Guiding Lessons from Workshop and Toy Models

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# Preface

This document is not meant to re-summarize the project’s other summaries of lessons from the toy models and the workshop. See the [fact sheets](https://github.com/NREL/portfolio/tree/master/workshop/fact%20sheets), [slide presentations](https://github.com/NREL/portfolio/tree/master/workshop/presentations), and [workshop report](https://github.com/NREL/portfolio/tree/master/workshop/report) for these. Rather, it states high-level conclusions that are actionable for continued development of the analytic framework.

# Conclusions

1. There is enough commonality between ***stochastic optimization*** methods (cf. the *Monte Carlo*, *Real Options*, and *TRL-TPL* models) and ***stochastic programming*** methods (cf. the *Biorefinery Model* and Gabriel’s work) that the analytic framework should be abstract and general enough to encompass both ensemble simulations, linear/non-linear programming, and dynamic programming, although it may be too much effort to formulate individual models so that they can be run in all three modes.
2. Models (*Polysilicon*, *Biorefinery*, and *Real Options*) are mildly ***non-linear***, so it likely is preferable to use non-linear solvers instead of forcing a linearization or an analytic solution.
3. Decision-theoretic approaches rely on similar themes of finding ***non-dominated solutions*** or ***robust decisions***, regardless of whether a probabilistic or (scenario-generative) non-probabilistic framework is used, though the probabilistic methods result in information such as confidence intervals.
4. ***Multi-objective*** optimization is a necessity.
5. ***Model complexity*** should be kept to a manageable (one or two dozen) set of system components, subcomponents, or decidable parameters. The *Polysilicon Model* probably represents the upper limit of complexity. Klemun’s work on overall system costs provides an important example of combining ***hard and soft costs*** for several systems and for the balance of the system. Highly leveragable investments needs to be represented via physics-based modeling.
6. ***Real options*** can be subsumed under the more general ***multi-stage stochastic optimization***, but two-stage optimization is advisable for R&D investment decisions, because of the uncertainty involved. Studying the performance of a two-stage decisions-support process might involve nesting within a higher level optimization. Discrete methods such as *Petri Nets* are not needed for two-stage decision models.
7. ***Expert opinion*** might be best represented as assessments of future trends in ***experience curves*** that are based on historical experience, perhaps as confidence intervals or odds ratios instead of detailed specificaitions of probability distributions.
8. Portfolio-level decisions will inevitably involve a ***hierarchy*** of programs, systems, subsystems, and components within and between portfolios.
9. ***Bayesian updating*** of expert opinions requires too much training history—especially where rare events might be an issue—and is not sufficiently informative to warrant the complexity it adds. Schemes not involving temporal updates are best for near-term development of the analytic framework.
10. The concepts of ***Technology Readiness Level*** and ***Technology Performance Level*** may be too high level for modeling, though they may be useful in communication.
11. In the long term, ***SEDS*** may play an important role in contextualizing and evaluating portfolios, so compatibility, both in method and software, needs consideration.