percentage* value results in increased number of points simulated.

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

The following figure shows that for *Stop Percentage* = 5%, the Monte Carlo run stops automatically after completing simulation of 75 sample points.

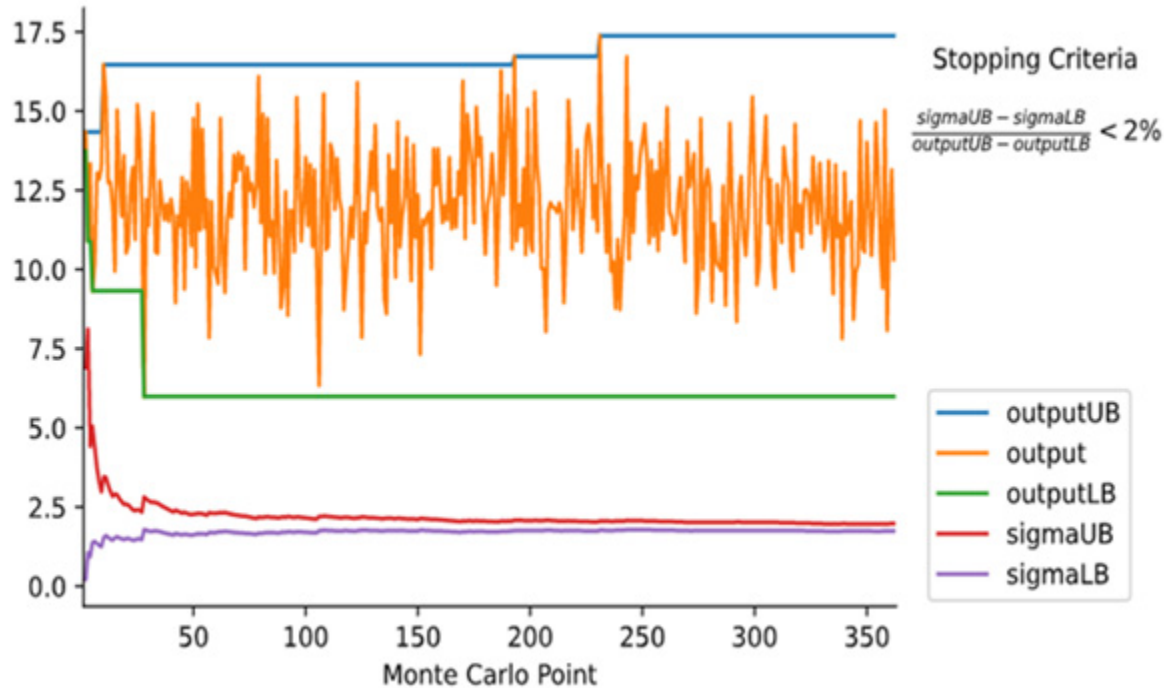


Note: This graphic is used only for reference to help you visualize how number of points completed vary with different values of *Stop Percentage*, *Confidence Level*, and *Confidence Sigma*. No such plot is actually generated in ADE Assembler or ADE Explorer.

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

The following figure shows that for *Stop Percentage* = 2%, the Monte Carlo run stops automatically after simulating 362 sample points.



Related Topics

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Outputs Supported by the Confidence Interval - Autostop Method](#)

[Running the Confidence Interval - Autostop Method](#)

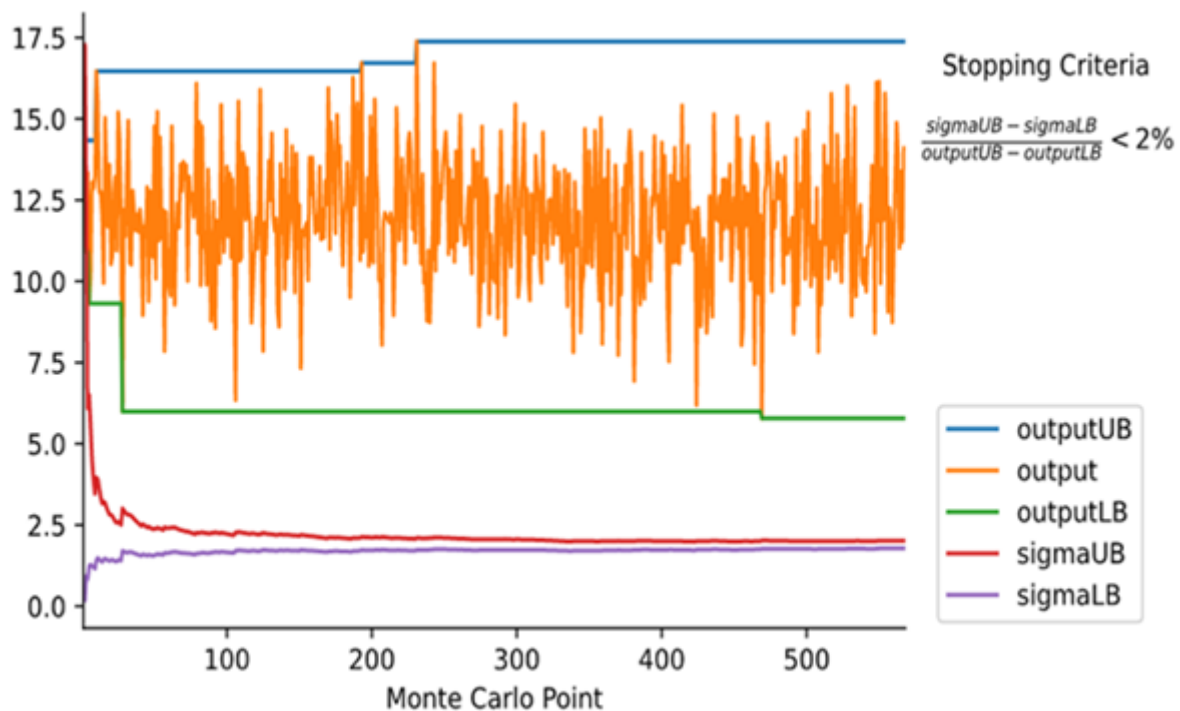
Advanced Options of the Confidence Interval - Autostop Method

Advanced options of the *Confidence Interval - Autostop* method are as follows:

- **Confidence Level:** Determines the confidence interval for the output standard deviation considered by the stopping criteria.

Increasing *Confidence Level* results in increased number of points simulated.

The following figure shows that the Monte Carlo run stops automatically after simulating 567 points for *Stop Percentage 2%* and *Confidence Level 98*.



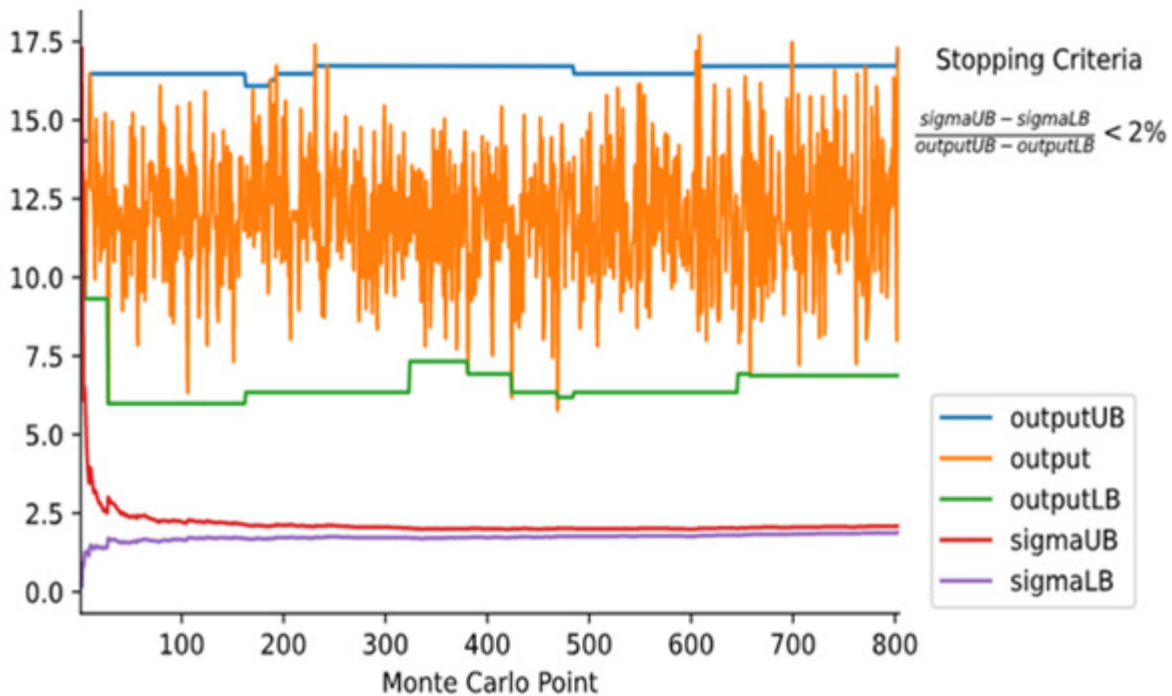
- **Confidence Sigma:** Determines the range of output variations considered by the stopping criteria.

Increasing *Confidence Sigma* results in decreased number of points, whereas decreasing *Confidence Sigma* results in increased number of points.

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

The following figure shows that the Monte Carlo run stops automatically after simulating 803 points for *Stop Percentage* = 2%, *Confidence Level* = 98, and *Confidence Sigma* = 2.5.



Related Topics

[The Confidence Interval - Autostop Method](#)

[Outputs Supported by the Confidence Interval - Autostop Method](#)

[Running the Confidence Interval - Autostop Method](#)

[confidenceAutoStopLevel](#)

[confidenceAutoStopSigma](#)

[showConfidenceAutoStopLevel](#)

[showConfidenceAutoStopSigma](#)

Outputs Supported by the Confidence Interval - Autostop Method

The following outputs are supported by the Confidence Interval - Autostop method:

- Outputs with specification type *info*. For such outputs, the specification target values are not required.
- Outputs with the following specification target values: *minimize*, *maximize*, *<*, *>*, *range*, and *tol*.

The following outputs are ignored by the Confidence Interval - Autostop method:

- Outputs with specification type *none*.
- Outputs that are disabled, that is, the outputs for which the *Plot* check box is not selected.

For example, outputs that are highlighted in green are considered and the outputs that are highlighted in red are ignored, as shown in the following outputs setup.

Test	Name	Type	Details	EvalType	Plot	Save	Spec
DC		signal (I)	/V1/PLUS	point	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	
DC		signal	/OUT	point	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	
DC	Current	expr	abs(IDC("/V1...	point	<input checked="" type="checkbox"/>	<input type="checkbox"/>	< 1.07m
DC	Voffset	expr	(VDC("/inm"...	point	<input checked="" type="checkbox"/>	<input type="checkbox"/>	< 7m
DC	Signal1	signal	/inm	point	<input type="checkbox"/>	<input checked="" type="checkbox"/>	
DC	Singnal2	signal	/inp	point	<input type="checkbox"/>	<input checked="" type="checkbox"/>	
DC	O1	expr	IF("/CO/MIN...	point	<input checked="" type="checkbox"/>	<input type="checkbox"/>	info

↓ ↓
↓ ↓
 Outputs to be ignored Outputs to be considered

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

Related Topics

[The Confidence Interval - Autostop Method](#)

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Running the Confidence Interval - Autostop Method](#)

Running the Confidence Interval - Autostop Method

Before you run the *Confidence Interval - Autostop* Method, ensure that the following environment variable is set to t:

```
envSetVal("maestro.monte" "showMethodCIAutoStop" 'boolean t)
```

To run the *Confidence Interval - Autostop* method:

1. Open your design in ADE Assembler or ADE Explorer.
2. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
3. Click the *Simulation Options* command.

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

The Monte Carlo form opens.

Monte Carlo

Method: Confidence Interval - Autostop

Variation: All

Max Points: 1000

Stop Percentage: 5 %

Confidence Level: 95 %

Confidence Sigma: 3

Points per Job: Group automatically, Max (10)

Save Waveforms (Simulation Data)

Save Statistical Parameter Data

Sampling Method: Low-Discrepancy Sequence

Seed: 12345

First Point: 1

Netlist Options:

Specify Instances/Devices (Not Specified)

Specify Mismatch ID (Not Specified)

Specify Design Variables (Not Specified)

OK Cancel Defaults Help

4. From the *Method* drop-down list, select *Confidence Interval - Autostop*.
5. From the *Variation* drop-down list, select variation as *All*, *Mismatch*, or *Process*.
6. In the *Max Points* field, specify the maximum number of sample points to simulate.
7. In the *Stop Percentage* field, enter the percentage value of stopping criteria for the *Confidence Interval - Autostop* method. The default value is 5.
8. In the *Confidence Level* field, specify confidence level for the output standard deviation considered by the stopping criteria.

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

9. In the *Confidence Sigma* field, specify the confidence sigma value that controls the range of output variation considered by the stopping criteria.

The *Confidence Level* and *Confidence Sigma* fields are hidden by default. You can set the `showConfidenceAutoStopLevel` and `showConfidenceAutoStopSigma` environment variables to `t` to view them.

10. In the *Sampling Method* drop-down, select either *Random* or *Low-Discrepancy Sequence*.
11. Specify the other fields as required.
12. Click *OK* to close the Monte Carlo form.
13. Click *Run Simulation* to run the *Confidence Interval - Autostop* method.

The simulation results are displayed in the *Results* tab, as follows:

Test	Name	Yield	Min	Target	Max	Mean	Std Dev	Cpk	Errors
Yield Estimate: 99.0196 % (101 passed/102 pts) Confidence Level: <not set> Filter: <not set>									
-	DC								
-	Current(summary)	99.0196% (101/102)	717.9u		1.07m	834.7u	9.348u	0.92	0
	Current	99.3333% (149/150)	1.022m	< 1.07m	1.07m	1.044m	9.348u	0.92	0
	Current_MC_0	100% (102/102)	717.9u	< 1.07m	749.2u	729.6u	6.178u	18.4	0
	Current_MC_01	100% (150/150)	717.9u	< 1.07m	749.2u	730.3u	6.092u	18.6	0
-	Voffset(summary)	100% (102/102)	-3.056m		6.556m	1.434m	1.115m	0.901	0
	Voffset	100% (150/150)	961.6u	< 7m	6.556m	3.986m	1.115m	0.901	0
	Voffset_MC_0	100% (102/102)	-3.056m	< 7m	2.462m	117.2u	1.164m	1.97	0
	Voffset_MC_01	100% (150/150)	-3.056m	< 7m	3.041m	200.1u	1.165m	1.95	0

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

The run log is shown, as follows:

```
Run Log | Log file viewer
File View Help
Starting Monte Carlo Sampling...
Current time: Fri Oct 30 20:59:15 2020
Variation: Mismatch
Sampling Method: Random
Seed: 12345
Method: Confidence Interval - Auto Stop
Stop Percentage: 5
Confidence Level: 95
Confidence Sigma: 3
MonteCarlo.26 stopped automatically because the confidence interval percentage target has been reached.
Number of points completed: 102
Number of simulation errors: 0
MonteCarlo.26 completed.
Current time: Fri Oct 30 21:03:47 2020
Monte Carlo Sampling yield summary:
Number of spec values are in this yield data: 6
DC      Nominal -
Current: Yield      99.3333%
Min 0.00102234      Max 0.00107029      Mean 0.00104419      Sigma to Target 2.76062      Number of errors 0
DC      MC_0 -
Current: Yield      100%
Min 0.000717936     Max 0.000749188     Mean 0.000729614     Sigma to Target 55.1      Number of errors 0
DC      MC_01 -
Current: Yield      100%
Min 0.000717936     Max 0.000749188     Mean 0.000730333     Sigma to Target 55.7582   Number of errors 0
DC      Nominal -
Voffset: Yield      100%
Min 0.00096164      Max 0.00655598      Mean 0.00398583      Sigma to Target 2.70386   Number of errors 0
DC      MC_0 -
Voffset: Yield      100%
Min -0.00305564     Max 0.00246207      Mean 0.000117209     Sigma to Target 5.91262   Number of errors 0
DC      MC_01 -
Voffset: Yield      100%
Min -0.00305564     Max 0.00304137      Mean 0.000200125     Sigma to Target 5.8374    Number of errors 0
DC
Overall Yield 99.0196%      Number of points passed 101      Total number of points 102
Estimated yield = 99.0196% (101/102), 0 errors
Estimated yield (No opregions) = 99.0196% (101/102)
Ready.
```

Related Topics

[Monte Carlo Form](#)

[showConfidenceAutoStopLevel](#)

[showConfidenceAutoStopSigma](#)

[Statistical Sampling Methods](#)

[The Confidence Interval - Autostop Method](#)

Virtuoso Variation Option User Guide

The Confidence Interval - Autostop Method

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Outputs Supported by the Confidence Interval - Autostop Method](#)

High Yield Estimation

Parametric high yield estimation is required on devices that have extremely high volume, that is memory devices, or when testing the circuit limits is a must when failure of the part is not an option, for example, automotive safety or medical devices.

The Virtuoso Variation Option provides two methods of simulation to meet and match your needs and conditions:

- Scaled-Sigma Sampling (SSS)

This method generates samples where the standard deviation has been scaled up.

- Worst-Case Distance (WCD)

This method defines the shortest distance from the nominal point to the specification boundary in the process/mismatch parameter space.

Related Topics

[The Scaled-Sigma Sampling Method](#)

[The Worst-Case Distance Method](#)

The Scaled-Sigma Sampling Method

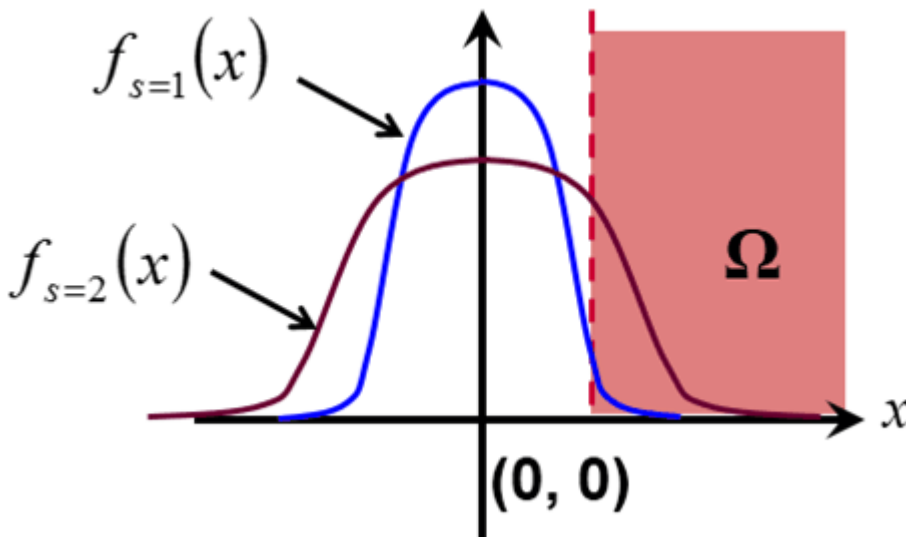
The Scaled-Sigma Sampling method generates samples where the standard deviation has been scaled up. This method is more accurate than the Worst-Case Distance method for nonlinear behavior and more efficient when there is a large number of statistical parameters and specifications. As a result, a larger number of samples fall into the failure region of the distorted distribution. The failure rate is then estimated from the scaled samples.

This method is selected by default when the yield is greater than 3 sigma.

The Scaled-Sigma Sampling method is a resource-intensive method, but offers the following advantages:

- Efficiency for high dimensionality (very large numbers of devices and statistical parameters)
- Accuracy even for cases of high non-linearity
- Efficiency when the design is constrained by a large number of specifications

This figure shows the unscaled performance distribution (scaling factor $s=1$) compared to the scaling factor $s=2$.



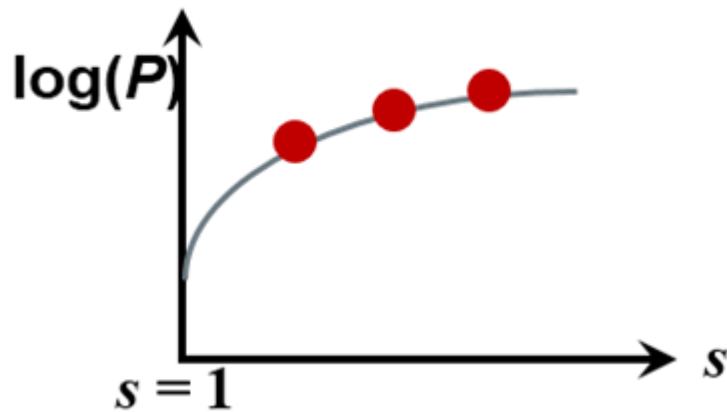
Here, x = process parameter and Ω = failure region.

Virtuoso Variation Option User Guide

High Yield Estimation

The failure rate can be calculated as:

$$\log(P) \approx \alpha + \beta \log(s) + \Upsilon/s^2$$



The above equation models the failure rate as a function of the scaling factor. The model has very few constraints on the failure region and can target multiple failure regions. The model is constructed based on a set of scaled Monte Carlo runs. Then, the unscaled yield estimate ($s=1$) can be found.

Related Topics

[High Yield Estimation](#)

[Confidence Interval and Number of Samples](#)

[Running the Scaled-Sigma Sampling Method](#)

Confidence Interval and Number of Samples

The change in confidence interval resulting from an increase or decrease in the total number of samples cannot be determined in advance because it depends on the given circuit and failure boundary.

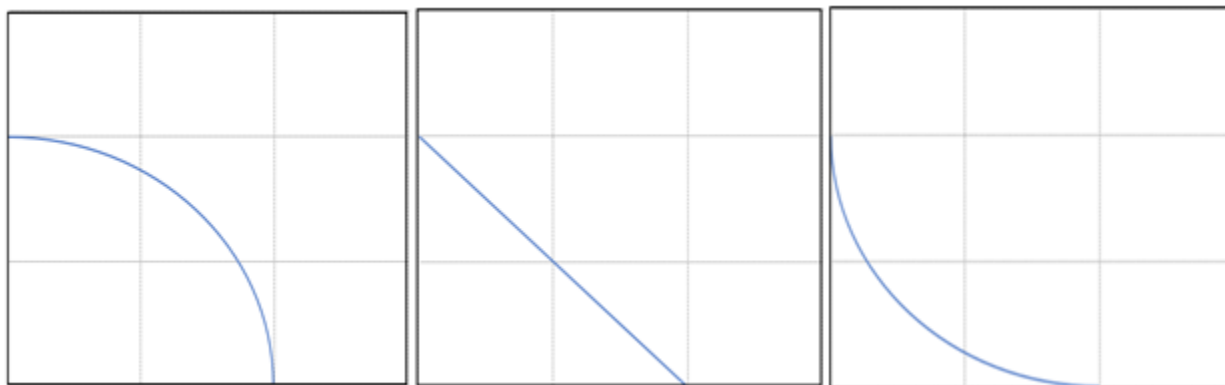
You can generate a quantitative example by running the Scales-Sigma Sampling method on a linear failure boundary case.

The following table reports the 5% and 95% quantile values generated based on 100 Scales-Sigma Sampling runs for each result (combination of number of samples and sigma target).

Number of Samples	4 Sigma	6 Sigma
1000	3.30 4.75	4.56 7.49
7000	3.62 4.32	5.31 6.75
50000	3.80 4.12	5.70 6.36

Depending on the failure boundary shape, the confidence interval may differ. The linear boundary results can be used as a reference because of the following reasons:

- Many failure boundaries are not very strongly nonlinear.
- The confidence interval tends to be:
 - Small: If the failure rate scales faster than linear boundary.
 - Large: If failure rate scales slower than linear boundary.



Superlinear

Linear

Sublinear

Virtuoso Variation Option User Guide

High Yield Estimation

Related Topics

[High Yield Estimation](#)

[The Scaled-Sigma Sampling Method](#)

[Running the Scaled-Sigma Sampling Method](#)

Running the Scaled-Sigma Sampling Method

Before you run the Scaled-Sigma Sampling (SSS) method, ensure that the following environment variable is set to `t`:

```
envSetVal("maestro.monte" "showMethodScaledSigmaSampling" 'boolean t)
```

To run the SSS method:

1. Open your design in ADE Assembler or ADE Explorer.
2. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
3. Click the *Simulation Options* command.

Virtuoso Variation Option User Guide

High Yield Estimation

The Monte Carlo form opens.

The screenshot shows the 'Monte Carlo' dialog box with the following settings:

- Method: Scaled-Sigma Sampling
- Variation: All
- Number of Points: 7000
- Target Yield: 3
- Points per Job: Group automatically, Max (10)
- Create Statistical Corners
- Save Waveforms (Simulation Data)
- Sampling Method: Low-Discrepancy Sequence
- Seed: 12345
- First Point: 1
- Netlist Options: (empty)
- Buttons: Specify Instances/Devices (Not Specified), Specify Mismatch ID (Not Specified), Specify Design Variables (Not Specified)
- Bottom Buttons: OK, Cancel, Defaults, Help

4. In the *What is the yield requirement?* field, .
5. From the *Method* drop-down list, select *Scaled-Sigma Sampling*.
6. In the *Target Yield* field, select a value greater than *3 sigma*.
7. In the *The Number of Points* field, specify the number of points you want to run. The default value is 7000.

This total number of points are divided across all of the scaled runs. Increasing the number of points improves accuracy and reduces the confidence interval of the yield

Virtuoso Variation Option User Guide

High Yield Estimation

estimate. If there are 7 scaled Monte Carlo iterations, and number of points = 7000, then each scaled iteration simulates 1000 points.

8. In the *Max Scaling Factor* field, specify the maximum scaling factor to be used for the Scaled-Sigma Sampling method. You can specify a value between 3–7. By default, this field is set to 7, which means that seven child histories using seven different scaling factors will be generated.

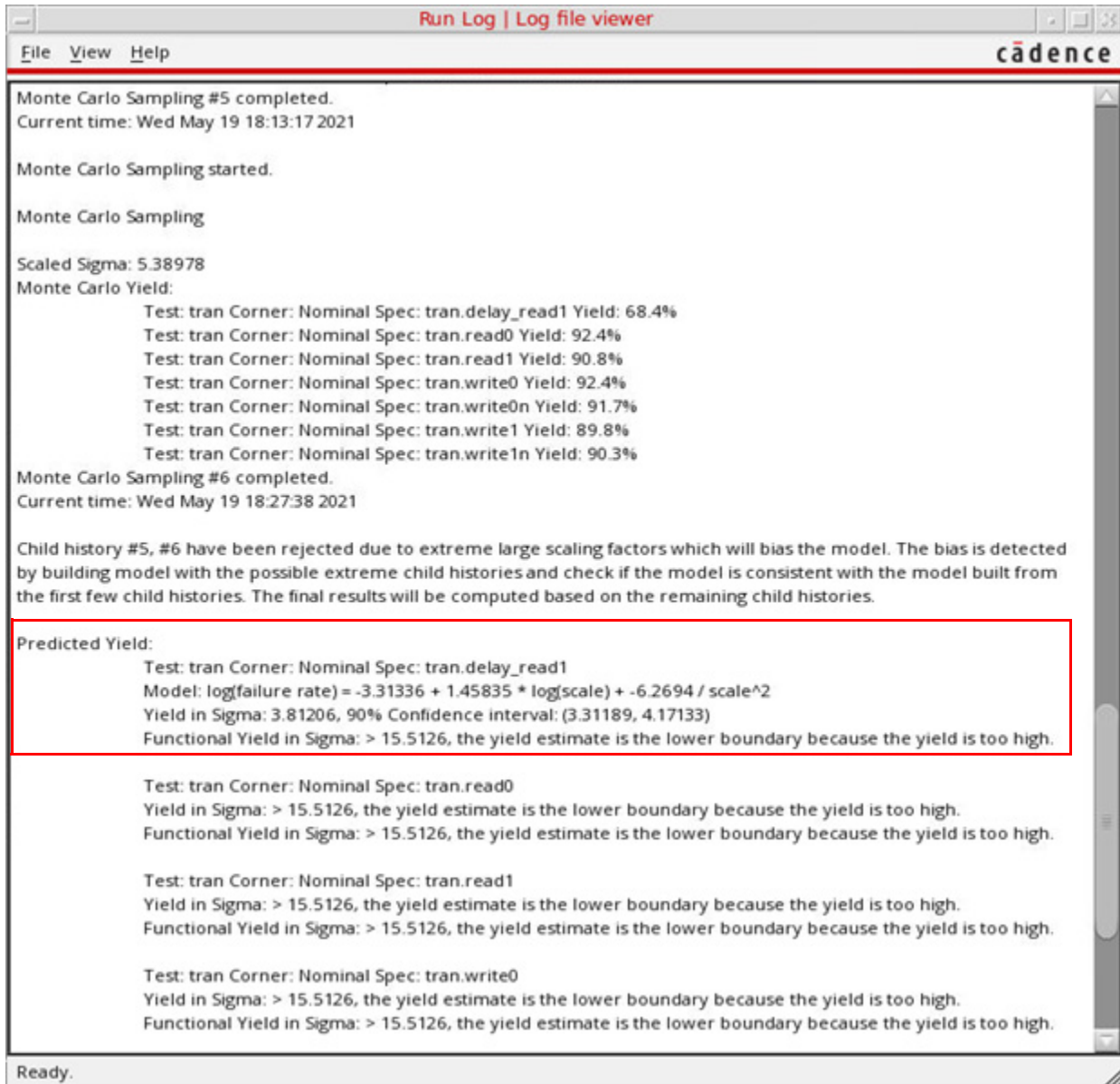
This field is hidden by default. You can set the [enableMaxScalingFactorForSSS](#) environment variable to `t` to view this field.

9. Select the *Create Statistical Corners* check box if you want to create statistical corners. When this option is selected, the task selection in the *Guided Mode* is changed to *Create statistical corners*.
10. From the *Sampling Method* drop-down list, select one of the following options: *Low-Discrepancy Sequence*, *Latin Hypercube*, or *Random*.
11. Click *OK* to close the Monte Carlo form.
12. Click *Run Simulation* to run the Monte Carlo simulation.

Virtuoso Variation Option User Guide

High Yield Estimation

The Run Log opens, displaying the important information about the run.



Run Log Information of the Scaled-Sigma Sampling Method

The Run Log of the in the Scaled-Sigma Sampling method reports the following information for each output:

Virtuoso Variation Option User Guide

High Yield Estimation

- The 90% confidence interval of the yield estimate in parenthesis. For example, (3.31189, 4.17133) is the 90% confidence interval for `delay_read1`, as shown in the figure above.
- K-Sigma target value, where K is the target yield specified on the Monte Carlo run options form. You can consider this target for the outputs to get K sigma performance of this design.

Note: This value is reported in the run log only when *Create Statistical Corner* is selected on the Monte Carlo form.

- The functional yield in sigma value, which is an estimate based on a functional pass or fail criteria. A failed point is counted only when the simulation or measurement evaluation fails.
- The model file (log failure) shows the internal model used to predict the failure rate. You can use this to inspect the model used for SSS algorithm.
- For the range and tolerance specifications, the output log prints the two confidence intervals in the following format:

```
Test: opamp090:full_diff_opamp_AC:1 Corner: Nominal Spec:
opamp090:full_diff_opamp_AC:1.Current
Yield in Sigma: -367.446e-3, 90% Confidence interval: (-553.439e-3, -181.885e-3)
4 sigma target: (0.00712165, 0.00713843), 90% Confidence intervals for low and high targets: (0.00712051, 0.00712278) (0.00713749, 0.00713916)
```

The model file (log failure) and K sigma target values are not reported for outputs when a model cannot be built either because the yield is too high or due to a failure in the model building process.

Related Topics

[showMethodScaledSigmaSampling](#)

[Monte Carlo Form](#)

[Statistical Sampling Methods](#)

[The Scaled-Sigma Sampling Method](#)

[Yield View of the Scaled-Sigma Sampling Method](#)

[Plotting a Normal Quantile Graph for the Scaled-Sigma Sampling Method](#)

Yield View of the Scaled-Sigma Sampling Method

After the Monte Carlo run for the Scaled-Sigma Sampling method completes, the *Yield* view of the *Results* tab shows the yield estimation.

Test	Name	Yield in Sigma	Yield in Percentage	MC Yield	Target	Status
Yield Estimation by Worst Case Distance Method						
- AC	Op_Region			100% (161/161)	< 1	
	Current	35.1262	100.0000000	100% (161/161)	< 1.5m	converged after 4 iterations
	UGF	1.79717	96.38460398	99.3789% (160/161)	> 533M	converged after 2 iterations
	Gain	15.0534	100.0000000	100% (161/161)	> 44	converged after 3 iterations
- TRAN	Swing	1.60724	94.59991681	100% (161/161)	> 0.98	converged after 2 iterations
	SettlingTime	3.21738	99.93531696	100% (161/161)	< 8n	least error WCD, did not converge after 10 iterations
	RelativeSwingPercent	1.90717	97.17504633	100% (161/161)	> 75	converged after 2 iterations
	PhaseMargin	1.4565	92.73731899	89.441% (144/161)	> 20	converged after 1 iterations

The following table describes the information displayed in different columns of the *Results* tab.

Column	Description
<i>Test</i>	Name of the test.
<i>Name</i>	Name of the specification.
<i>Yield in Sigma</i>	The yield value in sigma. This value is calculated using the following formula: $\text{Yield in Sigma} = \sqrt{2} \times \text{erfinv} \left(\frac{\text{Yield in Percentage}}{100} \right)$ where, <i>erfinv</i> is the inverse error function. If the yield in sigma is greater than 8.2, the yield in percentage is displayed as 100%.

Virtuoso Variation Option User Guide

High Yield Estimation

Column	Description
<i>Yield in Percentage</i>	Displays the yield value in percentage. This value is calculated using the following formula: The yield in percentage value is displayed with 10 digits by default. To change the number of digits to be displayed for this value, set the value of the <u>digitsToShowForYieldInPercentage</u> environment variable. You can display a maximum of 53 digits for these values.
<i>MC Yield</i>	The yield value from the Monte Carlo run.
<i>Target</i>	The target to be achieved for the given specification.
<i>Status</i>	The convergence status for each specification.

Related Topics

[The Scaled-Sigma Sampling Method](#)

[Running the Scaled-Sigma Sampling Method](#)

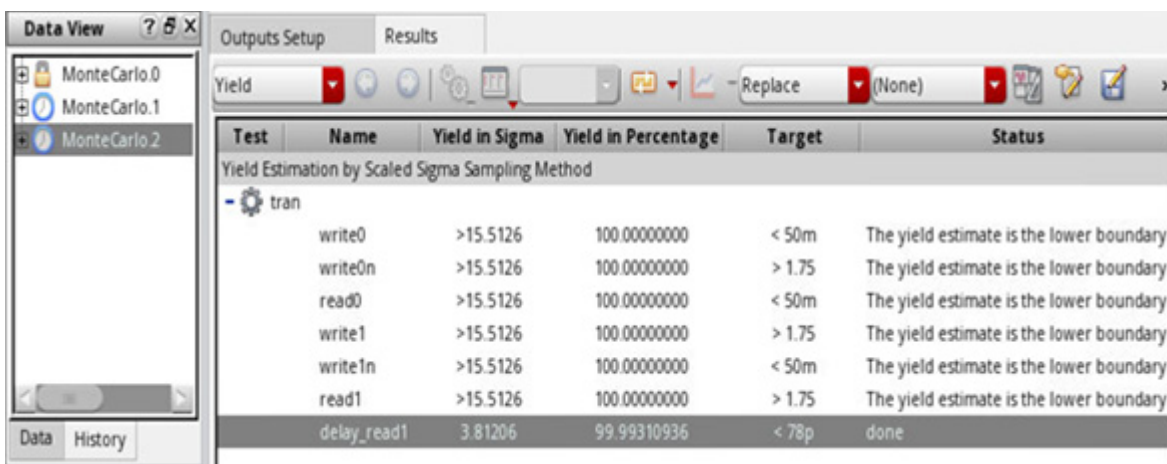
Plotting a Normal Quantile Graph for the Scaled-Sigma Sampling Method

After verifying yield using the Scaled-Sigma Sampling (SSS) method, you can plot a spec versus sigma normal quantile graph (QQ plot) to show the estimated result values at a number of normal quantiles. It also helps in comparing the result values for an output (delay_read1) with the values predicted for a standard normal distribution.

To plot a normal quantile plot for the SSS method:

1. In the *History* tab of the Data View assistant, right-click a Monte Carlo history for the SSS method, and then select *View Results*.

The results of the Monte Carlo run for the SSS method are displayed in the *Results* tab.



The screenshot shows the Data View assistant window with the Results tab selected. The table displays the following data:

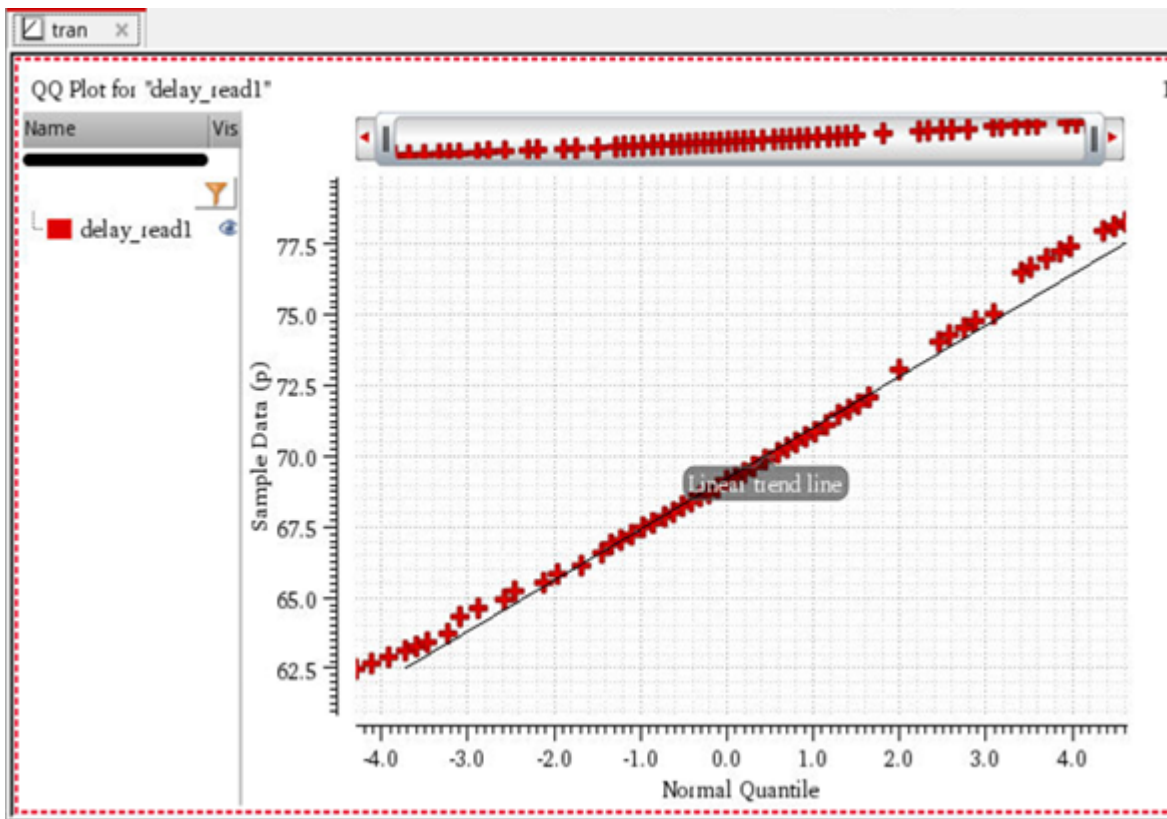
Test	Name	Yield in Sigma	Yield in Percentage	Target	Status
Yield Estimation by Scaled Sigma Sampling Method					
-	tran				
	write0	>15.5126	100.00000000	< 50m	The yield estimate is the lower boundary
	write0n	>15.5126	100.00000000	> 1.75	The yield estimate is the lower boundary
	read0	>15.5126	100.00000000	< 50m	The yield estimate is the lower boundary
	write1	>15.5126	100.00000000	> 1.75	The yield estimate is the lower boundary
	write1n	>15.5126	100.00000000	< 50m	The yield estimate is the lower boundary
	read1	>15.5126	100.00000000	> 1.75	The yield estimate is the lower boundary
	delay_read1	3.81206	99.99310936	< 78p	done

2. In the *Yield* view of the *Results* tab, right-click a specification, and then select *QQ Plot*.

Virtuoso Variation Option User Guide

High Yield Estimation

The graph window appears, showing the QQ plot.



In the graph, the y axis shows the estimated Monte Carlo results for output (`delay_read1`) and the x axis shows the normal quantiles of that sample data from -4 sigma to $+4$ sigma.

You can compare the normal quantile graph (shown in red) with the linear trend line, which is a reference line that signifies how the data is plotted if it is perfectly normally distributed. Points close to this line indicate that the data is close to normal distribution and the points far from this line indicate that the data is not close to normal distribution.

Related Topics

[The Scaled-Sigma Sampling Method](#)

[Running the Scaled-Sigma Sampling Method](#)

The Worst-Case Distance Method

The Worst-Case Distance (WCD) method defines the shortest distance from the nominal point to the specification boundary in the process/mismatch parameter space. WCD typically requires under 100 simulations for each spec and so is suitable for designs with a small number of specs/parameters that need to be monitored/changed.

When the target yield sigma value is greater than 4, you can select the WCD method to verify the yield of the design.

The worst case distance is a good indicator of circuit yield, where yield in percentage is approximately equal to:

$$\frac{1}{\sqrt{2}\Pi} \int_{-\infty}^{\text{wcd}} e^{-t^2/2} dt = \frac{1}{2} \left[1 + \text{erf} \left(\frac{\text{wcd}}{\sqrt{2}} \right) \right]$$

where, `erf` is the error function.

WCD provides accurate yield estimation when the specification boundary is linear in the process or mismatch parameter space. Strong non-linearity of the specification boundary can cause difficulty in finding the WCD points. A non-linear specification however may not result in a non-linear specification boundary in statistical space.

The Worst Case Corners method supports only statistical parameters that follow a normal distribution. It begins with a Monte Carlo Sampling run, uses the Monte Carlo results to filter non-high yield specifications (for which the Monte Carlo run gives accurate yield estimates), and then applies the WCD method on each high yield specification by doing the following:

1. Reads the process and mismatch parameter information from the Monte Carlo results
2. Performs parameter reduction based on the Monte Carlo results
3. Runs multiple sensitivity analysis iterations to find the WCD

Before you run Monte Carlo with this method, ensure that the Range and tolerance (`tol`) type specifications are disabled or deleted in the Outputs Setup tab of ADE Assembler. This is because these two specifications are not supported for Worst Case Distance. You can also convert the range and tolerance (`tol`) type specifications into two separate specifications for the min and max boundaries.

Virtuoso Variation Option User Guide

High Yield Estimation

Related Topics

[High Yield Estimation](#)

[Running the Worst-Case Distance Method](#)

Running the Worst-Case Distance Method

Before you run the Worst-Case Distance (WCD) method, ensure that the following environment variable is set to `t`:

```
envSetVal("maestro.monte" "showMethodWorstCaseDistance" 'boolean t)
```

To run the Worst-Case Distance method:

1. Open your design in ADE Assembler or ADE Explorer.
2. From the *Run Mode* drop-down list, select *Monte Carlo Sampling*.
3. Click the *Simulation Options* command.

Virtuoso Variation Option User Guide

High Yield Estimation

The Monte Carlo form opens.

The screenshot shows the 'Monte Carlo' dialog box with the following settings:

- Method: Worst Case Distance
- Variation: Process
- Number of Points: 200
- Points per Job: Group automatically, Max (10)
- Create Statistical Corners
- Save Waveforms (Simulation Data)
- Sampling Method: Random
- Seed: 12345
- First Point: 1
- Netlist Options: (empty)

Worst Case Distance Options

- Use Monte Carlo History (MonteCarlo.0)
- Automatic Number of Monte Carlo Points
- Automatic Variable Reduction
- Skip Specs With MC Yield < 3.0 sigma (99.86%)
- Max Number of Iterations: 10

Buttons at the bottom: Specify Instances/Devices (Not Specified), Specify Mismatch ID (Not Specified), Specify Design Variables (Not Specified), OK, Cancel, Defaults, Help.

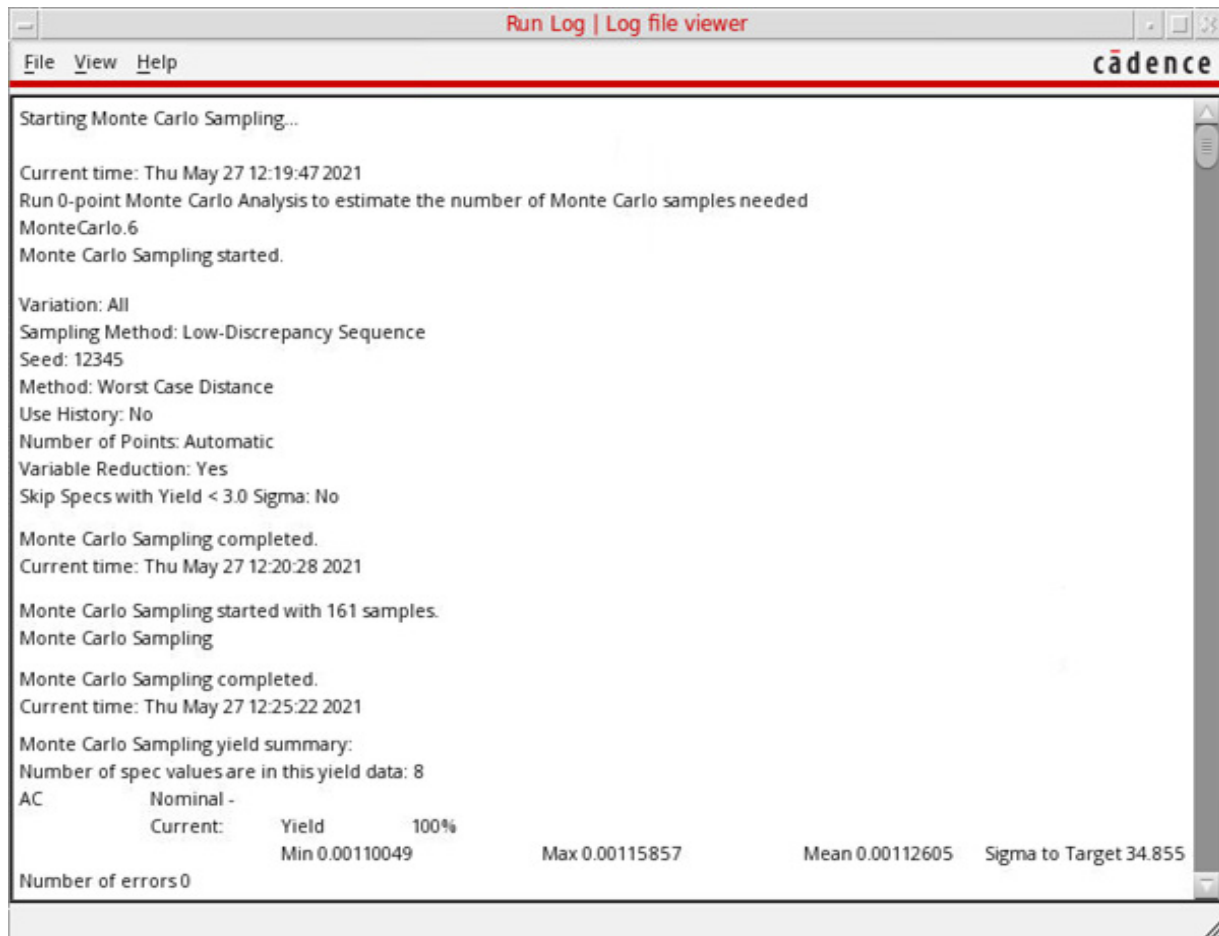
4. From the *Method* drop-down list, select *Worst Case Distance*.
5. From the *Variation* drop-down list, select one of the following options: *Mismatch*, *Process*, or *All*.

Virtuoso Variation Option User Guide

High Yield Estimation

6. The *Number of Points* field is set to 200 by default. This field is disabled when the *Automatic Number of Monte Carlo Points* check box is selected.
7. Select the *Create Statistical Corners* check box if you want to create statistical corners. When this option is selected, the task selection in the *Guided Mode* is changed to *Create statistical corners*.
8. From the *Sampling Method* drop-down list, select one of the following options: *Low-Discrepancy Sequence*, *Latin Hypercube*, or *Random*.
9. In the *Worst Case Distance Options* section, specify the fields as required.
10. Click *OK* to close the Monte Carlo form.
11. Click *Run Simulation* to run the Monte Carlo simulation.

The Run Log | Log File viewer window appears, displaying information about the progress of the initial Monte Carlo Sampling run, the yield estimate at each iteration, and the summary of the Monte Carlo run.



Virtuoso Variation Option User Guide

High Yield Estimation

The log file also displays the sigma of the statistical variable, which helps in understanding the results when you work with different units. The log file also displays the statistical parameter contribution values for the WCD point and device contribution values for the squared WCD values.

Related Topics

[showMethodWorstCaseDistance](#)

[Monte Carlo Form](#)

[Statistical Sampling Methods](#)

[High Yield Estimation](#)

[The Worst-Case Distance Method](#)

[Yield View of the Worst-Case Distance Method](#)

[Creating Statistical Corners from the Worst-Case Distance Method](#)

Yield View of the Worst-Case Distance Method

After the Monte Carlo run for the Worst-Case Distance (WCD) method completes, the *Yield* view of the *Results* tab shows the yield estimation.

Test	Name	Yield in Sigma	Yield in Percentage	MC Yield	Target	Status
Yield Estimation by Worst Case Distance Method						
- AC						
	Op_Region			100% (161/161)	< 1	
	Current	35.1262	100.0000000	100% (161/161)	< 1.5m	converged after 4 iterations
	UGF	1.79717	96.38460398	99.3789% (160/161)	> 533M	converged after 2 iterations
	Gain	15.0534	100.0000000	100% (161/161)	> 44	converged after 3 iterations
- TRAN						
	Swing	1.60724	94.59991681	100% (161/161)	> 0.98	converged after 2 iterations
	SettlingTime	3.21738	99.93531696	100% (161/161)	< 8n	least error WCD, did not converge after 10 iterations
	RelativeSwingPercent	1.90717	97.17504633	100% (161/161)	> 75	converged after 2 iterations
	PhaseMargin	1.4565	92.73731899	89.441% (144/161)	> 20	converged after 1 iterations

The following table describes the information displayed in different columns of the *Results* tab.

Column	Description
<i>Test</i>	Name of the test.
<i>Name</i>	Name of the specification.
<i>Yield in Sigma</i>	The yield value in sigma. This value is calculated using the following formula: $\text{Yield in Sigma} = \sqrt{2} \times \text{erfinv} \left(\frac{\text{Yield in Percentage}}{100} \right)$ <p>where, <i>erfinv</i> is the inverse error function.</p> <p>If the yield in sigma is greater than 8.2, the yield in percentage is displayed as 100%.</p>

Virtuoso Variation Option User Guide

High Yield Estimation

Column	Description
<i>Yield in Percentage</i>	<p>Displays the yield value in percentage. This value is calculated using the following formula:</p> $\text{Yield in Percentage} = 0.5 + 0.5 \times \text{erf} \left(\frac{WCD}{2\sqrt{2}} \right)$ <p>where, <code>erf</code> is the error function.</p> <p>The yield in percentage value is displayed with 10 digits by default. To change the number of digits to be displayed for this value, set the value of the <code>digitsToShowForYieldInPercentage</code> environment variable. You can display a maximum of 53 digits for these values.</p>
<i>MC Yield</i>	The yield value from the Monte Carlo run.
<i>Target</i>	The target to be achieved for the given specification.
<i>Status</i>	The convergence status for each specification.

Convergence Criteria and Convergence Statuses

The tool uses the following two convergence criteria in the WCD method:

- The predicted WCD point is on the specification boundary (within tolerance < 0.02). The log file reports the 'Spec value error' at each iteration.

```
spec_value_error_ratio = abs(spec_value - spec_target) /
max(abs(nominal_spec_value - spec_target), 6*spec_sigma)
```

- The angle between the gradient vector and the statistical variable vector is < 8 deg. The log file reports the 'Gradient direction error' at each iteration.

The following table describes the convergence statuses shown in the *Status* column of the *Yield* view in the *Results* tab.

Status	Description
<i>converged after x iterations</i>	<p>The yield estimate converged after x iterations.</p> <p>For example, the yield estimate for the <code>Gain</code> specification converged after 3 iterations.</p>

Virtuoso Variation Option User Guide

High Yield Estimation

Status	Description
<i>skipped because the Monte Carlo yield is less than <value in percentage></i>	<p>Yield estimation was skipped for the specification because the Monte Carlo yield estimate was too low.</p> <p>The low yield threshold value is specified in the Monte Carlo form in the <i>Skip specs with MC Yield < field</i>, which is by default set to 3 sigma or 99.86%.</p>
<i>least error WCD, did not converge after x iterations</i>	<p>Yield estimation did not converge after the maximum number of iterations has completed. The specification failure boundary is strongly non-linear or the maximum number of iterations is too small.</p> <p>The yield estimate with the least error among iterations is reported.</p>
<i>lower boundary, did not converge after x iterations</i>	<p>Yield estimation did not converge because the specification has an unrealistic yield estimate which is larger than 12 sigma in yield after the maximum number of iterations.</p> <p>The yield estimate increased at each iteration, but never converged.</p>
<i>estimate based on MC data lower boundary least error WCD, stopped because evaluating of the WCD point sensitivity failed on iteration x</i>	<p>Yield estimation stopped before reaching the maximum number of iterations because of a simulation or measurement error in evaluating the WCD point sensitivity.</p> <p>The lower boundary is reported if it is identified, if not, the yield estimate with the least error among iterations is reported.</p>
<i>estimate based on MC data lower boundary least error WCD, stopped because evaluation of the WCD point failed on iteration x</i>	<p>Yield estimation stopped before reaching the maximum number of iterations because of a simulation or measurement error in evaluating the WCD point.</p> <p>The lower boundary is reported if it is identified, if not, the yield estimate with the least error among iterations is reported.</p> <p>If the run was stopped on the first iteration, the estimate based on the Monte Carlo result is reported.</p>

Related Topics

[The Worst-Case Distance Method](#)

[Running the Worst-Case Distance Method](#)

Creating Statistical Corners from the Worst-Case Distance Method

If you run Monte Carlo for a design without skipping the specifications that have yield of less than 3 sigma or 99.86%, the results may show specifications that have yield value less than 3 sigma.

In the following example, the Monte Carlo yield for the specifications *UGF*, *Swing*, *RelativeSwingPercent*, and *PhaseMargin* is less than 3 sigma.

Test	Name	Yield in Sigma	Yield in Percentage	MC Yield	Target	Status
Yield Estimation by Worst Case Distance Method						
- AC	Op_Region			100% (161/161)	< 1	
	Current	35.1262	100.00000000	100% (161/161)	< 1.5m	converged after 4 iterations
	UGF	1.79717	96.38460398	99.3789% (160/161)	> 533M	converged after 2 iterations
	Gain	15.0534	100.00000000	100% (161/161)	> 44	converged after 3 iterations
- TRAN	Swing	1.60724	94.59991681	100% (161/161)	> 0.98	converged after 2 iterations
	SettlingTime	3.21738	99.93531696	100% (161/161)	< 8n	least error WCD, did not converge after 10 iterations
	RelativeSwingPercent	1.90717	97.17504633	100% (161/161)	> 75	converged after 2 iterations
	PhaseMargin	1.4565	92.73731899	89.441% (144/161)	> 20	converged after 1 iterations

To improve the yield for a specification, you can create a statistical corner based on the Worst-Case Distance (WCD) point of the specification.

1. In the *Yield* view of the Worst-Case Distance results, right-click a specification, and then select either *Create Corner (Specify Yield in Sigma)* or *Create Corner (Specify Yield in Percentage)*.

The High Yield Estimation Corner form opens.

Virtuoso Variation Option User Guide

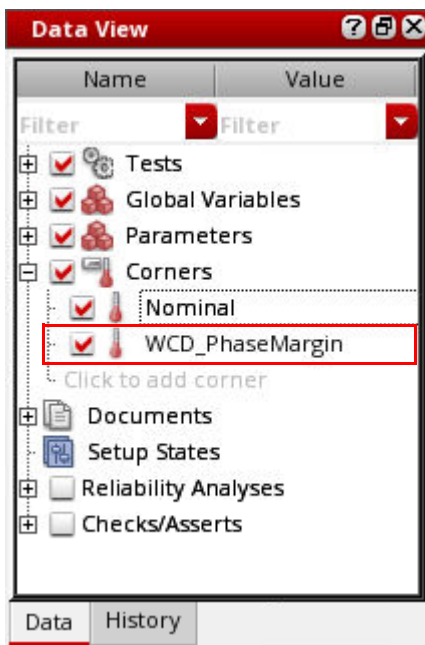
High Yield Estimation

2. In the *Specify corner sigma* field, specify the sigma value to which you want to extend the WCD point. If you selected *Create Corner (Specify Yield in Percentage)* in step 1, specify the target yield value to be achieved in percentage.

Note: For a high yield design, you can set a corner sigma value equal to 6.0. A good practice is to increase the sigma value by 0.5 to 1.0 in each iteration instead of increasing it by large amount.

3. Click *OK* to create the statistical corner.

The statistical corner is created with the name *WCD_specification_name*.



4. Enable this corner and run global optimization on the design.

Virtuoso Variation Option User Guide

High Yield Estimation

The results for the new statistical corners are displayed.

Point	Test	Output	Nominal	Spec	Weight	Min	Max	WCD_PhaseMargin
Parameters: vJd=1.3								
2	AC	Op_Region	0	< 1		0	0	disabled
2	AC	Current	1.126 mA	< 1.5m		1.126 mA	1.126 mA	disabled
2	AC	UGF	546.4 MHz	> 533M		546.4 MHz	546.4 MHz	disabled
2	AC	Gain	46.74 dB	> 44		46.74 dB	46.74 dB	disabled
2	TRAN	Swing	1.008	> 0.98		1.007	1.008	1.007
2	TRAN	SettlingTime	7.763 ns	< 8n		7.763 ns	7.829 ns	7.829 ns
2	TRAN	RelativeSwin...	77.51 %	> 75		77.43 %	77.51 %	77.43 %
2	TRAN	PhaseMargin	20.71 degree	> 20		18.75 degree	20.71 degree	18.75 degree
Parameters: vJd=1.5								
1	AC	Op_Region	0	< 1		0	0	disabled
1	AC	Current	1.197 mA	< 1.5m		1.197 mA	1.197 mA	disabled
1	AC	UGF	592.5 MHz	> 533M		592.5 MHz	592.5 MHz	disabled
1	AC	Gain	47.97 dB	> 44		47.97 dB	47.97 dB	disabled
1	TRAN	Swing	1.136	> 0.98		1.135	1.136	1.135
1	TRAN	SettlingTime	7.565 ns	< 8n		7.565 ns	7.619 ns	7.619 ns
1	TRAN	RelativeSwin...	75.74 %	> 75		75.64 %	75.74 %	75.64 %
1	TRAN	PhaseMargin	19.16 degree	> 20		17.37 degree	19.16 degree	17.37 degree

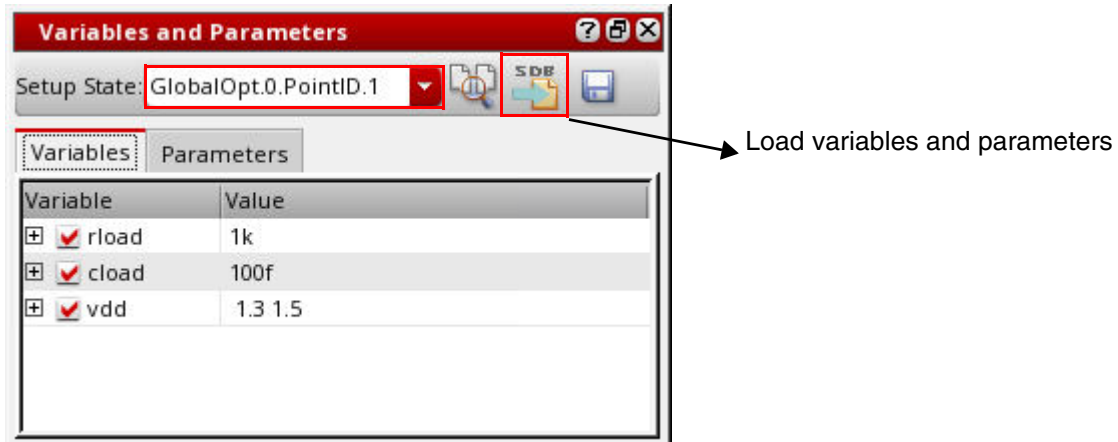
- From the results of the optimization run, right-click a design point, and select *Save variable and parameter values to Setup State* to save the values of variables and parameters from that point into a setup state.

The values of all the variables and parameters for this design point are saved as a state named as *history_name.PointID.pointID*. For example, *GlobalOpt.0.PointID.1*.

Virtuoso Variation Option User Guide

High Yield Estimation

- Open the Variables and Parameters assistant and select this setup state from the *Setup State* drop-down list.



- Click *Load variables and parameters*.
- Run the Monte Carlo simulation again using the same setup.

The results show significant improvement in the yield and the worst case distance values.

Related Topics

[High Yield Estimation](#)

[The Worst-Case Distance Method](#)

[Yield View of the Worst-Case Distance Method](#)

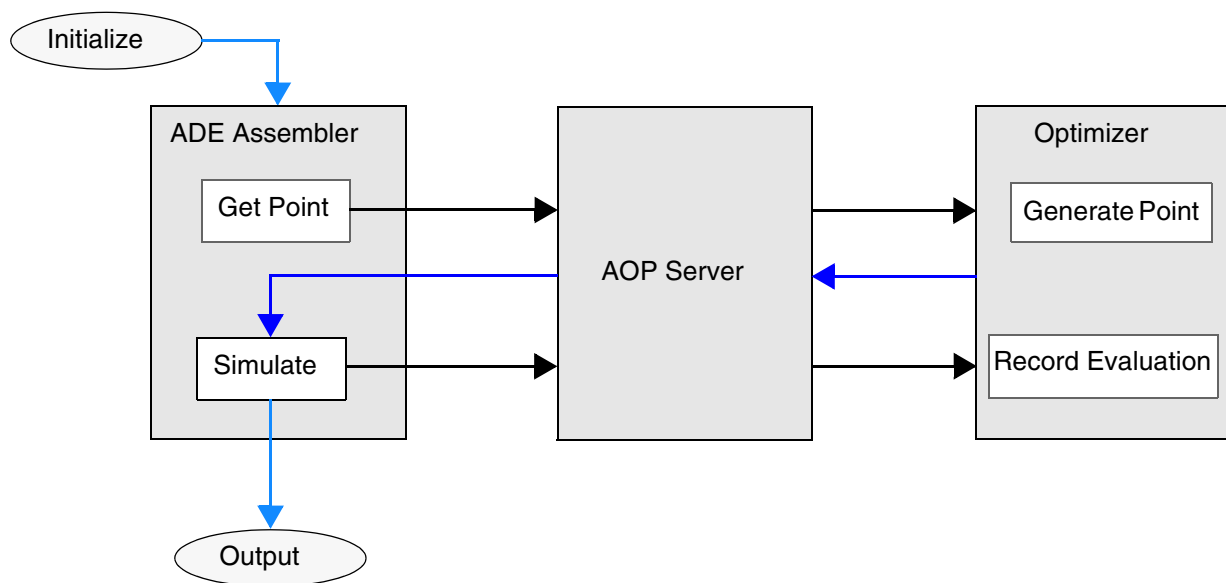
Virtuoso Variation Option User Guide

High Yield Estimation

Advanced Optimization

You can use Virtuoso ADE Assembler and Advanced Optimization Platform (AOP) to optimize your circuit designs. You can also write your custom optimization algorithm in C++ or Python, and integrate it into ADE Assembler using AOP.

The following figure shows the workflow of advanced optimization in ADE Assembler.



There are three key components in this workflow: ADE Assembler, AOP Servers, and Optimizer.

1. ADE Assembler initiates the process by providing a design space to the AOP Server. This design space represents the range of parameters or configurations for a particular system or problem.
2. The AOP Server employs an algorithm to sample this design space. The algorithm then sends the sampled points back to ADE Assembler for further evaluation.

Virtuoso Variation Option User Guide

Advanced Optimization

3. ADE Assembler takes these sampled points and performs simulations. It evaluates these points by applying specific mathematical expressions and computes a value for the cost function (or merit) based on predefined specifications and their corresponding weights.
4. AOP Server invokes a record evaluation method. This method is utilized by the optimization algorithm to determine the next steps in the optimization process.
5. The workflow iterates continuously until any of the stopping criteria are met. These criteria could include reaching a desired level of performance, minimizing costs, or achieving other optimization goals.

This workflow facilitates an iterative optimization process where ADE Assembler, AOP Server, and the Optimizer work together to explore and refine the design space until the desired objectives are achieved.

Related Topics

[Advantages of Advanced Optimization](#)

[Running Advanced Optimization](#)

[AOP Options Form](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

[Hyperparameters of Valhalla Optimizer](#)

Advantages of Advanced Optimization

Advantages of using advanced optimization in ADE Assembler are as follows:

- Lets you use different optimizers as per the need.
 - Comes with various algorithms, such as particle swarm optimization (PSO), Dakota, Optuna, and other surrogate model-based optimizers.
 - Supports custom optimization algorithms that you can write on your own.
 - Allows further tuning of hyperparameters of global optimizers (legacy optimizers).
- Provides multi-language support, C++ and Python.
- Provides better data management to share results using web server.

Related Topics

[Advanced Optimization](#)

[Running Advanced Optimization](#)

[AOP Options Form](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

Advanced Optimizers in ADE Assembler

The Advanced Optimization form in ADE Assembler lets you select the following optimizers:

- GRPR

GPRP optimizer is a combination of genetic algorithm (GA) and Simulated Annealing (SA) with a surrogate model.

- Valhalla

Valhalla is a combination of particle swarm optimization (PSO) and genetic algorithm (GA).

- Dakota

Dakota provides advanced parametric analyses that enable design exploration, model calibration, risk analysis, and quantification of margins and uncertainty with computational models.

- Optuna

Optuna is an open source hyperparameter optimization framework to automate hyperparameter search using Python. It searches large spaces and prune unpromising trials for faster results.

- Particle swarm optimization (PSO)

PSO is a swarm or population-based algorithm. It optimizes a problem by iteratively trying to improve a candidate solution.

In addition, you can also write your custom optimization algorithm in C++ or Python.

The factor that determines how fast an optimization algorithm converges is the cost function, which depends on the circuit, measurements, specifications, and design space.

Related Topics

[Hyperparameters of Valhalla Optimizer](#)

[Hyperparameters of Optuna Optimizer](#)

[Hyperparameters of Dakota Optimizer](#)

[Hyperparameters of Particle Swarm Optimizer](#)

[Example of Custom Optimization Algorithm](#)

Virtuoso Variation Option User Guide

Advanced Optimization

AOP Options Form

Example of Custom Optimization Algorithm

You can create a custom optimization algorithm either in C++ or Python.

The following piece of code shows an example of the custom optimization algorithm written in Python.

```
# *****
#           Copyright 2023 Cadence Design Systems, Inc.
#           All Rights Reserved.
#
# This work cannot be republished or copied in its original form
# without prior written permission from Cadence Design Systems, Inc.
#
# Permission is granted to modify this code for the purpose of
# developing new optimizers to run within Virtuoso Studio.
# *****

import dso
import numpy as np
import random

random.seed(1)

class RakOptimizer(dso.BaseOptimizer):
    def __init__(self):
        super().__init__()
        self.optimizer_info.set_optimizer_name(name='RAK Optimizer')
        self.optimizer_info.set_hyperparameter_property_range(
            hp='batchSize',
            hp_default=2,
            hp_min=2,
            hp_step=1,
            hp_max=1000,
            hp_description='Controls Batch Size')

    # def pre_processing(self):
    #     pass

    def get_points(self):
```

Virtuoso Variation Option User Guide

Advanced Optimization

```
point_dic = self.domain.sample(size=self.hyper_params['batchSize'])
point_array = point_dic.parse_into_object(out_type=np.ndarray)
ret = dso.GetPointsReturnType()
ret.parse_from_object(domain=self.domain, samples=point_array)
return ret
```

```
def record_evaluations(self, evaluation_result):
    pass
```

```
if __name__ == '__main__':
    RakOptimizer().run()
```

Methods Used in the Custom Optimization Algorithm Example

In the example of custom optimization algorithm, following methods are used:

■ `__init__()`

It is a Python constructor that is loaded with the AOP framework. It contains essential information about the optimization algorithm, such as name, description, and details of hyperparameters. Note that specific design space information is not accessible at this stage because simulation run in ADE Assembler has not started yet.

The details of optimizer hyperparameters can be defined as follows.

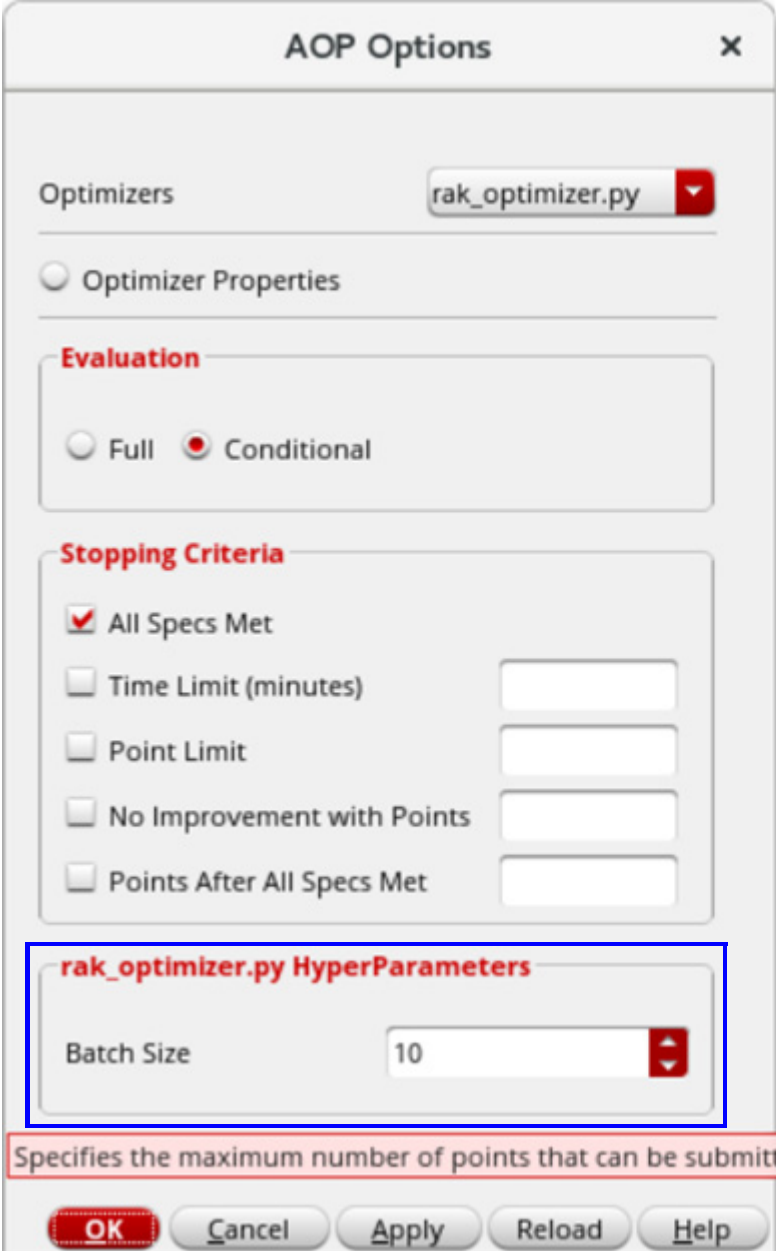
```
self.optimizer_info.set_hyperparameter_property_range(
    hp='Batch Size',
    hp_default=100,
    hp_min=10,
    hp_step=1,
    hp_max=1000,
    hp_description='Specifies the maximum number of points that can be
submitted by optimizer during one iteration')
```

In this example, a hyperparameter named *Batch Size* is defined. The default value of this parameter is 100. The minimum and maximum values for this hyperparameters is 10 and 1000, respectively. The tooltip for this hyperparameters reads: *Specifies the maximum number of points that can be submitted by optimizer during one iteration.*

Virtuoso Variation Option User Guide

Advanced Optimization

This hyperparameter option is displayed in the *rak_optimizer.py HyperParameters* section of the AOP Options form, as follows:



The screenshot shows the "AOP Options" dialog box. At the top, the "Optimizers" dropdown is set to "rak_optimizer.py". Below this, there are sections for "Evaluation" (with "Conditional" selected) and "Stopping Criteria" (with "All Specs Met" checked). The "rak_optimizer.py HyperParameters" section is highlighted with a blue border and contains a "Batch Size" spinner set to 10. A red tooltip box below this section contains the text: "Specifies the maximum number of points that can be submitted by optimizer during one iteration". At the bottom of the dialog are buttons for "OK", "Cancel", "Apply", "Reload", and "Help".

Where, *rak_optimizer.py* is the name of the custom optimization algorithm currently selected in the *Optimizers* drop-down list.

- `pre_processing()`

Virtuoso Variation Option User Guide

Advanced Optimization

This method is used to initialize settings that are necessary for the optimization run. Information about design space is available at this stage because optimization run is started in ADE Assembler.

- `get_points()`

This method is used by the AOP framework to request the optimization algorithm for the points to simulate.

- `record_evaluations()`

This method is used by AOP framework to return the merit values associated with the simulated points. In this example, the optimizer performs random sampling and does not use any information returned from ADE Assembler.

Related Topics

[Advanced Optimization](#)

[Advantages of Advanced Optimization](#)

[AOP Options Form](#)

[Running Advanced Optimization](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

Integrating a Custom Optimizer into ADE Assembler

After creating your custom optimization algorithm, you must integrate it into ADE Assembler. You can then select this algorithm from the Optimizers drop-down list in the AOP Options form when running the Advanced Optimization run.

To integrate the custom optimization algorithm into ADE Assembler:

1. Set the following Shell environment variable to specify the colon-separated directories where you want to save the custom optimization algorithms:

```
setenv DSO_HOME_OPTIMIZERS $CDSHOME/tools/DSO/optimizer/system/target:$PWD/  
custom_optimizers
```

Where, \$CDSHOME is the Cadence installation directory, and \$PWD is the current working directory.

You can specify another directory separated by a colon (:).

2. Save your custom optimization algorithms in either of the following directories:

```
setenv AOP_OPTIMIZERPATH  
$CDSHOME/tools/DSO/optimizer/system/target:$PWD/custom_optimizers
```

The algorithms saved in these directories are available to be selected from the *Optimizers* drop-down list in the AOP Options form.

Related Topics

[Advanced Optimization](#)

[Example of Custom Optimization Algorithm](#)

[Advantages of Advanced Optimization](#)

[AOP Options Form](#)

[Running Advanced Optimization](#)

Hyperparameters of Valhalla Optimizer

The following table describes the hyperparameters of Valhalla optimizer.

Hyperparameter	Description
<i>Budget</i>	Number of iterations to be run before optimizer stops.
<i>Elitist Percentage</i>	The percentage of top particles or individuals to be propagated to next iteration of optimization.
<i>No of Particles</i>	The number of particles or individuals in a population.
<i>No of DOE Points</i>	The number of points required before the initial surrogate model is created.
<i>Random Seed</i>	Seeds to initialize random number generators.
<i>Surrogate Iterations</i>	The number of iterations to be performed by internal optimizers using the generated surrogate model.

Related Topics

[Advanced Optimization](#)

[Advanced Optimizers in ADE Assembler](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

[AOP Options Form](#)

Hyperparameters of Optuna Optimizer

The following table describes the hyperparameters of Optuna optimizer.

Hyperparameter	Description
<i>Batch Size</i>	Maximum number of jobs to be run.
<i>Budget</i>	Number of points to be run before the optimizer stops.
<i>Random Seed</i>	Seeds to initialize pseudo-random number generators.
<i>Sampler</i>	Sampling algorithm
<i>Stopping Threshold</i>	Percent of budget which if consumed without a change in best point, causes optimization to exit.

Related Topics

[Advanced Optimization](#)

[Advanced Optimizers in ADE Assembler](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

[AOP Options Form](#)

Hyperparameters of Dakota Optimizer

The following table describes the hyperparameters of Dakota optimizer.

Hyperparameter	Description
<i>Batch Size</i>	Maximum number of jobs to be run
<i>LHS Sampling Size</i>	Sampling size for the Latin Hypercube method
<i>Max Iterations</i>	Number of batches
<i>Population Size</i>	Number of candidates in each iterations
<i>Seed</i>	Seeds to initialize pseudo-random number generators
<i>Sub Optimizer Choice</i>	Algorithm to be selected

Related Topics

[Advanced Optimization](#)

[Advanced Optimizers in ADE Assembler](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

[AOP Options Form](#)

Hyperparameters of Particle Swarm Optimizer

The following table describes the hyperparameters of Particle Swarm Optimizer (PSO).

Hyperparameter	Description
<i>Batch Size</i>	Maximum number of jobs to be run.
<i>Budget</i>	Maximum number of points that can be simulated.
<i>Number of Particles</i>	Number of candidates in each iterations.
<i>Seed</i>	Seeds to initialize pseudo-random number generators.
<i>W</i>	Inertia weight
<i>C1</i>	Cognitive constant
<i>C2</i>	Social constant

Related Topics

[Advanced Optimization](#)

[Advanced Optimizers in ADE Assembler](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

[AOP Options Form](#)

Running Advanced Optimization

To run advanced optimization:

1. Run a simulation for the design that you want to optimize. Ensure that the specifications have been defined for the outputs in the *Outputs Setup* tab in ADE Assembler.
2. The simulation results are displayed in the *Results* tab.

The screenshot shows the 'Results' tab in the Virtuoso ADE Assembler. The main table displays simulation results for various parameters across 13 test cases (C1.0 to C1.8). The parameters include temperature, vdd, and various op-amp outputs and characteristics. The results are color-coded: green for 'pass', yellow for 'near', and red for 'fail'. The 'Current' parameter for the 'Two_Stage_Opamp...' test is highlighted in red, indicating a failure.

Parameter					C1.0	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6	C1.7	C1.8
temperature					0	27	70	0	27	70	0	27	70
vdd					1.2	1.2	1.2	1.3	1.3	1.3	1.4	1.4	1.4

Test	Output	Spec	Pass/Fail	Min	Max	C1.0	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6	C1.7	C1.8
Two_Stage_Opamp...	/V1/PLUS													
Two_Stage_Opamp...	/OUT													
Two_Stage_Opamp...	/Vcm/MINUS													
Two_Stage_Opamp...	/Vcm/PLUS													
Two_Stage_Opamp...	/cmin													
Two_Stage_Opamp...	Current	< 1.0m	fail	1.084m	1.165m	1.085m	1.086m	1.084m	1.127m	1.126m	1.12...	1.165m	1.163m	1.159m
Two_Stage_Opamp...	Voffset	range -10m 10m	pass	2.744m	3.621m	2.807m	3.112m	3.621m	2.78m	3.065m	3.54...	2.744m	3.011m	3.455m
Two_Stage_Opamp...	CMRR	> 40	pass	42.12	49.8	45.8	44.36	42.12	48.04	46.55	44.27	49.8	48.31	46.01
Two_Stage_Opamp...	Gain	> 40	pass	44.93	48.02	46.67	46.01	44.93	47.38	46.74	45.7	48.02	47.39	46.36
Two_Stage_Opamp...	PSRR	> 50	near	48.23	56.62	53.56	51.28	48.23	54.99	52.68	49.56	56.62	54.26	51.09
Two_Stage_Opamp...	UGF	> 460M	near	458.8M	630.2M	578.4M	527.5M	458.8M	606M	553.3M	482....	630.2M	575.7M	503.7M

The cells in the results are highlighted in green, yellow, and red colors, which indicate that the measurements meet specification, almost meet specification, and do not meet specification, respectively.

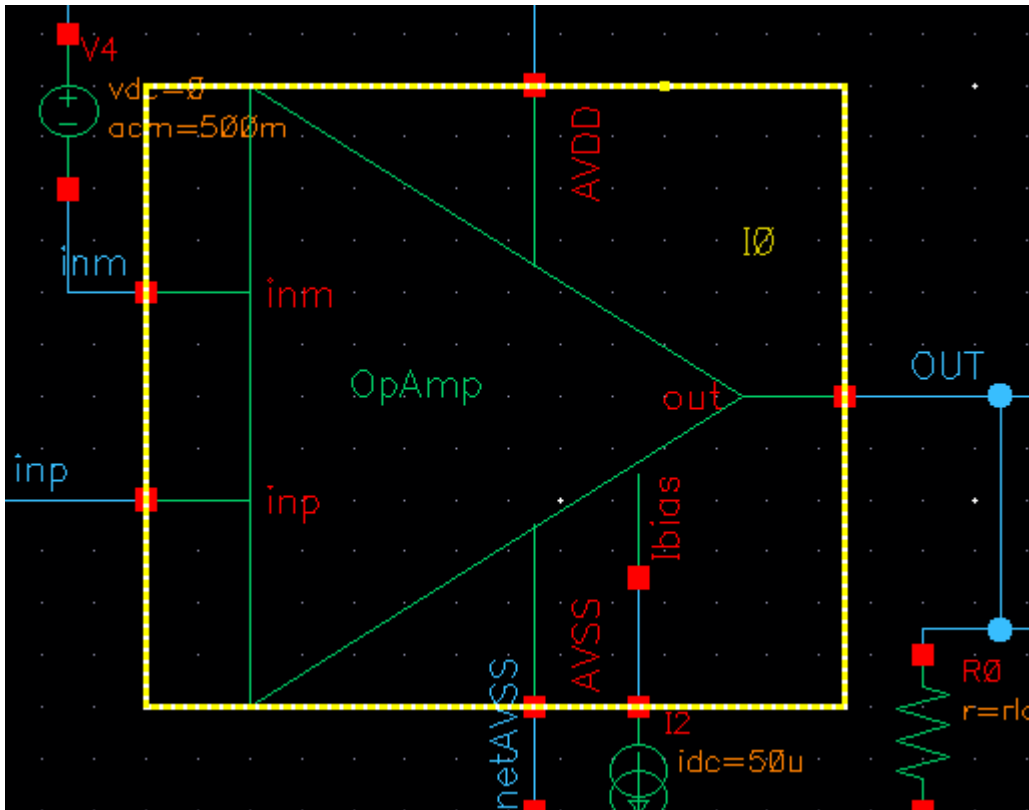
3. In the *Data View* assistant, right-click the name of the test, and choose *Open Design in Tab*.

The schematic design opens in a new tab.

Virtuoso Variation Option User Guide

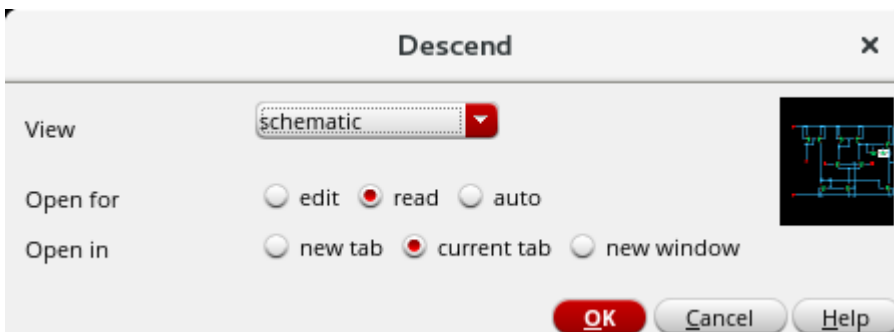
Advanced Optimization

4. Select an OpAmp instance, for example, I0.



5. Right-click the selected instance, and choose *Descend Read* to descend into the schematic of the selected design.

The Descend form opens.



6. Keep the default selection in the form and click *OK*.

The schematic of the selected instance opens in read-only mode in the current tab.

Virtuoso Variation Option User Guide

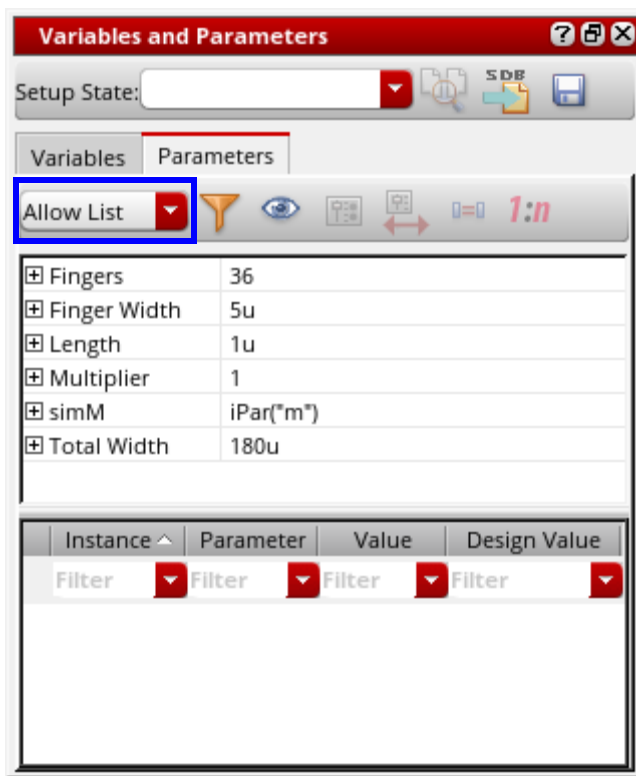
Advanced Optimization

7. Select multiple instances while holding down the `Shift` key on the keyboard. For example, `M1` and `NM0`.



8. From the menu bar of ADE Assembler, choose *Window – Assistants – Variables and Parameters*.

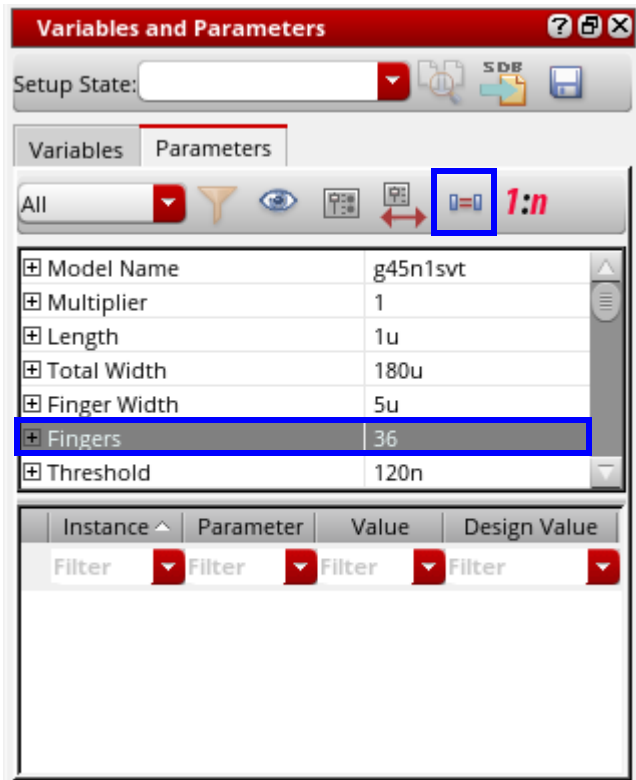
The Variables and Parameters assistant opens.



Virtuoso Variation Option User Guide

Advanced Optimization

9. In the *Parameters* tab of the Variables and Parameters form, select *All* from the highlighted drop-down list.

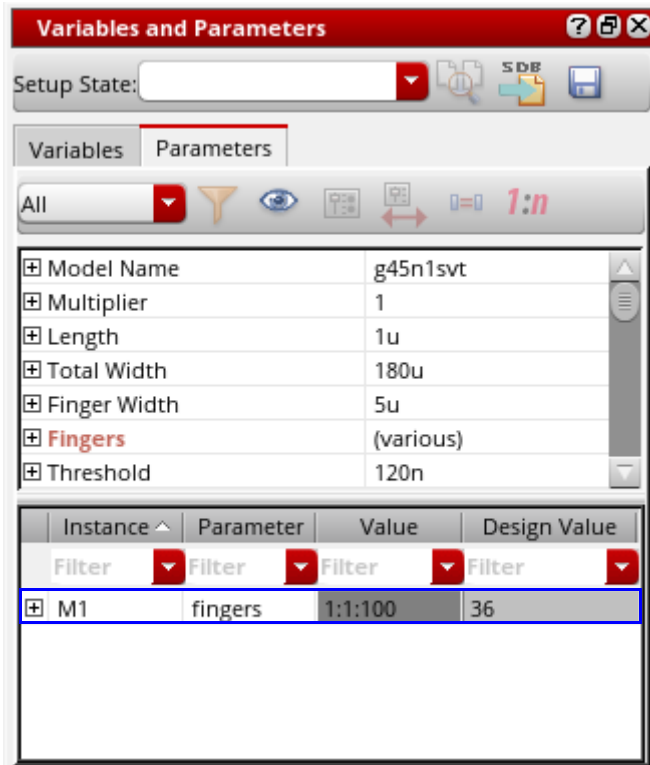


10. Click a parameter, for example, *Fingers*, and then click the *Match Parameters* icon.

Virtuoso Variation Option User Guide

Advanced Optimization

11. In the *Value* column, define the parametric sweep values for the instance *M*. For example, 1:1:100.

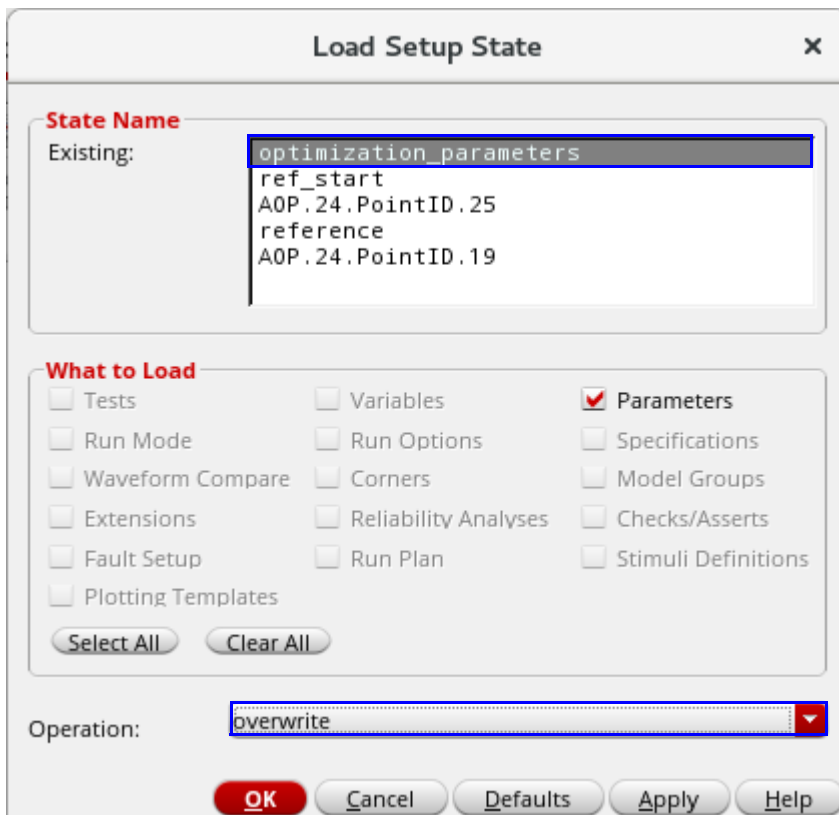


12. To load rest of parameters saved in a setup state:
- Click the *maestro* tab of ADE Assembler.
 - In the *Data View* assistant, expand *Setup States*.
 - Right-click a setup state, and then click *Load* to load the setup state. For example: *optimization_parameter*.

Virtuoso Variation Option User Guide

Advanced Optimization

The Load Setup State form opens.



13. Click OK to load the setup state.

All the parameters saved in the setup state are loaded.

14. From the *Run Mode* drop-down list in the *Run* toolbar of ADE Assembler, select *Advanced Optimization*. The history name is changed to *AOP*.

15. Click *Simulation Options*.

The AOP Options form is displayed.

16. From the *Optimizers* drop-down list, select a custom optimization algorithm you have created. For example, *PSO*.

17. Specify other options. You can also edit the values of hyperparameters defined for the custom optimization algorithm you selected from the *Optimizers* drop-down list.

18. Click *OK* to close the AOP Options form.

19. Click *Run Simulation*.

Virtuoso Variation Option User Guide

Advanced Optimization

The optimizer converges on a solution that meets all specification, as shown in the following figure.



The screenshot shows the 'Results' tab of the 'Advanced Optimization' window. It displays a table with columns for 'Parameter', 'C1.0' through 'C1.8', and 'Min' through 'Max'. The parameters listed are 'temperature', 'vdd', 'Current', 'UGF', 'Gain', 'Vofbet', 'CMRR', and 'PSRR'. The values for each parameter are shown for 17 different optimization points. The table is filtered to show 60/300 rows.

Parameter	C1.0	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6	C1.7	C1.8
temperature	0	27	70	0	27	70	0	27	70
vdd	1.2	1.2	1.2	1.3	1.3	1.3	1.4	1.4	1.4

Point	Test	Output	Spec	Min	Max	C1.0	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6	C1.7	C1.8
17	Two_Stage_...	Current	< 1.0m	854.3u	915.4u	854.3u	855.5u	856.1u	885.7u	885.8u	885.5u	915.4u	914.3u	912.8u
17	Two_Stage_...	UGF	> 460M	485.6M	663.6M	602.2M	554.1M	485.6M	630M	580.1M	510M	663.6M	603.6M	531.8M
17	Two_Stage_...	Gain	> 40	42.08	45.34	43.78	43.16	42.08	44.6	44.02	43.02	45.34	44.8	43.86
17	Two_Stage_...	Vofbet	range -10m ...	1.493m	1.963m	1.512m	1.675m	1.963m	1.505m	1.653m	1.914m	1.493m	1.628m	1.864m
17	Two_Stage_...	CMRR	> 40	45.87	52.46	49.24	47.93	45.87	50.87	49.58	47.52	52.46	51.18	49.15
17	Two_Stage_...	PSRR	> 50	53.02	62.37	59.47	56.6	53.02	60.79	57.88	54.24	62.37	59.38	55.67

The default history name for the Advanced Optimization run is $AOP.n$, where n is the number of advanced optimization run.

Related Topics

[Advanced Optimization](#)

[Advantages of Advanced Optimization](#)

[AOP Options Form](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

[Loading a Setup State](#)

Virtuoso Variation Option User Guide

Advanced Optimization

Yield Improvement

Virtuoso Variation Option provides the Improve Yield run mode that returns a design to a state where it meets all of the design criteria and has the highest possible yield. If no such point is reached, it runs iterative analyses on the current criteria and determines the conditions for highest possible yield for that design.

The Improve Yield run mode runs iterations of sizing and Monte Carlo analysis to arrive at a solution. When you start the Improve Yield run, Virtuoso Variation Option first generates the statistical corners, then, as the run progresses, evaluates points on a subset of those corners. Promising points are then evaluated on a larger set of corners. Eventually, the tool arrives at the best point—one that has been evaluated at all statistical corners and has the highest possible yield.

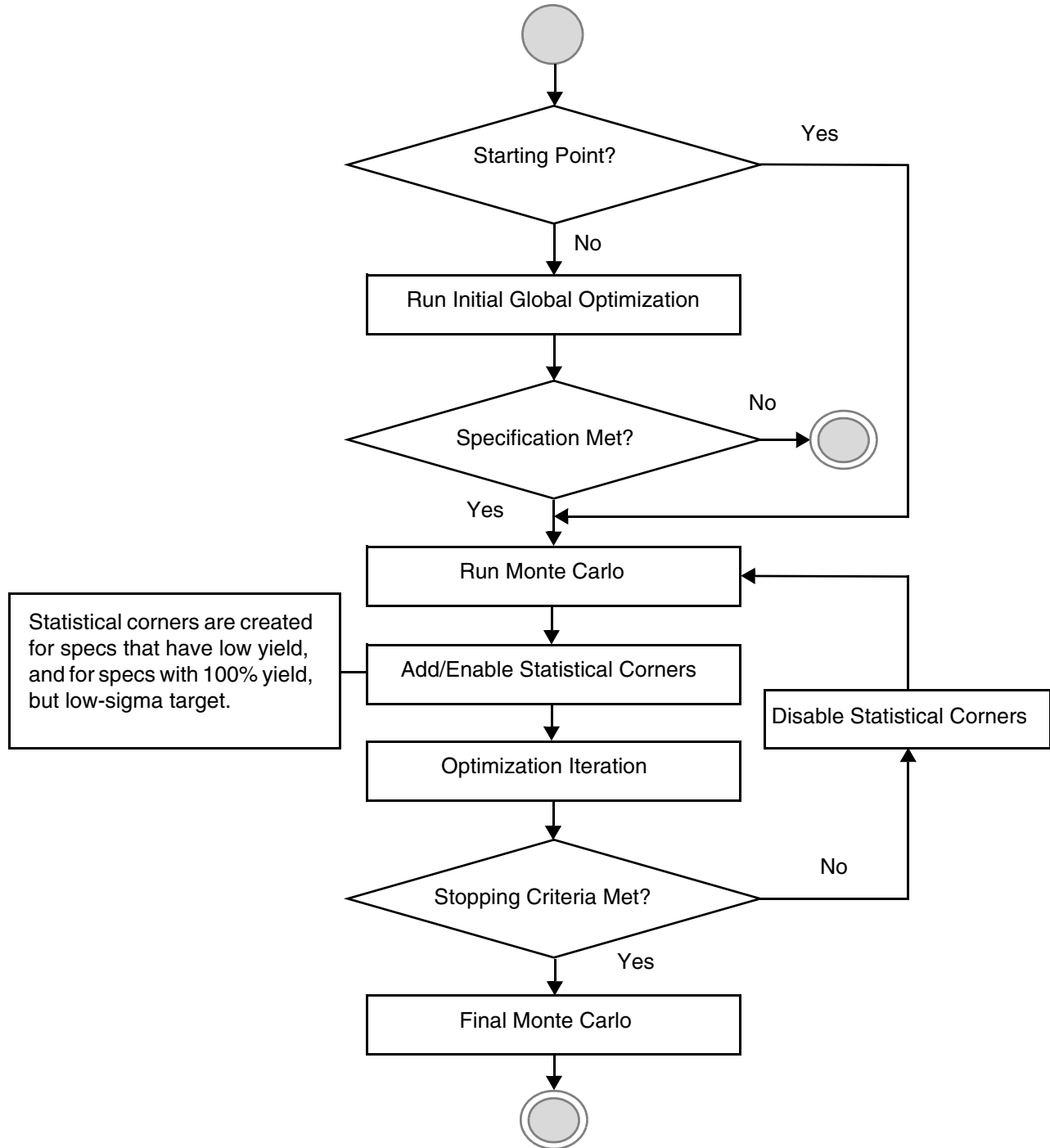
Also available are a number of stopping criteria, including time and points limits. Once the tool hits any of the specified options, it will end the improvement process.

Your design must include devices or device models for which you have specified statistically varying parameter values. You must have one or more specs defined and enabled. You must specify either global (process) or mismatch (per-instance) variations or both. You can also specify correlation information. After simulating, you can select the yield view to view mean and standard deviation information.

Virtuoso Variation Option User Guide

Yield Improvement

The following figure shows the workflow of the *Improve Yield* run mode.



Virtuoso Variation Option User Guide

Yield Improvement

Related Topics

[Improving Yield of a Design](#)

[Full Evaluation and Conditional Evaluation](#)

Full Evaluation and Conditional Evaluation

The optimization options in the Improve Yield mode provides the following evaluation types:

- Full Evaluation

Full evaluation runs all tests for each new design point to compare against the current lowest-cost point (best point).

- Conditional Evaluation

Conditional evaluation first simulates only the tests or corners that failed at the previous point. If the results of those tests and corners are worse than they were at the previous point, the remaining tests and corners are skipped for that design point. This evaluation saves time for optimization over many tests and corners.

Related Topics

[Improve Yield Form](#)

[Improving Yield of a Design](#)

[Advanced Optimization](#)

Improving Yield of a Design

To improve the yield of a design:

1. From the *Select a Run Mode* drop-down list, choose *Improve Yield*.
2. Click *Simulation Options*.

The Improve Yield form opens.

The screenshot shows the 'Improve Yield' dialog box with the following settings:

- Optimization** tab selected.
- Algorithm:** Global Optimization
- Starting Point:** No (Runs Initial Global Optimization)
- Evaluation:** Conditional
- Stopping Criteria:** Recommended
- Time Limit (minutes):** (unchecked)
- Number of Iterations:** 3
- Max Points Per Iteration:** 3000
- Stop Iteration Early If No Improvement:** (unchecked)

3. On the *Optimization* tab, from the *Algorithm* drop-down list, select an optimization algorithm.
4. From the *Starting Point* options, select a starting point for the simulation run.
5. From the *Evaluation* options, select one of the following evaluation types:
 - Full*

Virtuoso Variation Option User Guide

Yield Improvement

Conditional

6. In the *Stopping Criteria* section, select the *Recommended* check box to use the following recommendations for stopping criterion:

- Three sizing/Monte Carlo iterations
- 3000 points run per iteration

If you want to modify the recommended options, select the *Custom* check box, and then select one or more of the following stopping criteria:

- To set a time limit for the run, select the *Time Limit (minutes)* check box and enter a value.
- To specify the number of sizing/Monte Carlo iterations, select the *Number of Iterations* check box and enter the number in the field.
- If you want to specify the maximum number of points processed per iteration, select the *Max Points Per Iteration* check box and enter the number of points in the field.
- If you want to stop the process early if the sizing results in no improvement, select the *Stop Iteration Early If No Improvement* check box.

7. Click the *Monte Carlo* tab to specify the options for Monte Carlo run.

8. From the *Statistical Variation* options, select *Process*, *Mismatch*, or *All*.

9. From the *Sampling Method* drop-down list, select *Random*, *Latin Hypercube*, or *Low-Discrepancy Sequence*.

10. In the *Number of Points* field, specify the number of Monte Carlo points to simulate.

11. If the *Sampling Method* is selected as *Latin Hypercube*, specify the number of bins (subdivisions) in the *Number of Bins* field.

12. (Optional) In the *Monte Carlo Seed* field, enter the seed number. If you do not specify any value the default value 12345 is used.

13. (Optional) If you want to specify a starting run number, select the *Starting Run Number* check box and enter the starting run number.

14. Click *Specify Tests for Monte Carlo* to select the tests for which you want to run the Monte Carlo simulation.

15. Click *OK* to close the form.

16. Click *Run Simulation*.

Virtuoso Variation Option User Guide

Yield Improvement

When the Improve Yield run is finished, the Data View lists the Improve Yield check point. Expanding this check point displays the different runs that make up a full Improve Yield run, including iterations of Optimization and Monte Carlo. You can view the results of any of these runs by right-clicking and choosing View Results.

Several factors are considered in generating statistical corners, which includes overall yield estimate, individual yield of each specification, and sigma to target value of each specification. Statistical corners are created for specs that have low yield as well as for specs that have yield estimate=100%, but low sigma to target value. When the overall yield is high, statistical corners are created at the worst sample. When the yield is low, the Improve Yield method is less effective in creating statistical corners.

Related Topics

[Improve Yield Form](#)

[Full Evaluation and Conditional Evaluation](#)

[Yield Improvement](#)

Virtuoso Variation Option User Guide

Yield Improvement

Virtuoso Variation Option Forms

This section describes the forms used in Virtuoso Variation Option.

- The Monte Carlo form:
The Monte Carlo form lets you set up options to run various Monte Carlo methods.
- The Improve Yield form:
The Improve Yield form lets you specify the options for running Improve Yield mode.
- The AOP Options form:
The AOP Options form lets you specify the options to run advanced optimization.

Related Topics

[Monte Carlo Form](#)

[Improve Yield Form](#)

[AOP Options Form](#)

Monte Carlo Form

The Monte Carlo form lets you set up options to run various Monte Carlo methods.

Field	Description
<i>Method</i>	<p>Lets you select one of the following methods to run Monte Carlo sampling:</p> <ul style="list-style-type: none"> ■ <i>Standard Monte Carlo</i> ■ <i>FMC Worst Samples</i> ■ <i>Sensitivity Accuracy</i> ■ <i>Yield Verification - Autostop</i> <p>In addition, you can also select the following options provided that the corresponding environment variables are set to t.</p> <ul style="list-style-type: none"> ■ <i>Confidence Interval - Autostop</i> <u>showMethodCIAutoStop</u> ■ <i>K-Sigma Corners</i> <u>showMethodKSigmaCorners</u> ■ <i>Yield Verification - Reorder Samples</i> <u>showMethodYieldVerificationReorderSamples</u> ■ <i>Worst Samples</i> <u>showMethodWorstSamples</u> ■ <i>Scaled-Sigma Sampling</i> <u>showMethodScaledSigmaSampling</u> ■ <i>Worst Case Distance</i> <u>showMethodWorstCaseDistance</u>
<i>Variation</i>	<p>Selects one of the following statistical variation options:</p> <ul style="list-style-type: none"> ■ <i>Mismatch</i>: For per-instance statistical variations. ■ <i>Process</i>: For process statistical variations. ■ <i>All</i>: For both process and per-instance statistical variations.

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Max Points</i>	Specifies the maximum number of sample points to simulate while trying to build an accurate model. If a model cannot be constructed even after simulating the maximum number of points, the Monte Carlo run is stopped.
<i>Number of Points</i>	Specifies the number of sample points to simulate. You can use scientific notation to specify values in this field. For example, you can use either <code>1e3</code> or <code>1k</code> to specify 1000 points.
<i>Max Scaling Factor</i>	Specifies the maximum scaling factor to be used for the Scaled-Sigma Sampling method. You can specify a value between 3–7. By default, this field is set to 7, which means that seven child histories using seven different scaling factors will be generated. Environment variable: <code>enableMaxScalingFactorForSSS</code>
<i>Total Samples</i>	Specifies the maximum number of points to be simulated for FMC Worst Sample method.
<i>Target Yield</i>	Specifies the yield value that you want to achieve for your design. It can be expressed either as a sigma value or as a percentage value. The target yield can be any value between <i>3–6 sigma</i> or <i>99.865%</i> .
<i>Tail Samples</i>	Specifies the number of tail samples. If you do not specify the number of tail samples, it is calculated automatically using <i>Total Samples</i> and <i>Target Yield</i> values.
<i>Budget</i>	Specifies the number of simulations to be run for FMC method. For example, <code>500</code> , which indicates that no more than 500 points are simulated for the FMC method. This is an optional field.

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Initial Points</i>	<p>Specifies the number of initial points based on which metrics, such as mean and standard deviations are calculated and annotated in histograms.</p> <p>Specifying higher number of initial points improves the accuracy of the mean and standard deviation measurements.</p> <p>In FMC method, an initial model is built after the initial sampling group finishes. The initial model can be built with additional data points by increasing the number of initial points.</p> <p>This is an optional field.</p>
<i>Points per Job</i>	<p>Lets you control the grouping of Monte Carlo points (Spectre <code>montecarlo numruns</code>):</p> <ul style="list-style-type: none">■ <i>Group automatically</i>: Select this option if you want the tool to determine the grouping and to automatically set the <code>numruns</code> value based on the number of <i>Max Jobs</i>.■ <i>Max</i>: Lets you specify the number of Monte Carlo points. For example, if you specify 1, a separate Spectre netlist is created with <code>numruns=1</code> for each Monte Carlo point.
<i>Create Statistical Corners</i>	<p>Lets you create statistical corners that can further be used in optimizing and debugging the design.</p> <p>This option is available only for <i>Scaled-Sigma Sampling</i> and <i>Worst-Case Distance</i> methods.</p>
<i>Save Waveforms (Simulation Data)</i>	<p>Saves output data (psf files) for every Monte Carlo iteration so that you can perform post-processing operations, such as plotting, printing, annotation, and re-evaluation on individual iterations.</p> <p>This option is not available for <i>Scaled-Sigma Sampling</i> and <i>Worst-Case Distance</i> methods.</p>
<i>Distribution Type and Scaling</i>	<p>Lets you specify the distribution types for Monte Carlo process and mismatch variations.</p> <p>Environment variable: <code>showOptionDistributionTypeAndScaling</code></p>

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Process</i>	<p>Specifies the distribution type for Monte Carlo process variations. The valid values are <i>Gaussian</i> and <i>Uniform</i>.</p> <ul style="list-style-type: none">■ For <i>Gaussian</i>, specify the value by which you want to scale the standard deviation of process variation parameters in the <i>Std Scale</i> field.■ For <i>Uniform</i>, specify the n-scale value for process variation parameters in the <i>N Scale</i> field.
<i>Mismatch</i>	<p>Specifies the distribution type for Monte Carlo mismatch variations. The valid values are <i>Gaussian</i> and <i>Uniform</i>.</p> <ul style="list-style-type: none">■ For <i>Gaussian</i>, specify the value by which you want to scale the standard deviation of mismatch variation parameters in the <i>Std Scale</i> field.■ For <i>Uniform</i>, specify the n-scale value for mismatch variation parameters in the <i>N Scale</i> field.
<i>Probability</i>	<p>Specifies the probability value in percentage.</p> <p>Probability values closer to 100% will require more simulations before the yield estimate can be determined to be lower or higher than the target. Smaller probability values require fewer simulations before autostop is triggered.</p> <p>The default probability is 95%.</p> <p>Environment variable: <u>yieldProbability</u></p>
<i>Stop Percentage</i>	<p>Specifies the percentage value of stopping criteria for the Confidence Interval - Autostop method.</p> <p>Environment variable: <u>confidenceAutoStopPercentage</u></p>
<i>Confidence Level</i>	<p>Determines the confidence interval for the output standard deviation considered by the stopping criteria.</p> <p>Environment variables: <u>confidenceAutoStopLevel</u> and <u>showConfidenceAutoStopLevel</u>.</p>
<i>Confidence Sigma</i>	<p>Determines the range of output variations considered by the stopping criteria.</p> <p>Environment variables: <u>confidenceAutoStopSigma</u> and <u>showConfidenceAutoStopSigma</u>.</p>

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Sampling Method</i>	<p>Selects one of the following statistical sampling methods:</p> <ul style="list-style-type: none">■ <i>Random</i>■ <i>Latin Hypercube</i>■ <i>Low-Discrepancy Sequence</i> <p>For more information, see Statistical Sampling Methods.</p>
<i>Seed</i>	<p>Specifies a seed for the Monte Carlo analysis. You can reproduce a previous experiment by specifying the same seed. If you do not specify a seed, the default value 12345 is used.</p>
<i>First Point</i>	<p>Specifies a starting run number. The first point specifies the run that Monte Carlo begins with. By specifying this number, you can reproduce a particular run or sequence of runs from a previous experiment (for example, to examine an earlier case in more detail).</p>
<i>Netlist Options</i>	<p>Specifies additional analysis options that you want to generate in the netlist.</p> <p>You cannot specify the <code>numruns</code>, <code>firstrun</code>, and <code>seed</code> options in this field.</p> <p>For example: <code>"nullmfactorcorrelation=yes"</code></p>
<i>Specify Instances/ Devices</i>	<p>Click to specify the sensitive instances and devices you want to either include or exclude for applying mismatch variations.</p> <p>For more information, see Specifying Instances for Monte Carlo Mismatch and Process Variation in <i>Virtuoso ADE Explorer User Guide</i>.</p>
<i>Specify Mismatch ID</i>	<p>Click to specify the mismatch ID.</p> <p>For more information see, Introduction to Mismatch ID in <i>Virtuoso ADE Assembler User Guide</i>.</p>
<i>Specify Design Variables</i>	<p>Click to specify design variables that you want to vary with statistical distribution in Monte Carlo analysis.</p> <p>For more information see, Varying Design Variables with Statistical Distribution in <i>Virtuoso ADE Assembler User Guide</i>.</p>

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Worst Case Distance Options</i>	Provides additional options that are related to the Worst-Case Distance method.
<i>Use Monte Carlo History</i>	<p>Selects a reference Monte Carlo run history from the list of available histories. It is essential that the simulation data of the selected history contains the process and mismatch data. If any one of these data is not available, an error message is displayed.</p> <p>The <i>Use Monte Carlo History</i> option is enabled if you have already run a Monte Carlo simulation. You can use the process and mismatch data from the history of that run.</p>
<i>Automatic Number of Monte Carlo Points</i>	<p>Enables the automatic selection of number of Monte Carlo points. When you select this check box, the <i>Number of Points</i> and <i>Automatic Variable Reduction</i> fields become unavailable.</p> <p>To manually specify the number of Monte Carlo points to be simulated, disable this check box.</p>
<i>Automatic Variable Reduction</i>	<p>Reduces the set of statistical variables by eliminating insignificant variables—variables that have no variation or have no influence on the WCD point. Insignificant variables bring noise and require more simulations for sensitivity analysis. Therefore, it is recommended to enable variable reduction.</p> <p>By default, the <i>Automatic Variable Reduction</i> check box is disabled. To enable this check box, first deselect the <i>Automatic Number of Monte Carlo Points</i> check box.</p>
<i>Skip Specs With MC Yield <</i>	<p>Ignores the specifications for which Monte Carlo yield is less than a specified percentage. The default value of this field is 3 σ; therefore, specifications for which the Monte Carlo yield is less than 99.86% are ignored.</p> <p>If you want to run high yield estimation on all the specifications, deselect the <i>Skip Specs With MC Yield <</i> check box.</p>
<i>Max Number of Iterations</i>	Specifies the maximum number of iterations to be run for each specification. The default number of iterations is 10.

Related Topics

Running the Fast Monte Carlo Method

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

[Running the Confidence Interval - Autostop Method](#)

[Statistical Sampling Methods](#)

[Running Mismatch Contribution Analysis](#)

[Running the Yield Verification - Reorder Sample Method](#)

[Running the K-Sigma Corners Method](#)

[Running the Worst Sample Method](#)

[Running the Scaled-Sigma Sampling Method](#)

[Running the Worst-Case Distance Method](#)

[Creating Statistical Corners](#)

[Performing a Standard Monte Carlo Run](#)

Improve Yield Form

The Improve Yield form lets you specify the options for running the *Improve Yield* mode. The form contains the following tabs:

Tab	Description
<u>Optimization Tab</u>	Lets you specify the optimization algorithm, starting point of the simulation run, evaluation type, and stopping criteria.
<u>Monte Carlo Tab</u>	Lets you specify the Monte Carlo run options for the Improve Yield mode.

Optimization Tab

The following table describes the fields available on the *Optimization* tab of the Improve Yield form.

Field	Description
<i>Algorithm</i>	Selects one of the following optimization algorithms: <ul style="list-style-type: none">■ <i>Global Optimization</i>■ <i>BFGS</i>■ <i>Conjugate Gradient</i>■ <i>Brent-Powell</i>■ <i>Hooke-Jeeves</i>

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Starting Point</i>	<p>Selects one of the following options to specify a starting point for the simulation run:</p> <ul style="list-style-type: none">■ <i>Use Starting State</i>: To use the setup state as the starting point for the optimization. Select a setup state that defines a set of fixed values for every global variable or parameter that defines a range of values in the active setup. <p>You must have a setup state available to use this option.</p> <p>Note: If the setup of your cellview earlier used a reference point as a starting point, the details of the starting point have been saved in a setup state named <i>ref_point_migrated</i>. Name of this state is automatically selected in the <i>Use Starting State</i> drop-down list on the form.</p> <ul style="list-style-type: none">■ <i>No (Runs Initial Global Optimization)</i>: To perform an initial global optimization on the nominal corner and to use its best point as the starting point for the run. If you select this option, ensure that:<ul style="list-style-type: none"><input type="checkbox"/> The nominal corner is not disabled in the Run Summary pane.<input type="checkbox"/> For tests that are enabled in the Data View pane, the nominal corner is not disabled in the Corners Setup form.
<i>Evaluation</i>	<p>Lets you select one of the following evaluation methods:</p> <ul style="list-style-type: none">■ Full■ Conditional <p>For more information, see Full Evaluation and Conditional Evaluation.</p>
<i>Stopping Criteria</i>	Lets you use either the recommended options or custom options for stopping criteria.
<i>Time Limit (minutes)</i>	Sets a time limit for the run.
<i>Number of Iterations</i>	Specifies the number of sizing/Monte Carlo iterations. The default is 3.

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Max Points Per Iteration</i>	Specifies the maximum number of points processed per iteration. The default is 3000.
<i>Stop Iteration Early If No Improvement</i>	Stops the process early if the sizing results in no improvement. This option is applied to each optimization iteration. This stopping criteria is similar to the No Improvement with Points stopping criteria for the global or local optimization run modes for which the user also specifies the number of points. In the case of iterative run modes, the number of points is calculated as <i>Max Points Per Iteration</i> / 3.

Monte Carlo Tab

The following table describes the fields available on the *Optimization* tab of the Improve Yield form.

Field	Description
<i>Statistical Variation</i>	Selects one of the following statistical variation options: <ul style="list-style-type: none">■ <i>Mismatch</i>: For per-instance statistical variations.■ <i>Process</i>: For process statistical variations.■ <i>All</i>: For both process and per-instance statistical variations.
<i>Sampling Method</i>	Selects one of the following statistical sampling methods supported by Spectre: <ul style="list-style-type: none">■ <i>Random</i>■ <i>Latin Hypercube</i>■ <i>Low-Discrepancy Sequence</i> For more information, see Statistical Sampling Methods .
<i>Number of Points</i>	Specifies the number of Monte Carlo points to be simulate.

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Number of Bins</i>	<p>Specifies the number of bins (subdivisions) for the Latin Hypercube method.</p> <ul style="list-style-type: none">■ If a number is specified, the number of bins will be the specified number, or (Number of Points + Starting Run Number - 1), whichever is greater. <p>For example, if the specified number of bins is 90, the number of points specified in the <i>Number of Points</i> field is 100 and the starting run number specified in the <i>Starting Run Number</i> field is 6, the value 105 (100+6-1) is used.</p> <ul style="list-style-type: none">■ If no number is specified, a default value of (<i>Number of Points</i> + <i>Starting Run Number</i> - 1) is used. <p>For example, if the number of points specified in the <i>Number of Points</i> field is 100 and the starting run number specified in the <i>Starting Run Number</i> field is 6, the default value of 105 (100+6-1) is used.</p>
<i>Run Normal Simulation</i>	Runs normal simulation.
<i>Monte Carlo Seed</i>	<p>Specifies a seed for the Monte Carlo analysis.</p> <p>By always specifying the same seed, you can reproduce a previous experiment.</p> <p>If you do not specify a seed, the value 12345 is used by default.</p>
<i>Starting Run Number</i>	<p>Specifies the run that Monte Carlo begins with.</p> <p>By specifying this number, you can reproduce a particular run or sequence of runs from a previous experiment, for example, to examine an earlier case in detail.</p> <p>Note: To reproduce a run or sequence of runs, you need to specify the same value in the <i>Starting Run Number</i> and the <i>Monte Carlo Seed</i> fields.</p>
<i>Specify Instances/ Devices</i>	<p>Click to specify the sensitive instances and devices you want to either include or exclude for applying mismatch variations.</p> <p>For more information, see Specifying Instances for Monte Carlo Mismatch and Process Variation in <i>Virtuoso ADE Explorer User Guide</i>.</p>

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Specify Tests for Monte Carlo</i>	Click to select the tests for which you want to run Monte Carlo simulation.

Related Topics

[Improving Yield of a Design](#)

[Full Evaluation and Conditional Evaluation](#)

[Statistical Sampling Methods](#)

AOP Options Form

The AOP Options form lets you specify the options to run advanced optimization method.

Field	Description
<i>Method</i>	Lets you select the optimization algorithm. You can create your custom optimization algorithm in either C++ or Python.
<i>Starting State</i>	Lets you select the setup state you want to use as the starting state. ADE Assembler allows you to create setup states that contain complete or part of the simulation setup. You can later restore the simulation setup from the setup state by loading all or part of the settings in the setup state.
<i>Optimizer Properties</i>	Lets you view the properties of the selected optimization algorithm.
<i>Evaluation</i>	Lets you select one of the following evaluation methods: <ul style="list-style-type: none">■ Full■ Conditional For more information, see Full Evaluation and Conditional Evaluation .
<i>Stopping Criteria</i>	Lets you specify criteria of duration of time for which advanced optimization must run. <ul style="list-style-type: none">■ <i>All Specs Met</i>: Runs until all goals are met■ <i>Time Limit (minutes)</i>: Sets a time limit for the run■ <i>Point Limit</i>: Sets a limit for the number of points to run■ <i>No Improvement with Points</i>: Stops sizing when no improvement is seen for a specified number of points You cannot select both the <i>Point Limit</i> and <i>No Improvement with Points</i> check boxes simultaneously.■ <i>Points After All Specs Met</i>: Continues exploring the design space for a better solution even all specifications are met. You cannot select both the <i>All Specs Met</i> and <i>Points After All Specs Met</i> check boxes simultaneously.

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Field	Description
<i>Optimizer</i> <i>HyperParameters</i>	Groups hyperparameters defined in the selected custom optimization algorithm.

Related Topics

[Advanced Optimization](#)

[Advantages of Advanced Optimization](#)

[Running Advanced Optimization](#)

[Example of Custom Optimization Algorithm](#)

[Integrating a Custom Optimizer into ADE Assembler](#)

[Loading a Setup State](#)

[Hyperparameters of Valhalla Optimizer](#)

[Hyperparameters of Optuna Optimizer](#)

[Hyperparameters of Dakota Optimizer](#)

[Hyperparameters of Particle Swarm Optimizer](#)

Virtuoso Variation Option User Guide

Virtuoso Variation Option Forms

Environment Variables

This section provides information on the names, descriptions, and graphical user interface equivalents of the environment variables used in Virtuoso Variation Option.

confidenceAutoStopLevel

confidenceAutoStopPercentage

confidenceAutoStopSigma

digitsToShowForYieldInPercentage

enableMaxScalingFactorForSSS

maxPointsForSensitivityAccuracy

showConfidenceAutoStopLevel

showConfidenceAutoStopSigma

showMethodCIAutoStop

showMethodKSigmaCorners

showMethodScaledSigmaSampling

showMethodWorstCaseDistance

showMethodWorstSamples

showMethodYieldVerificationAutoStop

showMethodYieldVerificationReorderSamples

showOptionDistributionTypeAndScaling

sortVariablesOpt

Virtuoso Variation Option User Guide

Environment Variables

useDoubleSidedSigma

WCCEnableNewlyCreatedCorners

yieldProbability

yieldViewKSigma

Virtuoso Variation Option User Guide

Environment Variables

confidenceAutoStopLevel

```
maestro.monte confidenceAutoStopLevel float confidenceLevel
```

Description

Specifies the default value of *Confidence Level* to be used in the Confidence Interval - Autostop method. You can specify any floating point value between 0.0–100000.0.

The default value is 95.0.

GUI Equivalent

Form	The <i>Advanced - Show All Options</i> section on the Monte Carlo form.
Field	<i>Confidence Level</i>

Examples

```
envGetVal("maestro.monte" "confidenceAutoStopLevel")  
envSetVal("maestro.monte" "confidenceAutoStopLevel" 'float 100.0)
```

Related Topics

[The Confidence Interval - Autostop Method](#)

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Monte Carlo Form](#)

confidenceAutoStopPercentage

```
maestro.monte confidenceAutoStopPercentage float stopPercentage
```

Description

Specifies the default value of *Stop Percentage* to be used in the Confidence Interval - Autostop method. You can specify any floating point value between 0.0–100000.0.

The default value is 5.0.

GUI Equivalent

Form	The <i>Advanced - Show All Options</i> section on the Monte Carlo form.
Field	<i>Stop Percentage</i>

Examples

```
envGetVal("maestro.monte" "confidenceAutoStopPercentage")  
envSetVal("maestro.monte" "confidenceAutoStopPercentage" 'float 100.0)
```

Related Topics

[The Confidence Interval - Autostop Method](#)

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Monte Carlo Form](#)

confidenceAutoStopSigma

```
maestro.monte confidenceAutoStopSigma float confidenceSigma
```

Description

Specifies the default value of *Confidence Sigma* to be used in the Confidence Interval - Autostop method. You can specify any floating point value between 0.0–100000.0.

The default value is 3.0.

GUI Equivalent

Form	The <i>Advanced - Show All Options</i> section on the Monte Carlo form.
Field	<i>Confidence Sigma</i>

Examples

```
envGetVal("maestro.monte" "confidenceAutoStopSigma")  
envSetVal("maestro.monte" "confidenceAutoStopSigma" 'float 5.0)
```

Related Topics

[The Confidence Interval - Autostop Method](#)

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Monte Carlo Form](#)

Virtuoso Variation Option User Guide

Environment Variables

digitsToShowForYieldInPercentage

```
adexl.gui digitsToShowForYieldInPercentage int digitsInYieldPercentage
```

Description

Specifies the number of digits to be displayed for values in the *Yield In Percentage* column on the *Results* tab for High Yield Estimation run. You can specify any integer value between 10–53.

The default value is 10.

GUI Equivalent

None

Examples

```
envGetVal("adexl.gui" "digitsToShowForYieldInPercentage")  
envSetVal("adexl.gui" "digitsToShowForYieldInPercentage" 'int 12)
```

Related Topics

[High Yield Estimation](#)

[Yield View of the Scaled-Sigma Sampling Method](#)

[Yield View of the Worst-Case Distance Method](#)

Virtuoso Variation Option User Guide

Environment Variables

enableMaxScalingFactorForSSS

```
maestro.monte enableMaxScalingFactorForSSS boolean { t | nil }
```

Description

Specifies whether to show the *Max Scaling Factor* field in the *Advanced - Show All Options* section of the Monte Carlo form when the *Method* is *Scaled-Sigma Sampling*.

The default value is `nil`, which indicates that the *Max Scaling Factor* field is hidden.

GUI Equivalent

Form	The <i>Advanced - Show All Options</i> section on the Monte Carlo form.
Field	<i>Max Scaling Factor</i>

Examples

```
envGetVal("maestro.monte" "enableMaxScalingFactorForSSS")
envSetVal("maestro.monte" "enableMaxScalingFactorForSSS" 'boolean t)
```

Related Topics

[The Scaled-Sigma Sampling Method](#)

[Monte Carlo Form](#)

Virtuoso Variation Option User Guide

Environment Variables

maxPointsForSensitivityAccuracy

```
maestro.monte maxPointsForSensitivityAccuracy int maxPointsToSimulate
```

Description

Specifies the maximum number of sample points to be simulated for the Sensitivity Accuracy method. You can specify any integer value between 1–100000.

The default value is 100000.

GUI Equivalent

None

Examples

```
envGetVal("maestro.monte" "maxPointsForSensitivityAccuracy")  
envSetVal("maestro.monte" "maxPointsForSensitivityAccuracy" 'int 50000)
```

Virtuoso Variation Option User Guide

Environment Variables

showConfidenceAutoStopLevel

```
maestro.monte showConfidenceAutoStopLevel boolean { t | nil }
```

Description

Specifies whether to show the *Confidence Level* field in the Monte Carlo form when the *Method* is selected as *Confidence Interval - Autostop*.

The default value is `nil`, which indicates that the *Confidence Level* field is hidden.

The *Confidence Interval - Autostop* method is hidden from the *Method* drop-down list by default. Set the following environment variable to `t` to display it.

```
envSetVal("maestro.monte" "showMethodCIAutoStop" 'boolean t)
```

GUI Equivalent

The *Confidence Level* field in the Monte Carlo form.

Examples

```
envGetVal("maestro.monte" "showConfidenceAutoStopLevel")
envSetVal("maestro.monte" "showConfidenceAutoStopLevel" 'boolean t)
```

Related Topics

[The Confidence Interval - Autostop Method](#)

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Monte Carlo Form](#)

[showMethodCIAutoStop](#)

Virtuoso Variation Option User Guide

Environment Variables

showConfidenceAutoStopSigma

```
maestro.monte showConfidenceAutoStopSigma boolean { t | nil }
```

Description

Specifies whether to show the *Confidence Sigma* field in the Monte Carlo form when the *Method* is selected as *Confidence Interval - Autostop*.

The default is `nil`, which indicates that the *Confidence Sigma* field is hidden.

The *Confidence Interval - Autostop* method is hidden from the *Method* drop-down list by default. Set the following environment variable to `t` to display it.

```
envSetVal("maestro.monte" "showMethodCIAutoStop" 'boolean t)
```

GUI Equivalent

The *Confidence Sigma* field in the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showConfidenceAutoStopSigma")
envSetVal("maestro.monte" "showConfidenceAutoStopSigma" 'boolean t)
```

Related Topics

[The Confidence Interval - Autostop Method](#)

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Monte Carlo Form](#)

[showMethodCIAutoStop](#)

Virtuoso Variation Option User Guide

Environment Variables

showMethodCIAutoStop

```
maestro.monte showMethodCIAutoStop boolean { t | nil }
```

Description

Specifies whether to show the *Confidence Interval - Autostop* option in the *Method* drop-down list of the Monte Carlo form.

The default is `nil`, which indicates that the *Confidence Interval - Autostop* option is hidden.

GUI Equivalent

The *Confidence Interval - Autostop* option in the *Method* drop-down list of the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showMethodCIAutoStop")
envSetVal("maestro.monte" "showMethodCIAutoStop" 'boolean t)
```

Related Topics

[The Confidence Interval - Autostop Method](#)

[Advanced Options of the Confidence Interval - Autostop Method](#)

[Monte Carlo Form](#)

[showConfidenceAutoStopLevel](#)

[showConfidenceAutoStopSigma](#)

showMethodKSigmaCorners

```
maestro.monte showMethodKSigmaCorners boolean { t | nil }
```

Description

Specifies whether to show the *K-Sigma Corners* option in the *Method* drop-down list of the Monte Carlo form.

The default is `nil`, which indicates that the *K-Sigma Corners* option is hidden.

GUI Equivalent

The *K-Sigma Corners* option in the *Method* drop-down list of the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showMethodKSigmaCorners")  
envSetVal("maestro.monte" "showMethodKSigmaCorners" 'boolean t)
```

Related Topics

[The K-Sigma Corners Method](#)

[Running the K-Sigma Corners Method](#)

[Monte Carlo Form](#)

showMethodScaledSigmaSampling

```
maestro.monte showMethodScaledSigmaSampling boolean { t | nil }
```

Description

Specifies whether to show the *Scaled-Sigma Sampling* option in the *Method* drop-down list of the Monte Carlo form.

The default is `nil`, which indicates that the *Scaled-Sigma Sampling* option is hidden.

GUI Equivalent

The *Scaled-Sigma Sampling* option in the *Method* drop-down list of the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showMethodScaledSigmaSampling")  
envSetVal("maestro.monte" "showMethodScaledSigmaSampling" 'boolean t)
```

Related Topics

[The Scaled-Sigma Sampling Method](#)

[Running the Scaled-Sigma Sampling Method](#)

[Monte Carlo Form](#)

showMethodWorstCaseDistance

```
maestro.monte showMethodWorstCaseDistance boolean { t | nil }
```

Description

Specifies whether to show the *Worst Case Distance* option in the *Method* drop-down list of the Monte Carlo form.

The default is `nil`, which indicates that the *Worst Case Distance* option is hidden.

GUI Equivalent

The *Worst Case Distance* option in the *Method* drop-down list of the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showMethodWorstCaseDistance")  
envSetVal("maestro.monte" "showMethodWorstCaseDistance" 'boolean t)
```

Related Topics

[The Worst-Case Distance Method](#)

[Running the Worst-Case Distance Method](#)

[Monte Carlo Form](#)

showMethodWorstSamples

```
maestro.monte showMethodWorstSamples boolean { t | nil }
```

Description

Specifies whether to show the *Worst Samples* option in the *Method* drop-down list of the Monte Carlo form.

The default is `nil`, which indicates that the *Worst Samples* option is hidden.

GUI Equivalent

The *Worst Samples* option in the *Method* drop-down list of the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showMethodWorstSamples")  
envSetVal("maestro.monte" "showMethodWorstSamples" 'boolean t)
```

Related Topics

[The Worst Samples Method](#)

[Running the Worst Sample Method](#)

[Monte Carlo Form](#)

showMethodYieldVerificationAutoStop

```
maestro.monte showMethodYieldVerificationAutoStop boolean { t | nil }
```

Description

Specifies whether to show the *Yield Verification - Autostop* option in the *Method* drop-down list of the Monte Carlo form.

The default is `nil`, which indicates that the *Yield Verification - Autostop* option is hidden.

GUI Equivalent

The *Yield Verification - Autostop* option in the *Method* drop-down list of the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showMethodYieldVerificationAutoStop")
envSetVal("maestro.monte" "showMethodYieldVerificationAutoStop" 'boolean t)
```

Related Topics

[Yield Verification](#)

[Monte Carlo Form](#)

showMethodYieldVerificationReorderSamples

```
maestro.monte showMethodYieldVerificationReorderSamples boolean { t | nil }
```

Description

Specifies whether to show the *Yield Verification - Reorder Samples* option in the *Method* drop-down list of the Monte Carlo form.

The default is `nil`, which indicates that the *Yield Verification - Reorder Samples* option is hidden.

GUI Equivalent

The *Yield Verification - Reorder Samples* option in the *Method* drop-down list of the Monte Carlo form

Examples

```
envGetVal("maestro.monte" "showMethodYieldVerificationReorderSamples")  
envSetVal("maestro.monte" "showMethodYieldVerificationReorderSamples" 'boolean t)
```

Related Topics

[Yield Verification](#)

[Workflow of the Yield Verification - Reorder Samples Method](#)

[Running the Yield Verification - Reorder Sample Method](#)

[Monte Carlo Form](#)

showOptionDistributionTypeAndScaling

```
maestro.monte showOptionDistributionTypeAndScaling boolean { t | nil }
```

Description

Specifies whether to show *Distribution Type and Scaling* options in the Monte Carlo form.

The default is `nil`, which indicates that the *Distribution Type and Scaling* options are hidden.

GUI Equivalent

None

Examples

```
envGetVal("maestro.monte" "showOptionDistributionTypeAndScaling")  
envSetVal("maestro.monte" "showOptionDistributionTypeAndScaling" 'boolean t)
```

Related Topics

[Monte Carlo Form](#)

Virtuoso Variation Option User Guide

Environment Variables

sortVariablesOpt

```
adexl.algorithm sortVariablesOpt boolean { t | nil }
```

Description

Specifies whether the variables and parameters are sorted before generating random samples for an optimization run.

The default value is `nil`, which indicates that the variables are not sorted before the run is started. However, you can sort them by setting this variable to `t` to ensure that the results of different optimization runs are the same irrespective of the order of variables and parameters.

GUI Equivalent

None

Examples

```
envGetVal("adexl.algorithm" "sortVariablesOpt")  
envSetVal("adexl.algorithm" "sortVariablesOpt" 'boolean t)
```

Virtuoso Variation Option User Guide

Environment Variables

useDoubleSidedSigma

```
adexl.algorithm useDoubleSidedSigma boolean { t | nil }
```

Description

Specifies whether to create single-sided or double-sided K-Sigma statistical corners.

The default is `nil`, which indicates that single-sided K-Sigma corners are created.

GUI Equivalent

None

Examples

```
envGetVal("adexl.algorithm" "useDoubleSidedSigma")
envSetVal("adexl.algorithm" "useDoubleSidedSigma" 'boolean t)
```

Related Topics

[The K-Sigma Corners Method](#)

[Running the K-Sigma Corners Method](#)

[Creating K-Sigma Corners from a Standard Monte Carlo Run](#)

WCCEnableNewlyCreatedCorners

```
adexl.gui WCCEnableNewlyCreatedCorners boolean { t | nil }
```

Description

Specifies whether to enable or disable the statistical corners that are created after worst-case corner simulation.

The default is `t`, which indicates that the worst-case corners are enabled.

GUI Equivalent

None

Examples

```
envGetVal("adexl.gui" "WCCEnableNewlyCreatedCorners")  
envSetVal("adexl.gui" "WCCEnableNewlyCreatedCorners" 'boolean nil)
```

yieldProbability

`adexl.monte yieldProbability float percentageValue`

Description

Specifies the yield probability (significance level) in percentage. Probability values closer to 100% require more simulations before the yield estimate is determined to be lower or higher than the target. Smaller probability values require fewer simulations before the auto-stop is triggered.

You can specify any floating point value between 0.0–100.0. The default is 95.0.

GUI Equivalent

None

Examples

```
envGetVal("adexl.monte" "yieldProbability")
envSetVal("adexl.monte" "yieldProbability" 'float 100.0)
```

Related Topics

[Monte Carlo Form](#)

[Running the Yield Verification - Reorder Sample Method](#)

[Running the Worst Sample Method](#)

Virtuoso Variation Option User Guide

Environment Variables

yieldViewKSigma

```
maestro.gui yieldViewKSigma string listOfKSigmaValues
```

Description

Specifies the value or a list of values of K-Sigma that you want to display as columns in the *Yield* view of a Monte Carlo result. You can specify a list of either comma-separated values or space-separated values.

The default value is 3.

GUI Equivalent

The *K-Sigma* field in the Set K-Sigma form.

Examples

```
envGetVal("maestro.gui" "yieldViewKSigma")
envSetVal("maestro.gui" "yieldViewKSigma" 'string "1,3,4.5")
envSetVal("maestro.gui" "yieldViewKSigma" 'string "1 3 4.5")
```

Related Topics

[Displaying Mean K-Sigma and Median Columns in the Yield View](#)