Distribution Network Expansion Planning (DNEP)

In monopolistic environment for energy transmission network capacities were designed with a wide safety margin, so for a long time expansion planning in electrical energy systems was concentrated on generation expansion planning (GEP) with the goal to cover cumulative demand uncertainty based on averaged historic demand data. These were modeled as stochastic optimization problems with a one dimensional demand distribution represented by 2-stage or multi-stage scenario trees that were generated by Monte Carlo methods. The models went to the limit of computational possibilities at any point in time,
included binary decision variable, with a risk neutral approach and, then, only expected values in the objective function where considered in the time horizon over the scenarios. Very limited use was made of risk averse measures.

In order to solve the large scale problems, decomposition methods played a central role, in particular the following methodologies:

- Two-stage Benders Decomposition (BD) for linear problems [11]. See [8,37,55], among many others.
- Multistage Benders Decomposition (BD) methodology for linear problems. See [13] among others.
- Two-stage Lagrangean Decomposition (LD) heuristic methodology. See [14,1718,29,28,33,41,42], among many others. See also [2, 56] for two surveys on the state-of-the-art of two-stage stochastic unit commitment, and using LD with bundle methods. See also [1,16,51] two-stage LD approaches with bundle methods applied to energy problems.
- Multistage Clustering Lagrangean Decomposition (MCLD) heuristic methodology. See [21,22,23,38], among some others.
- Regularization methods. See [9, 33, 39, 49, 50, 53], among others.
- Progressive Hedging algorithm (PHA) for multistage primal decomposition. See [47,57], among others.
- Multistage Stochastic Dynamic Programming (SDP). See [4,15,25,26,30,32,40,44,45,48,54], among others.
- Multistage cluster primal decomposition. See [5,7,10,19,24,38,43,52,58], among others.
- Parallelized decomposition algorithms. See [3,4,5,6,9,12,34,39,43,48,52,58], among others.

Today, new power production possibilities, technological developments and deregulation bring along several new sources of uncertainty with highly differing levels of variability. In addition to traditional demand these are foremost dependencies on wind, market prices, mobile electricity consumers like cars, power exchanges on international level, local energy producers on distribution network level and, to a lesser extent, solar radiation. This introduces complex and volatile load and demand structures that pose a severe challenge for strategic planning in production and transmission and, on a shorter time scale, in distribution. Networks may now be equipped with new infrastructure like Phase Measurement Units (PMUs) and other information technology in order to improve their cost efficiency. At the same time these upgraded networks should ensure high standards in reliability in their daily use and resilience against natural or human caused disasters. Companies now have teams devoted to the task of generating suitable planning data.

In optimization models, the emphasis has shifted to high dimensional stochastic data and to considering risk reduction measures instead of expected values. Computationally integrated models considering all relevant aspects are out of scope. Even for simplified models it is often difficult or not known how to provide stochastic data of sufficient quality [63]. Alternatives are then:

- robust optimization, where distributions are replaced by "easier" uncertainty sets [59],
- fuzzy methods, where uncertainties are replaced by a kind of interval arithmetic equipped with scenario dependent probabilities [60],
- information gap decision theory that aims at hedging against information errors [61,62].

Methods for solving these stochastic optimization problems with binary decision variables employ the same decomposition approaches listed above, but much more care needs to be devoted to the properties of the decomposition. For risk averse measures in multistage models, methods are distinguished regarding their "time consistency" or "time inconsistency". So far, stochastic dynamic programming approaches are the most suitable ones for dealing with the time consistency property of risk measures, so that the original stochastic problem may be decomposed more easily via scenario clustering and cluster dependent risk levels.

In power generation optimization models for big companies the following are the issues of relevance, mainly addressed in the context of market competition:

- when and where to install how much new production capacity, mainly considering wind generators and thermal plants (decisions on nuclear power are political)
- how to extend or renew hydro plants and where to install what pumping capacities. Today, solar power is typically handled at the level of distribution networks.

In contrast, competition is not an issue for transmission and distribution network operators. Regulations on efficiency, reliability and resilience levels are the driving force in the following problems:

- when and where to install how much network capacity and information equipment,
- reducing transmission losses,
- reducing distribution losses (technical and detecting non-technical ones).

Challenges today and for the future comprise:

- The robust approach allows for safe optimization with uncertain data. What information can be extracted from these robust solutions e.g. on which additional data would be needed to improve the quality of the model?
- Several risk averse measures have been proposed, each with its advantages and disadvantages. How to make use of them in the best way?
- How to deal with endogenous uncertainty, i.e., with optimizing big player decisions that influence the probability distributions that are optimized over?
- How to construct hierarchical decomposition approaches in a consistent way?
- How to make use of high performance computing (HPC, multi-core or Distributed) in decomposition approaches?

- How to integrate chance constraints (ICC), e.g. with respect to reliability or resilience?

General goals for future models include: increasing the level of integration; bringing models closer to reality by avoiding the excessive linearization of nonlinear aspects; reducing the gap between methods used in academia and those applied in practice; making use of new monitoring devices and communication systems; exploring the chances of cooperation between electric and other energy commodity systems.

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