Unit Commitment under uncertainty

The integration of the production of renewable sources, due to its uncertainty, must be adequately addressed to avoid affecting the operational reliability of a power system. Unit commitment (UC) is a critical decision process which consists in an optimization problem to generate the outputs of all the generators to minimize the system cost. Generally, UC decisions are made once a day, 24 or more hours before the actual operation.

The main principle in operating an electrical system is to cover the demand for electricity at all times and under different conditions depending on the season, weather and time. The common goal of UC formulations is to minimize the operating cost, while ensuring sufficient reserve to accommodate real-time realization of uncertainty. The main difference between models is the representation of this uncertainty.

The deterministic UC formulation is a traditional solution in which the net load is modeled using a single forecast for each renewable output and the associated uncertainty is managed using ad hoc rules (i.e. the generating units are committed to meeting the deterministic prediction and the uncertainty is managed by imposing reserve requirements [1]). This approach is easy to implement in practice, but ad hoc rules do not necessarily adequately reflect uncertainty. For this reason, different approaches are used to manage the UC under uncertainty.

The UC available approaches in literature are[2]:

- **Stochastic UC**

Stochastic UC is based on probabilistic scenarios. A finite set of scenarios is generated with assigned weight for each scenario. The basic idea is to generate a large number of scenarios where each scenario represents a possible realization of the underlying uncertain factors. Stochastic UC is generally formulated as a two-stage problem that determines the generation schedule to minimize the expected cost over all of the scenarios respecting their probabilities. There is a difference between commitment and dispatch decisions: the first are the same for all the scenarios, the second are different for each scenario. The large number of scenarios in the model requires high computational demand for simulations. Similar scenarios are aggregated based on, for example, their probability or the cost [2]. The structure of scenarios can be a number of parallel scenarios in a two-stage problem or a scenario tree in a multistage problem. Monte Carlo simulation [3] is often used to populate the scenarios based on probability distribution functions learned from historical data and to generate scenario trees based on stochastic processes. However, increasing the number of scenarios may lead to small improvements in the solution quality. Thus, Sample Average Approximation (SAA) [4] can be used to test the convergence of the solution. Scenario reduction techniques are used in the literature [5]–[7]. The goal is to reduce the number of scenarios without sacrificing their accuracy to a large extent.

- **Robust UC**

In Robust UC formulations a deterministic set of uncertainty is used, instead of a probability distribution on the uncertain data. For example, the two-stage model in [8] has the first stage which finds the optimal commitment decision, and the second stage which generates the worst case dispatch cost under a fixed solution from the first stage. The range of uncertainty is defined by the upper and lower bounds on the net load at each time period. In place of minimizing the total expected cost as in Stochastic UC, Robust UC reduces the worst costs to the minimum for all possible results of uncertain parameters [9]. These models produce conservative solutions, but they are better from a computational point of view because they can avoid incorporating a large number of scenarios. In the power system literature, Robust UC models have been used to address uncertainties from net electricity injection [10], wind power availability [11], demand-side management [12].

- **Interval UC**

Interval UC formulations minimize the cost of covering the most probable load forecast by ensuring feasibility in the uncertainty range that is delimited with upper and lower bounds as in robust unit commitment formulations. The formulation is more efficient than the stochastic unit commitment formulation: the model can be composed by three scenarios. In particular, the scenarios are: the central forecast, the upper and lower bounds. The transition constraints are modeled as constraints. The interval unit commitment can also be formulated as a two stage problem where the optimal solution is found in the first stage and then tested in the second stage for feasibility. A method is proposed in [13].

- **Hybrid UC**

To improve the advantages and reduce disadvantages of the models presented in the previous parts, hybrid models have been proposed in the last years. Some of these models are unified stochastic and robust unit commitment formulation [14] and stochastic/interval unit commitment formulation [15]. [14] proposes a model able to achieve low expected total cost while ensuring the system robustness. [15] proposes a model that applies the stochastic formulation to the initial hours of the optimization horizon and then switches to the interval formulation for the remaining hours.

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