Views on Important Direction in Design Automation

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My primary research experience in design automation has been almost entirely at the lower levels: circuits, interconnect, and MEMS, with some recent efforts in photonics and carbon nanotubes. So even though I believe there are important research directions at the higher levels of design automation, I do not feel sufficiently informed to comment.

From my perspective, an exciting era of design tool development is being generated by a combination of worsening design problems and emerging methodological innovations. The worsening problems are broadening technological diversity and increasing manufacturing variability, and the methodological innovations are in fast solvers, parameterized and nonlinear model reduction, and robust optimization. More specifically, in order to enable the design of working complicated systems, designers of functional blocks (e.g. an RF front end, an electro-optical low-skew clock distribution system) will need to be far more aggressive in the use of techniques which generate variability insensitive designs, while also incorporating incomprehensively-characterized emerging technology. These designers will need a collection of new tools to analyze and synthesize such reliable functional blocks, and such new tools can be developed by leveraging recent methodical innovations. I list a few examples below.

Fast worst case analysis

At the circuit level, the standard approaches for determining worst case performance under process variation is to perform either process corner analysis or monte carlo analysis. In these two approaches, many simulations are performed where the parameters of each transistor are adjusted. In monte carlo analysis, the adjustment is random, in process corner analysis the parameters are adjusted by selecting from a process corner set. Either approach to worst case analysis is too expensive and perhaps too error prone to be useful during design. The worst-case analysis problem becomes even less tractable when emerging technology is considered, as often the only available models for such technology are systems of partial differential equations.
A faster strategy might be to extract approximate parameterized nonlinear models (PNLMOR), and then use the extracted model to determine worst case parameter sets, greatly accelerating the simulation. For emerging technology, it may be possible to design robust devices by developing fast methods for finding worst-case solutions to parameterized partial differential equations.

Robust Optimization Coupled with Fast Solvers for Emerging Technology

For components using emerging technology, such as nanophotonic devices, many MEMS components, nanowire or carbon nanotube transistors, or even for novel passive structures using interconnect,the only available models may be partial differential equations. In order to synthesize components to be manufacturable, and therefore robust to process variation, it is natural to try to develop robust optimization algorithms that interact efficiently with models given by partial differential equations. Possible approaches might simultaneously find the robust optimum while solving the partial differential equation (PDE), or could apply robust optimization to a parameterized model extracted from the PDE. In either case, fast solvers will be needed to resolve the PDE, but these fast solvers must be flexible enough so that they: need not be written from scratch for every new PDE, can be coupled for multiphysics problems, and can be efficiently modified to couple to robust optimization.

Hierarchical Robust Optimization

One major advantage indicated by the recent developments in robust optimization is that, unlike nominal optimization methods, robust methods find good designs even when the underlying models are in error (nominal optimization often exploits modeling errors to create erroneous "excellent" designs). This aspect of robust optimization implies that hierarchical approaches may succeed even when errors are introduced while moving up the hierarchy. Characterizing the landscape of "allowable" errors may lead to efficient automatic reduction strategies useful for robust optimization. Such strategies would not require a general solution to the nonlinear reduction problem, as finding such a general solution has proved remarkably stubborn.